Factors that influence the adoption of mCommerce applications for purchasing athletic fashion apparel

by

Karen van Niekerk

A dissertation submitted in fulfilment for the Degree

of

Master of Commerce

in

Marketing Management

at the

College of Business and Economics

University of Johannesburg

Supervisor: Prof Mornay Roberts-Lombard

Co-supervisor: Dr Isolde Lubbe

2020

DECLARATION

I certify that the *dissertation s*ubmitted by me for the degree *Master of Commerce (Marketing Management)* at the University of Johannesburg is my independent work and has not been submitted by me for a degree at another university.

KAREN VAN NIEKERK

____

(Name in block letters – no signature)

DEDICATION

I dedicate this study to my family. Thank you for your encouragement, love, patience and support throughout this journey. In the words of Michael J. Fox, who said it so perfectly: “Family is not an important thing. It’s everything.”

ACKNOWLEDGEMENTS

To my husband, for supporting me, motivating me, high-fiving me and keeping me focused. The last three years have not been easy, with us both committing to do our Master's degrees. I could not have walked this path with anyone else.

To my parents, for raising me to be diligent, committed and determined. You gave me the foundation on which my life has been built. You are my biggest fans, always cheering me on. For all that you are – thank you!

To my friends, for checking in, supporting, offering to read my chapters and keeping me going with motivational messages.

To my supervisors, for challenging me, pushing me, keeping me motivated and dealing with all the tears, fears and doubt. Thank you for believing in me and helping me reach this milestone.

And with that I give you, (hopefully), the first of many contributions to digital marketing literature in South Africa.

ABSTRACT

Globally, the fashion industry contributes 2% of the world's gross domestic product (GDP) and employs in excess of 57.8 million people. Over the past decade, the industry has grown at a consistent rate of 5.5% per annum, and is currently valued at over US$3 trillion. The biggest driver of this growth has been athletic wear, enjoying a 6.5 to 7.5% sales growth in 2017. This growth reflects a global movement towards a more active lifestyle and the advent of 'athleisure', a term used to describe clothing that can be used for both exercising and general wear. Similarly, in South Africa the athletic wear retail category grew by 36% over the past five years. Athleisure is reported to be the major trend driving this growth. These purchases have, however, been concentrated at retail stores and not online. The majority of South African consumers' average online spend was allocated to airlines (US$197), hotels (US$163) and paid-for video websites (US$123). Electronic products accounted for US$69 and clothing and accessories for US$49. On mobile platforms, clothing and accessories did not even feature as a category for average mobile spend. Moreover, 47% of South Africans purchased airtime using their mobile phones, 25% purchased apps and related in-app purchases, 33% did not purchase anything on their mobile phones and only 7% purchased clothes, fashion items or beauty products (Erken, 2017). This poses the question: Why do South African shoppers not use their mobile phones to purchase fashion apparel, and more specifically, athleisure apparel, considering its impact on the growth of the athletic wear retail category in South Africa? In order to answer this question, an empirical investigation was conducted. The primary objective of this study was to determine the constructs that influence consumers' acceptance and use of mCommerce apps to purchase athleisure apparel in South Africa. The proposed conceptual model and hypotheses for this study were based on the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2). This model was selected as it has been proven to outperform all the other technology acceptance models. The UTAUT2 has been proven successful in explaining behavioural intention in the fields of mobile payments, mobile Internet and mobile banking research. However, it remains underutilised in mobile shopping research. This study added two additional constructs to the UTAUT2 – perceived risk and trust. These have been repeatedly cited as two key variables impacting consumers' acceptance and use of mCommerce.

The study applied a descriptive research design and used a survey strategy to collect data. A questionnaire was selected as it allowed for the collection of standardised data from a large population. Both self-completed and interviewer-administered questionnaires were used. Five hundred respondents were selected by means of non-probability sampling, specifically quota and convenience sampling. Quotas represented South African consumers who had used an mCommerce app to purchase athleisure apparel over the last 12 months as well as consumers who had purely used it for browsing purposes. The study was conducted in two phases. Phase 1 (Model A) tested the influence of specific constructs on behavioural intention to determine consumers' acceptance of mCommerce apps to purchase athleisure apparel. Phase 2 (Model B) tested the influence of specific constructs on actual use to determine consumers' use of mCommerce apps to purchase athleisure apparel.

The outcome of the SEM analysis for Model A revealed that performance expectancy, habit and trust had a significant influence on behavioural intention. Interestingly, perceived risk was also found to have a significant negative influence on trust. The outcome of the T-test analysis for Model B revealed that habit had a significant influence on when consumers last used a mobile shopping app to purchase athleisure apparel, behavioural intention had a significant influence on the amount of items purchased, facilitating conditions had a borderline significant influence on the amount of time spent shopping per week, habit had a borderline significant influence on the number of mobile shopping apps visited in a given month and behavioural intention had a significant influence on the approximate Rand value of the purchases.

A valid and reliable model was developed to better understand the factors that influence consumers' behavioural intention to use mCommerce apps to purchase athleisure apparel. Twenty-seven recommendations were provided to assist South African fashion retailers and mCommerce app owners to adjust their business strategies accordingly, securing a stronger relational focus, with a beneficial value-add for all parties in the relationship.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1

INTRODUCTION AND BACKGROUND TO THE STUDY

CHAPTER 1: Introduction and background to the study	CHAPTER 2: Evolution of the retail industry in South Africa and the advent of mCommerce	CHAPTER 3: Foundational theories and models grounding the study	CHAPTER 4: Exploring the UTAUT2 with perceived risk and trust
CHAPTER 5: Conceptual model and hypotheses development	CHAPTER 6: Research methodology	CHAPTER 7: Research results	CHAPTER 8: Conclusion and recommendations

1.1 Introduction

Chapter 1 introduces the study by presenting a background to the research. Insights are provided into the international and South African fashion apparel industries and the uptake and usage of mobile commerce or mCommerce platforms, with a particular focus on the purchasing of 'athleisure' apparel. The research problem is then stated, followed by the objectives of the study. A brief literature review explicates the underlying theories supporting the study. The chapter concludes with the proposed research methodology.

1.2 Background

The global fashion industry accounts for 2% of the world's gross domestic product (GDP) and employs more than 57.8 million people. The industry is worth an estimated US$3 trillion and has consistently grown at a rate of 5.5% annually over the past decade (Fashion United, 2019). Athletic wear in particular seems to be leading this growth, with a 6.5 to 7.5% sales growth in 2017 (Amed, Berg, Brantberg & Hedrich, 2017:12). Athletic wear, also referred to as 'activewear' or 'sportswear', is described by the Merriam Webster (2020a) dictionary as attire designed for informal wear or leisure and includes clothing (apparel) and shoes. Globally, the athletic wear category grew by 8 to 8.5% – twice as fast as other categories, including clothing, footwear, watches, jewellery and the like (Amed *et al.,* 2017:43). This growth reflects a global movement towards a more active lifestyle and the advent of ‘athleisure’, a term used to describe clothing that can be used for both exercising and general wear. This type of clothing addresses consumer needs for clothing that is both functional and stylish (Team, 2016). If this category continues to grow at its 10% compound annual growth rate (CAGR) of the past decade, it will soon be able to compete on equal terms with the clothing and footwear categories (Amed *et al.,* 2017:43).

In South Africa, the athletic wear retail category grew by 6% in 2016 alone and 36% over the past five years. It is predicted to reach R70 billion by 2021. Athleisure is reported to be the major trend impacting this growth. This is evident when considering that athletic apparel, in particular, represents 54% of the category, equating to R38 billion (Euromonitor International, 2017b).

The fashion sector, however, is not without its challenges. Consumers have become more astute in their choices, more demanding in their expectations and less predictable in their behaviour – attributed largely to the advent of new technologies (Amed *et al.,* 2017:11-12; Magni, Martinez & Motiwala, 2016). One such technology is the smartphone. The advent of this revolutionary technology has been a topic of heated debate among academic researchers. Statista (2019a) estimates smartphone adoption to increase by 18.75% between 2019 and 2021, equating to almost four billion global smartphone users by 2021. Sub-Saharan Africa boasts the highest growth rate of mobile subscribers, according to Gilbert (2016), compared to any other region in the world. Smartphone penetration passed the one-third mark in 2016, between 37 and 45% (Mybroadband, 2016), and passed the 80% mark in 2019 (Gilbert, 2019). Statista (2019b) predicted 22 million South African smartphone users by the end of 2019 and 26.3 million by 2023 – an estimated growth rate of 19.5% over four years.

A phone is classified as a smartphone if it is built on an advanced mobile operating system (OS) that allows it to run mobile apps (Cassavoy, 2017). Smartphones have radically extended traditional shopping hours by offering the consumer the means to purchase whatever they want, whenever they want, wherever they want (Hyben, Mladenow, Novak & Strauss, 2015:3; eMarketer, 2013). These devices have also provided consumers with advanced mobile computing capability, similar to that of a personal computer (PC), only without the cable (Hsaio, 2013:217). In addition, the functionality, value and utility offered by smartphones can be enhanced through the download of mobile apps (Miladinovic & Xiang, 2016:7; Ting, Lim, Patanmacia, Low & Ker, 2011:194). Smartphone access and more specifically, mobile app access, has opened up a world of possibilities to consumers across the globe.

Mobile apps can be described as software designed to run on a mobile device such as a tablet or smartphone; they provide users with a similar service that can be accessed from a traditional desktop computer (Techopedia, 2020; Miladinovic & Xiang, 2016:7). Apps were popularised by Apple and the launch of its 'app store' in 2008. By 2016, the Apple App store boasted over two million apps, all of which were downloaded some 130 billion times in the eight years since its launch (Golson, 2016). By June 2017, this number had reached 180 billion, and this is just one single app store (Statista, 2017). The proliferation of apps and their widespread adoption has paved the way to a world of possibilities for consumers – one of which is mobile shopping.

Shopping via an app, commonly referred to as mCommerce, is a type of eCommerce. However, it occurs by means of a wireless handheld device such as a smartphone (Bloomenthal, 2019b; Persson & Berndtsson, 2015:2). The growth of mCommerce is said to be 200% faster than that of eCommerce (Kolowich, 2016) and offers consumers many more benefits, including personalisation, localisation and identification (Zhang, Zhu & Liu, 2012:1902). Globally, more and more consumers are shifting from eCommerce to mCommerce (Euromonitor International, 2016). According to Upadhyay (2016) and YourStory.com (2016), global mCommerce sales reached US$220 billion in 2016 – 53% more than in 2015. Online spending via mobile devices (including smartphones and tablets) in South Africa, according to Moneyweb (2017), reached R9.5 billion in 2016 and this figure is expected to continue growing exponentially over the next decade.

eCommerce, mCommerce and digitisation, such as virtual reality (VR) were marked as the single biggest opportunity in the fashion sector in 2016 (Amed *et al.,* 2017:18). In 2019, executives in the fashion industry are fully acknowledging the impact of technology (Amed, Berg, Balchandani, Andersson, Hedrich & Young, 2019:11). Consumers are increasingly more willing to adopt new technologies which is reflected in the aforementioned figures. Retailers have noticed this and have started capitalising on it by creating mobile apps that allow consumers to browse and purchase their products and services via their smartphones (Groß, 2015:221).

A study conducted by HubSpot shows that globally, 64% of shoppers prefer to shop via mobile apps. Indeed, in China, the United States (US) and Mexico, shopping via an app is more popular than shopping via a mobile browser (Kolowich, 2016). In 2015, Google Insights revealed that globally, four out of five smartphone owners prefer to shop via their mobiles (Kahn, 2015). In South Africa, a study conducted by Ipsos in 2015 revealed that 45% of mobile shoppers prefer to shop via an app, compared to 26% who prefer mobile browsers (Business Tech, 2015). Two surveys conducted by ComScore.com in 2011 and the Baymard Institute in 2013, revealed that globally, digital products including apps, music, movies, eBooks, etc. were the most-purchased items via mobile phones, with clothing and accessories coming in at second place (Kahn, 2015; Baymard Institute, 2013; ComScore.com, 2011).

In South Africa, however, the situation is different. According to a study by Goldstuck (2014:10), the majority of South African consumers' average online spend was allocated to airlines (US$197), hotels (US$163) and paid-for video websites (US$123). Electronic products accounted for US$69 and clothing and accessories for US$49. In contrast, clothing and accessories did not even feature as a category for average mobile spend (Goldstuck, 2014:27). Another study, conducted by Effective Measure in 2017, indicates that 47% of South Africans purchase airtime using their mobile phones, 25% purchase apps and related in-app purchases, 33% do not purchase anything on their mobile phones and only 7% purchase clothes, fashion items or beauty products (Erken, 2017). This poses the question: Why do South African shoppers not use their mobile phones to purchase fashion apparel, and more specifically, athleisure apparel, considering its impact on the growth of the athletic wear retail category in South Africa (Euromonitor International, 2017b)? As most South

Africans use their apps to shop (Business Tech, 2015), it is imperative for South African fashion retailers selling athleisure apparel, to understand the reasons for consumers not using mCommerce apps to purchase their products.

Many industry professionals have attempted to understand the reasons why consumers do not purchase fashion apparel via mCommerce apps. Some of the reasons cited include security concerns, a lack of trust (Chen, 2015:62; Goldstuck, 2014:13; Forsythe, Liu, Shannon & Gardner, 2006:57; Huang & Oppewal, 2006:339) and a lack of real, physical interaction with items (Al-Debei, Akroush & Ashouri, 2015:708; Forsythe *et al.,* 2006:57). The first and third reasons provided above, i.e. security concerns and a lack of physical interaction with items, can be combined into a single construct referred to as ‘perceived risk’. Perceived risk is defined as “the nature and amount of risk perceived by a consumer in contemplating a particular purchase decision” (Chen, 2013:316; Forsythe & Shi, 2003:869). Research conducted by Çelik and Yilmaz (2011:155) and Bhatnagar and Ghose (2004:1353) indicates that the risk associated with shopping in a traditional brick-and-mortar store is significantly lower than shopping in a digital environment such as an online or mobile shop. Velarde (2012:22) explains that in online or mobile environments, certain cues that evoke trust are absent – notably, the characteristics of the product, being in a physical store or simply talking to a sales person. This diminishes trust while increasing the perceived risk. Farivar *et al.* (2017:597) concur, stating that perceived risk does influence consumers’ intention to purchase online.

The second reason mentioned above, namely, the lack of trust, is one of the most frequently cited reasons for not shopping via a digital medium (Monsuwé, Dellaert & Ruyter, 2004:114). Ter Huurne, Ronteltap, Corten and Buskens (2017:486) define trust as “the willingness of a party to be vulnerable to the actions of another party based on the expectation that the other will perform a particular action important to the trustor, irrespective of the ability to monitor or control that other party”. Trust in the context of online or mobile shopping, according to Ribbink, van Riel, Liljander and Streukens (2004:447), is described as the degree of confidence which consumers place in online or mobile exchanges. Rogers (2010:26-27) adds that trust refers to a consumer’s anticipation surrounding the website, mobile site or app; in other words, is the information believable, will it meet the consumer’s expectations and will it gain the consumer's confidence? Trust is established once the consumer forms a positive impression of the online platform and is willing to accept their own vulnerability.

In South Africa specifically, trust has been listed as the most common reason for low online shopping rates (IT News Africa, 2016). Trust is critical in stimulating purchases in an online shopping environment, according to Farivar *et al.* (2017:597) and Jarvenpaa, Tractinsky and Vitale (2000:45). Çelik and Yilmaz (2011:155) specify that trust directly and positively affects consumers' online shopping intentions. From a mobile point of view, a study by Joubert and van Belle (2013:33) concurs with the above findings, indicating that trust significantly influences consumers' intention to use mCommerce. This view is further confirmed in a study by Chaouali, Yahia and Souiden (2016:211), who maintain that trust is fundamental in the digital retailing domain.

The two constructs of perceived risk and trust also have a relationship between each other. Amoroso and Hunsinger (2009:25) found that if trust diminishes, perceived risk increases and correspondingly, consumers' intention to purchase decreases (Lim, 2003:218). Trust therefore mediates the influence of perceived risk on behavioural intention. This notion is supported by Farivar *et al.* (2017:597), who report that trust has both a direct influence on consumers' behavioural intention to conduct online transactions as well as an indirect influence on reducing consumers' perceived risk.

Perceived risk and trust are two constructs of interest in this research and are therefore added to the model proposed in this study (refer to Figure 1.9 below). The other constructs included in Figure 1.9 originate from a model developed by Venkatesh, Thong and Xu (2012:158). This model is referred to as the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2), which attempts to ascertain the various constructs that influence consumers' acceptance and use of new technologies, such as online or mobile shops. This model identifies specific key constructs, namely, performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value and habit. The model then indicates how these affect the consumer's behavioural intention to use a specific technology (Miladinovic & Xiang, 2016:16-17) and how in turn, behavioural intention predicts actual use (Venkatesh *et al.,* 2012:158).

A number of international studies, elaborated on below, have explored the factors influencing consumers' acceptance and use of mCommerce apps. Miladinovic and Xiang (2016), for example, conducted a study in Sweden where they tested the key constructs of the UTAUT2 including performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value and habit, as well as one additional construct of trust. The study examined the influence of these constructs on consumers' behavioural intention to use mobile shopping fashion apps in Sweden. The trust construct was added as the researchers found it to have a direct effect on behavioural intention. The findings revealed that out of the eight constructs tested, only four were proven to influence behavioural intention, namely, performance expectancy, facilitating conditions, hedonic motivation and habit (Miladinovic & Xiang, 2016:20; 44-46).

Another Swedish study, conducted by Persson and Berndtsson in 2015, tested the UTAUT2 constructs of performance expectancy, effort expectancy and social influence, as well as two additional constructs of trust and location. The study looked at the effect of these constructs on the behavioural intention of consumers to shop via smartphones and the influence of behavioural intention on actual use. In the first part of the study, which tested the constructs' influence on behavioural intention, only two of the five hypotheses were supported – social influence and location. The location insights in particular, revealed that consumers would not shop via their smartphones if a computer was available. In the second part of the study, regression analysis revealed that behavioural intention had a relatively strong predicting power of actual use (Persson & Berndtsson, 2015:22; 61; 67-69).

A three-year study conducted by Fai (2011) in Hong Kong tested three of the UTAUT2 constructs, namely, performance expectancy, effort expectancy and social influence, as well as a fourth construct of disturbance concerns and the influence these have on behavioural intention. All constructs were found to have a positive effect upon consumers' behavioural intention to use mCommerce, with the most significant being social influence and disturbance concerns (Fai, 2011:94; 121).

In 2012, Lee, Kim and Choi investigated the constructs influencing smartphone app acceptance in Singapore using the first UTAUT with only four core constructs, namely, performance expectancy, effort expectancy, social influence and facilitating conditions as influencing behavioural intention and ultimately actual use. The effect of the first three constructs on behavioural intention was tested, along with the effect of the fourth construct and behavioural intention on actual use (Lee *et al.,* 2012:29). The results indicated that performance expectancy and effort expectancy influenced behavioural intention, however, social influence did not. Facilitating conditions had no effect on actual use either, but behavioural intention did (Lee *et al.,* 2012:31-32).

In South Africa, Magan (2016) used a combination of constructs from a number of models – including the Technology Acceptance Model (TAM) and Theory of Planned Behaviour (TPB) – to determine which factors positively or negatively influenced consumers' behavioural intention to use mCommerce. The constructs tested included perceived usefulness, perceived ease of use, subjective norm, trust, cost and mCommerce as an alternative to eCommerce. The findings revealed that perceived usefulness, perceived ease of use and mCommerce as an alternative to eCommerce positively influenced consumers' behavioural intention to use mCommerce, while cost negatively influenced consumers' behavioural intention to use mCommerce (Magan, 2016:34; 94-95). Again in South Africa, Joubert and van Belle (2013:36) investigated the role of trust and risk in the acceptance and use of mCommerce, specifically among early adopters of technology. The researchers built a model of trust based on, amongst others, the TAM and the Innovation Diffusion Theory (IDT). The findings revealed that perceptions related to trust and risk did in fact influence consumers' acceptance and use of mCommerce.

As is evident from the discussion above, none of the aforementioned studies have examined the influence of perceived risk and trust on South African consumers' acceptance and use of mCommerce apps to purchase athleisure apparel. The study of Magan (2016) only tested the influence of selected constructs on behavioural intention and not actual use. This study addresses this gap.

1.3 Problem statement

Although the mCommerce industry is growing, research on this industry in South Africa is still in its infancy (Groß, 2015:222). Studies have been conducted on mCommerce and user behaviour in Hong Kong (Fai, 2011), constructs that affect the behavioural intention to use mobile shopping fashion apps in Sweden (Miladinovic & Xiang, 2016), determinants of smartphone shopping acceptance and use in Sweden (Persson & Berndtsson, 2015), the drivers of mobile commerce in Saudi Arabia (Alkhunaizan & Love, 2012), constructs that affect smartphone application acceptance in Singapore (Lee *et al.,* 2012), constructs that influence mCommerce acceptance and use in South Africa (Magan, 2016), understanding perceived risks involved in mobile payment acceptance in China (Yang, Liu, Li & Yu, 2015), and the role of trust and risk in mCommerce acceptance and use in South Africa (Joubert & van Belle, 2013). To date, however, there is no research on the constructs that influence consumers' acceptance and use of mCommerce apps to purchase athleisure apparel in South Africa.

Based on the background information provided above, the research problem can be formulated as follows:

Most South Africans access the Internet via their mobile phones (Space Station, 2017) and prefer to utilise apps to shop (Business Tech, 2015). However, of those who do shop via their mobile phones, the category of clothing and accessories does not feature prominently (Erken, 2017; Goldstuck, 2014:27). With athleisure being a major trend impacting global and local growth in the fashion industry (Amed *et al.,* 2017:12; Euromonitor International, 2017b), it is imperative for South African fashion retailers selling athleisure apparel to understand the reasons for this low purchasing behaviour. This study provides insights into this phenomenon by determining the constructs that influence consumers' acceptance and use of mCommerce apps to purchase athleisure apparel in South Africa. In addition, the constructs of perceived risk and trust are repeatedly cited as two key variables impacting consumers' acceptance and use of mCommerce (Farivar *et al.,* 2017:597; Dai & Chen, 2015:42; Wu & Wang, 2005:726; Lim, 2003:218). However, these constructs do not feature in the UTAUT2, therefore this study seeks to enhance the model by adding these two constructs (refer to Figure 1.9).

1.4 Purpose of the study

This study sheds light onto the reasons why South African consumers do not purchase athleisure apparel via their mobile phones by determining the constructs influencing consumers' acceptance and use of mCommerce apps to purchase athleisure apparel in South Africa. From the literature, it is clear that South Africans are shopping on their mobile phones through apps (Business Tech, 2015). However, the category of clothing and accessories does not seem to feature prominently (Erken, 2017; Goldstuck, 2014:27). There is scant research on constructs influencing mCommerce acceptance and use (Magan, 2016) as well as the role of trust and risk in mCommerce acceptance and use in South Africa (Joubert & van Belle, 2013). A better understanding of this phenomenon will enable South African fashion retailers selling athleisure apparel to better understand the factors that influence their consumers' behavioural intention to use mCommerce apps to purchase their products. This will allow these retailers to adjust their business strategies accordingly, securing a stronger relational focus, with a beneficial value-add for all parties to the relationship.

The study is grounded in relationship-building theory, through the lens of Social Exchange Theory (SET), the Transaction Cost Theory (TCT) as well as Technology Acceptance Theory through a considered look at the IDT, the Theory of Reasoned Action (TRA), Social Cognitive Theory (SCT), the TAM and the TPB within an emerging African economy such as South Africa. With this in mind, the following research objectives have been formulated for this study.

1.5 Research objectives

The primary research objective is to determine the constructs that influence consumers' acceptance and use of mCommerce apps to purchase athleisure apparel in South Africa.

The secondary research objectives are as follows:

- To determine whether performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, habit and trust have a positive influence on the behavioural intention of consumers to use mCommerce apps to purchase athleisure apparel.

- To establish whether facilitating conditions and habit have a positive influence on consumers' actual use of mCommerce apps to purchase athleisure apparel.
- To investigate whether perceived risk has a negative influence on the behavioural intention of consumers to use mCommerce apps to purchase athleisure apparel.
- To determine whether perceived risk has a negative influence on consumers' actual use of mCommerce apps to purchase athleisure apparel.
- To establish whether trust mediates the influence of perceived risk on the behavioural intention of consumers and consumers' actual use of mCommerce apps to purchase athleisure apparel.
- To determine whether behavioural intention has a positive influence on consumers' actual use of mCommerce apps to purchase athleisure apparel.
- To determine which of the independent variables has the largest influence on the behavioural intention of consumers to use mCommerce apps to purchase athleisure apparel.
- To determine which of the independent variables has the largest influence on consumers' actual use of mCommerce apps to purchase athleisure apparel.

1.6 Significance of the research

From an academic perspective, this study tests an adapted version of the UTAUT2 in South Africa. Such a study has not yet been conducted in an emerging African economy. The seven constructs of the UTAUT2 are tested, along with two additional constructs – perceived risk and trust. The inclusion of these two constructs is informed by research indicating that these are two of the main variables impacting consumers' use of mCommerce (Farivar *et al.,* 2017:597; Dai & Chen, 2015:42; Wu & Wang, 2005:726; Lim, 2003:218).

There is limited research on mCommerce in emerging economies (Magan, 2016:12). The data gathered from testing this model augments the existing body of knowledge in this field, shedding light on mobile shopping via apps in emerging markets such as South Africa. From an industry perspective, insights gathered from the study provide

South African business owners with a more in-depth understanding of the factors which stimulate consumers' desire to use mCommerce apps as well as those which drive them to ultimately purchase athleisure apparel.

1.7 Literature review

Consumers' acceptance and use of new technologies has been an area of interest for researchers since the 1980s (Rondan-Cataluña, Arenas-Gaitán & Ramírez-Correa, 2015:788). A number of theories and models, as can be seen in Figure 1.1, have been proposed over the years to explain technology acceptance and use (Venkatesh *et al.,* 2012:157), including the IDT developed by Rogers in 1962, the TRA developed by Fishbein and Ajzen in 1975, the SCT developed by Bandura in 1986, the TAM developed by Davis in 1986 and the TPB developed by Ajzen in 1991. The focus of these technology acceptance theories and models is to identify the various constructs that predict behavioural intention or acceptance and adoption or actual use (Agudo-Peregrina, Hernández-García & Pascual-Miguel, 2014:301).

The literature review chronologically examines the theoretical paradigms which underpin the model proposed in this study. These theories and models are discussed in order of foundation year and how each theory/model contributed to the development of the following theory/model in the development of the UTAUT2. This is followed by the discussion of two relationship-building theories that are of interest to this study. The SET, developed by Homans in 1958, is considered in terms of the value derived from using an mCommerce app by both the buyer and the seller. The TCT, developed by Williamson in 1981, is then discussed, with a focus on perceived risk and trust and their impact on the transaction. Finally, the model on which this study is based, the UTAUT2, is discussed, followed by an overview of the South African fashion industry, with a specific focus on athleisure apparel. The section concludes with the proposed model for this study.

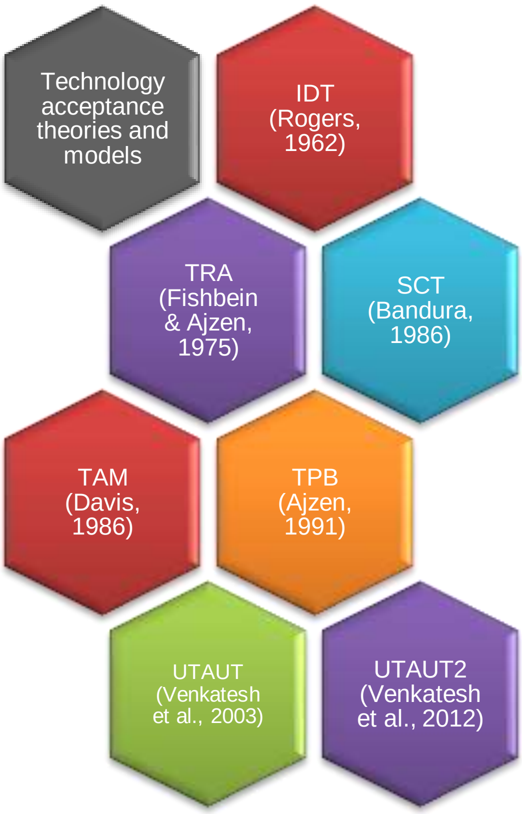


Figure 1.1: Technology acceptance theories and models grounding the study

1.7.1 Theoretical paradigms

The theoretical paradigms section provides an overview of the various theories and models that underpin the study. As the study's main focus is on the UTAUT2, the theories and models used to compile this theory, i.e. the IDT, TRA, SCT, TAM and TPB are reviewed below. This is followed by a review of the relationship-building theories, i.e. the SET and TCT. The development of the UTAUT2 is then presented.

1.7.1.1 Innovation Diffusion Theory (IDT)

Innovation is defined as "an idea, practice or object perceived as new by an individual" (Wang, Yuen, Wong & Teo, 2018:238; Rogers, 2003:1). The IDT was developed by Rogers in 1962 and aims to explain users' acceptance and use of technology and their decision-making process. The theory posits that five key characteristics of an innovation govern its adoption rate, namely, compatibility, complexity, observability, trialability and relative advantage (Chung & Holdsworth, 2012:226-227; Khalifa &

Shen, 2008:111; Wu & Wang, 2005:721; Rogers, 2003:1). Diffusion, on the other hand, is described as the process that an innovation follows when it is communicated over a period of time by a group of individuals. As it is an innovation that is being communicated, there is a degree of perceived risk and uncertainty present in the process. This can be reduced by obtaining information on the innovation (Hoffmann, Probst & Christinck, 2007:37; Rogers, 2003:1). The innovation adoption curve, depicted in Figure 1.2, was created based on the IDT. It shows the various categories that members of a social system are classified into based on the speed at which they adopt a new innovation (Hoffmann *et al.,* 2007:44). The categories include innovators, early adopters, early majority, late majority and laggards (Lai, 2017:23). The IDT is one of the key theories incorporated in the UTAUT2, however, it was not considered in the formulation of any of the foundation theories used in this study.

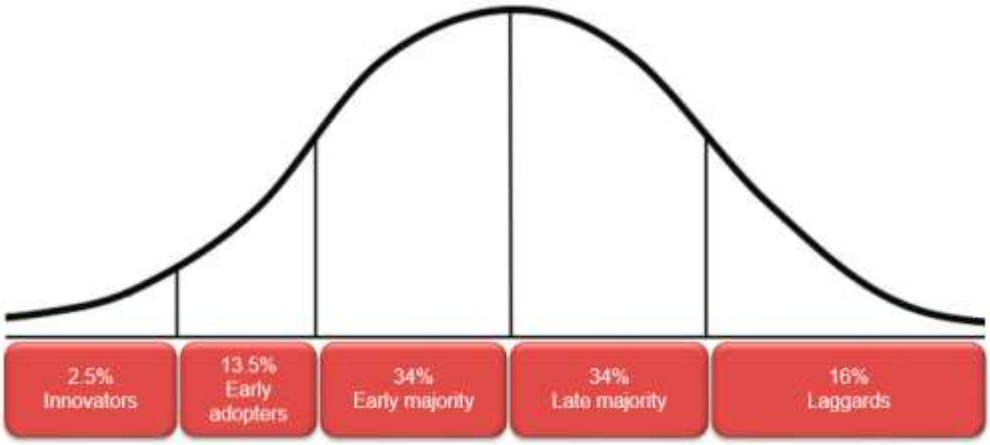


Figure 1.2: IDT – innovation adoption curve
Source*: Rogers (2003:2)*

1.7.1.2 Theory of Reasoned Action (TRA)

Fishbein and Ajzen developed the TRA in 1975, as depicted in Figure 1.3. The theory is built on the basis that an individual performing a specified behaviour is determined by their intention to do so, referred to as behavioural intention. The behavioural intention is determined by the individual's attitude (their belief that applying a specific technology will result in a positive outcome) and the subjective norm (their intent to use a specific technology given the opinions of the social groups they are part of) (Miladinovic & Xiang, 2016:13; Zhang *et al.,* 2012:1903; Venkatesh, Morris, Davis &

Davis, 2003:428). Many studies on the acceptance and use of technological innovations have applied the TRA as a learning model to predict and explain behaviour (Ratten, 2011:40). The TRA was a key theory used in the formulation of the UTAUT2. Both theories indicate that behavioural intention directly influences ultimate behaviour, which in this instance, is the use of mCommerce apps to purchase athleisure apparel (Rondan-Cataluña *et al.,* 2015:794).

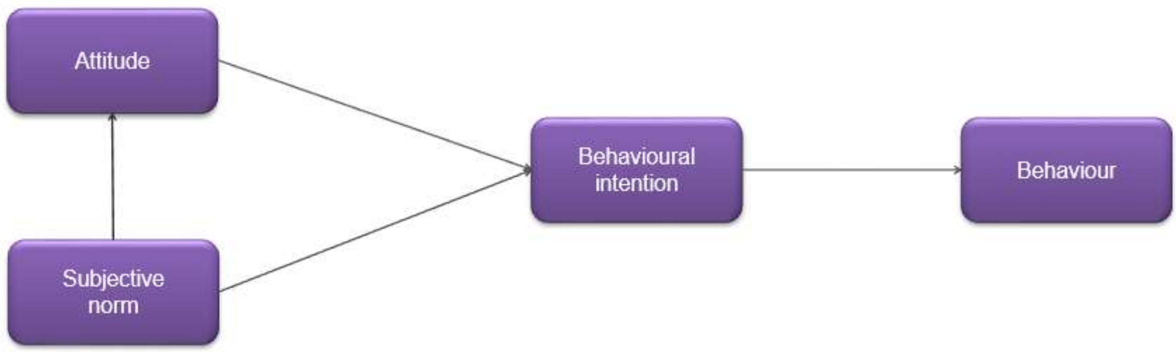


Figure 1.3: TRA
Source*: Fishbein and Middlestadt (1987:363)*

1.7.1.3 Social Cognitive Theory (SCT)

Developed by Bandura in 1986, the SCT attempts to create a more comprehensive understanding of an individual's behavioural intention to accept and use a new technology (Ratten, 2011:41). The theory, depicted in Figure 1.4, postulates that an individual's learning takes place within a social context that comprises three elements in a reciprocal relationship – the person (cognitive factors), the environment (situational factors) and the behaviour (Bandura, 1989:2). One of the foundational concepts of the SCT is the ability of human beings to not only influence their own behaviour through reading and learning about technological innovations, but also to learn through the observation of others, such as friends and family (Ratten, 2011:41; Straub, 2011:629). This theory provides a more holistic understanding of an individual's behavioural intention as it includes their interactions with the internal and external environment (Ratten, 2011:41).

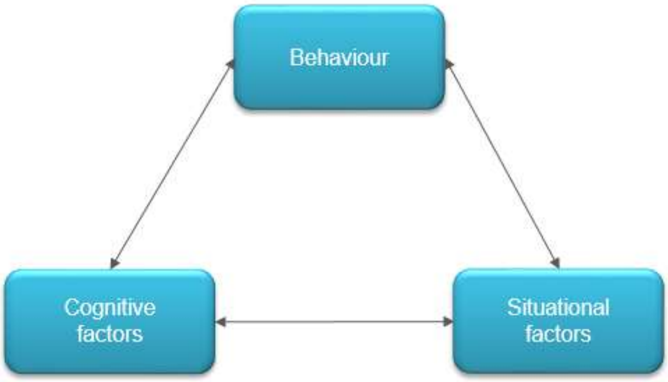


Figure 1.4: SCT

***Source**: Bandura (1989:3)*

1.7.1.4 Technology Acceptance Model (TAM)

The TRA forms the foundation on which the TAM was built (van Slyke, 2008:xi; Davis, 1986:13). The TAM, depicted in Figure 1.5, was originally developed by Davis in 1986 (Rondan-Cataluña *et al.,* 2015:791). The TAM is built on the premise that a consumer's motivation to accept and use a new technology is influenced by three elements, namely the perceived ease of use, perceived usefulness and attitude (Dlodlo & Mafini, 2013:2; Pinho & Soares, 2011:119). The model has proved that technology use can be predicted from user intention. This reinforces the findings of the TRA which shows that behavioural intention is the main determining construct in actual behaviour (Miladinovic & Xiang, 2016:14). This is aligned to the UTAUT2 which also indicates that behavioural intention directly influences ultimate behaviour.

Of all the technology acceptance models, the TAM is the most commonly applied (Zhu, So & Hudson, 2017:2220; Ratten, 2015:27). It is, however, often considered too simplistic in its approach and is thought be incomplete (Liébana-Cabanillas, Marinković & Kalinić, 2017:15; Ratten & Ratten, 2007:91). A number of researchers such as Liébana-Cabanillas *et al.* (2017:15), Zhang *et al.* (2012:1903), Wu and Wang (2005:725-726) and Featherman and Pavlou (2003:468), have suggested that the TAM should be extended to incorporate additional constructs to better explain behavioural intention. Liébana-Cabanillas *et al.* (2017:16; 19; 21) tested an adapted TAM to determine the antecedents of mCommerce acceptance in Serbia. In addition to perceived usefulness and perceived ease of use, their model also tested the influence of trust, mobility, customisation and customer involvement on consumers' behavioural intention to use mCommerce. The results showed a significant positive relationship between trust and behavioural intention. In Serbia, similar to South Africa, mCommerce and mobile payments have not yet become common practice, therefore this finding highlights the importance of trust when it comes to mobile transacting. Zhang *et al.* (2012:1903) note that the addition of certain constructs to the TAM better explains behavioural intention. Examples of such constructs include perceived risk and trust. Amongst others, these two additional constructs were tested in an adapted TAM/TPB/IDT model to determine the acceptance and use of mCommerce and the moderating effects of culture. Zhang *et al.*'s (2012:1903-1904; 1909) research found significant relationships between both perceived risk and behavioural intention, as well as trust and behavioural intention. Wu and Wang (2005:726) investigated the drivers behind mCommerce using an adapted TAM with the added constructs of perceived risk and cost. The findings revealed a significant negative relationship between perceived risk and behavioural intention. Featherman and Pavlou (2003:456) concur in their study on the acceptance and use of eServices, using the TAM as theoretical foundation supplemented by various types of perceived risk constructs. The researchers believed it was critical to include perceived risk into the TAM as consumers identify certain risks during the process of evaluation when it comes to purchasing a new product, which can create anxiety. Their research found perceived risk to have a significant influence on consumers' behavioural intention to use eServices. These empirical research findings validate the addition of perceived risk and trust to enhance the proposed model for this study (refer to Figure 1.9).

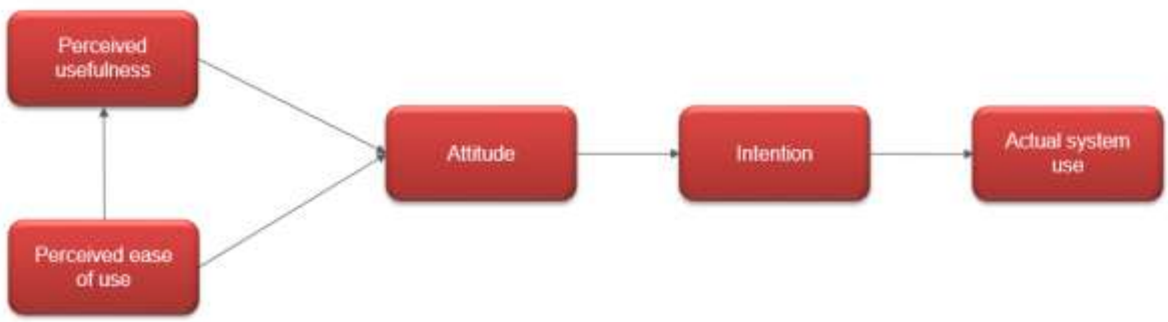


Figure 1.5: TAM

***Source**: Davis (1986:24)*

1.7.1.5 Theory of Planned Behaviour (TPB)

Ajzen further extended the TRA in 1991 to develop the TPB, depicted in Figure 1.6. This theory includes one additional construct – perceived behavioural control – which is described as a person's perception of how easy or difficult it is to perform particular behaviour. This construct determines both the intention to use the specific technology in question and the actual use. According to this theory, the higher the perceived behavioural control, the higher the intention to use; and the higher the intention to use, the higher the degree of usage behaviour (Miladinovic & Xiang, 2016:13-14; Zhang *et al.,* 2012:1903; Venkatesh *et al.,* 2003:429).

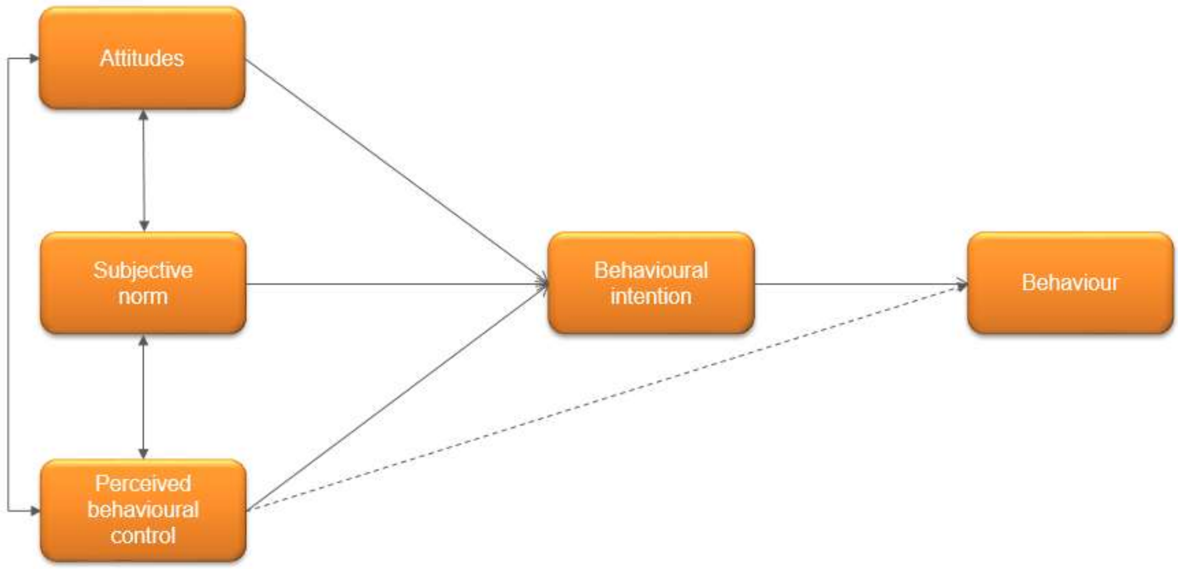


Figure 1.6: TPB
Source*: Ajzen (1991:182)*

The following two theories are rooted in relationship-building and are completely separate from the above theories that were discussed in support of the development of the UTAUT2. The first theory is the SET, developed by Homans in 1958. This theory is of interest to understand the cost and reward factors present in an mCommerce exchange. The second theory is the TCT, formulated in 1981 by Williamson. In online and mCommerce transactions, the funds, time and effort invested on the consumer's part are considered the costs of the transaction (Che, Peng, Lim & Hua, 2015:589; Liang & Huang, 1998:29).

1.7.1.6 Social Exchange Theory (SET)

Developed by Homans in 1958, the SET states that buyers and sellers interact in order to minimise cost while exploiting reward (Shiau & Luo, 2012:2432). A consumer's decision, as a buyer, regarding whether or not to transact with a seller, is very much based on the cost that must be paid to off-set the potential reward the consumer can obtain (Dai & Chen, 2015:42). Within social exchange, however, the cost factor goes beyond pure economic exchange, but into perceptions of the social exchange, including potential risk, service quality and convenience (Dai & Chen, 2015:42; Devaraj, Fan & Kohli, 2006:1091). For the purposes of this study, cost represents the construct of perceived risk (Chen, 2013:1221). Matikiti, Roberts-Lombard and Mpinganjira (2016:30) state that perceived risk has been found to deter consumers from using new technologies. Perceived usefulness (referred to as performance expectancy in the UTAUT2) of the acceptance and use of an innovative technology such as an mCommerce app, as well as the mobility and convenience mobile phones provide to consumers, fulfils the role of reward (Dai & Chen, 2015:47). In addition, trust becomes an important construct for consideration as rewards in a social exchange cannot be guaranteed. Trust can therefore assist in reducing potential feelings of being exploited, or reducing the perceived cost associated with the exchange (Montazemi & Qahri-Saremi, 2015:212). Research conducted by Montazemi and Qahri-Saremi (2015:220) on the constructs affecting online banking acceptance and use revealed that consumers' trust in online banking had a significant influence on their behavioural intention to use online banking. This empirical research by Matikiti *et al.* (2016:30) and Montazemi and Qahri-Saremi (2015:220) further validates the addition of the perceived risk and trust constructs to enhance the proposed model for this study (refer to Figure 1.9).

1.7.1.7 Transaction Cost Theory (TCT)

The TCT was developed by Williamson in 1981 and is based on the principle that consumers favour conducting transactions in the most economical way (Teo & Yu, 2004:452). This theory is completely separate from the SET. Williamson (1981:552) describes a transaction as the transfer of goods or services across distinguishable technological interfaces. In order to conduct a transaction, a consumer is required to search for information, action the transaction and monitor the process (Teo & Yu, 2004:452). Costs involved in such activities are termed transaction costs. In the electronic and mCommerce domain, these transaction costs primarily refer to uncertainty with the process and the product, as well as specificity in terms of the money, effort and time invested in the transaction (Che *et al.,* 2015:589; Liang & Huang, 1998:29). Uncertainty with the process and the product can be alleviated through trust. Che *et al.* (2015:591) concurs, stating that trust is key to reducing perceived risk and, in turn, transaction cost. This research further validates the addition of the constructs of perceived risk and trust to enhance the proposed model for this study (refer to Figure 1.9).

As mentioned above, many theories and models have been developed over the years to understand the constructs that affect consumers' choices surrounding how and when they will accept and use new technologies (Rondan-Cataluña *et al.,* 2015:788). One such theory is the UTAUT2, which also forms the model of focus for this study. The following section provides an overview of this model.

1.7.2 Unified Theory of Acceptance and Use of Technology 2 (UTAUT2)

Venkatesh *et al.* developed the unified model of acceptance and use of technology in 2003, as can be seen in Figure 1.7. Dubbed the Unified Theory of Acceptance and Use of Technology (UTAUT), this theory was developed by combining eight well-established theories including the TRA, the Motivational Model (MM), the TPB, a combined TAM and TPB model, the Model of PC Utilisation, the IDT and the SCT (Yang, 2010:263). The UTAUT argues that four core constructs, namely performance expectancy, effort expectancy, social influence and facilitating conditions influence, behavioural intention and ultimately behaviour. These core constructs are then moderated by individual differences such as gender, age, experience and voluntariness of use (Venkatesh *et al.,* 2012:159).

The UTAUT has been empirically tested by a number of researchers in technology acceptance studies since its inception in 2003 (Martins, Oliveira & Popovič, 2014:3). A number of these studies use the UTAUT as a theoretical foundation, enhanced by incorporating additional constructs, such as perceived risk and trust. In Oman, Riffai, Grant and Edgar (2012:247) examined Internet banking acceptance and use. They found solid substantiation for the role of trust in affecting behavioural intention. Chaouali *et al.* (2016:215) corroborates these findings. Their study explores Tunisian consumers' behavioural intention to use Internet banking using the UTAUT as theoretical foundation, augmented with additional constructs, one of which being trust. Their findings, similar to those of Riffai *et al.* (2012) indicate a strong relationship between trust and behavioural intention. Martins *et al.* (2014:9) looked at Internet banking acceptance and use, also based on the UTAUT as a theoretical foundation, enhanced with the addition of various types of risk. Their findings revealed that adding perceived risk to the UTAUT strengthened the predictive capability of the model. These studies therefore validate the addition of perceived risk and trust to the model proposed in this study (refer to Figure 1.9).

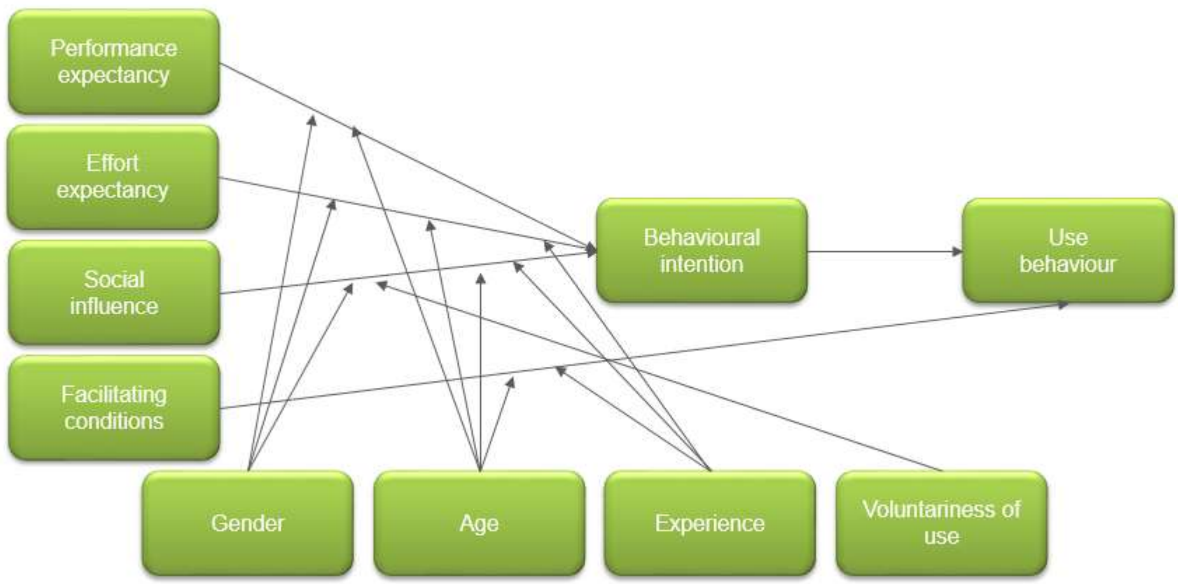


Figure 1.7: UTAUT

***Source**: Venkatesh et al. (2003:447)*

Venkatesh *et al.* (2012:158) then proceeded to enhance the UTAUT for a consumer use context, thereby developing the UTAUT2. This is a theory which includes key additional constructs and relationships, as shown in Figure 1.8. Thus, the constructs of hedonic motivation, price value and habit were added to the UTAUT2. Habit specifically was added as research suggested that more than just behavioural intention affects actual use. Habit was therefore introduced as a new potential critical predictor of actual technology use (Venkatesh *et al.,* 2012:158). In this model, the various constructs of performance expectancy, effort expectancy, social influence and facilitating conditions, along with hedonic motivation, price value and habit, are shown to affect a consumer's behavioural intention (Miladinovic & Xiang, 2016:16-17) and, ultimately, the actual use of the technology (Venkatesh *et al.,* 2012:160).

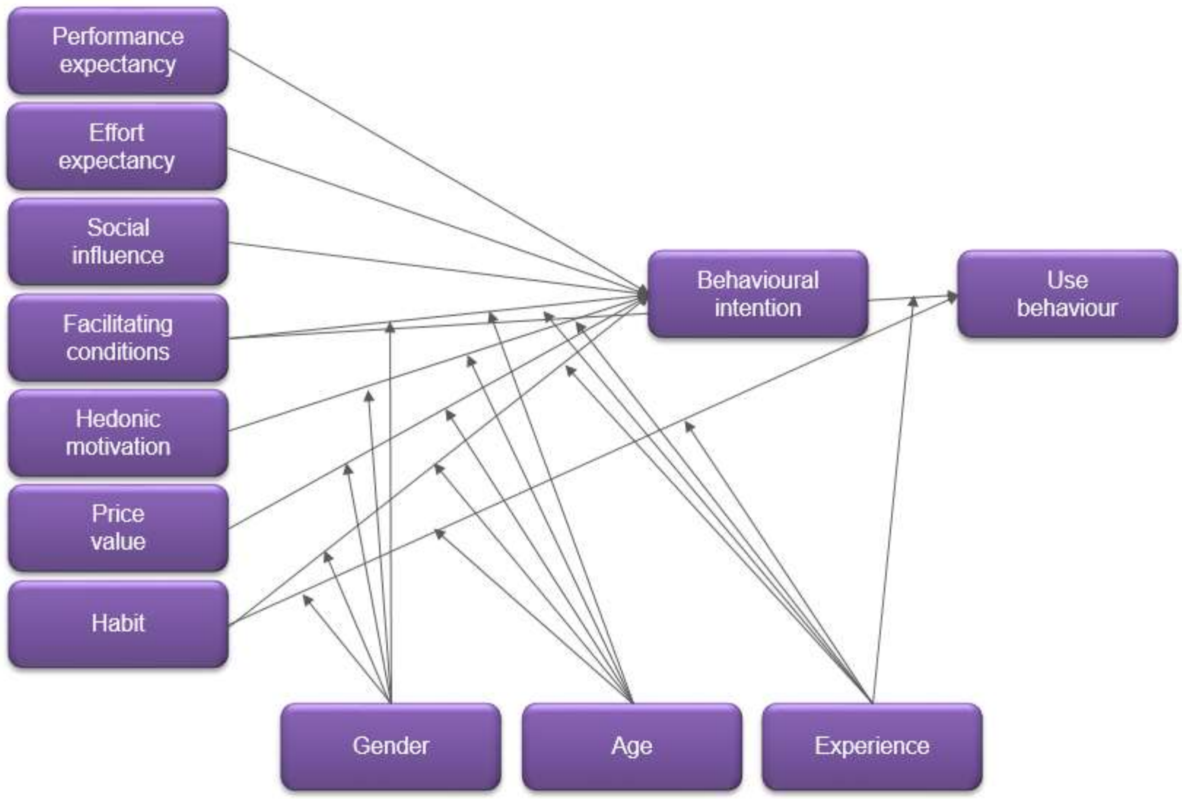


Figure 1.8: UTAUT2

***Source**: Venkatesh et al. (2012:160)*

The proposed conceptual model and hypotheses for this study are based on the UTAUT2 (see Figure 1.8). The reason for this is that this model has been proven to outperform all the other technology acceptance models (Miladinovic & Xiang, 2016:19). The UTAUT2, according to Marriott and Williams (2016:264), has also been proven successful in explaining behavioural intention in the fields of mobile payments, mobile Internet and mobile banking research. However, it remains underutilised in mobile shopping research. This is corroborated by Rondan-Cataluña *et al.* (2015:797-798) who tested a number of different technology acceptance models for mobile Internet users against one another. These included, amongst others, the TRA, variations of the TAM, the UTAUT and UTAUT2. The findings revealed that the

UTAUT2 had 26% better explanatory power compared to the rest of the TAM variations, indicating that this was the best model from a consumer use point of view. Alalwan, Dwivedi, Rana and Algharabat (2018:133) further enhanced the predicting power of the UTAUT2 by adding perceived risk. They conducted a study in Jordan to test constructs that influence consumers' behavioural intention to use and actual use of Internet banking. The standard UTAUT2's constructs were able to predict a 58% variance in behavioural intention. The addition of perceived risk increased this by 10.3% to 64%. This is aligned with the findings of Martins *et al.* (2014:9), elaborated on earlier in this section. The empirical findings of this study justify the addition of perceived risk to enhance the proposed model for this study (refer to Figure 1.9).

Based on the aforementioned arguments, an adapted UTAUT2 with the additional constructs of perceived risk and trust is proposed for this research (refer to Figure 1.9). As this study investigates the constructs that influence consumers' acceptance and use of mCommerce apps to purchase athleisure apparel in South Africa, this model is well-suited to this research. The following section examines the athleisure apparel industry in greater detail.

1.7.3 The South African athleisure apparel industry

The two top fashion markets on the African continent are South Africa and Nigeria (Brown, 2017). The South African market is refined and shows great promise, offering a blend of established economic infrastructure coupled with an exciting, emerging economy (Flanders Investments & Trade, 2016:5). A unique characteristic of the retail apparel sector in South Africa is that only a few large retail groups own and operate quite a number of different brands (Flanders Investments & Trade, 2016:12). For example, Edcon owns and operates Edgars, Red Square, CNA and Boardmans; the Foschini Group (TFG) owns and operates Foschini, Due South and Sportscene. The six big clothing retailers, i.e. Edcon, TFG, Woolworths, Mr Price, Truworths and Pepkor, dominate the market and have, over the past decade, grown their combined market share from 62% to 73% (City Press, 2017). That being said, since the first democratic elections in 1994, South African consumers have been spoiled for choice with more international fashion brands such as Cotton On, Zara, H&M, Call It Spring launching locally.

According to a report issued by the Fibre Processing and Manufacturing Sector Education and Training Authority (FPM SETA, 2014:2), the South African clothing and textile industry is mature and diverse. PwC (2012:27) asserts that the industry forms one of the top ten sources of employment in the country. The sector has also enjoyed solid growth since 2005 thanks to market demand for apparel in South Africa being on a persistent increase (PwC, 2012:27).

The apparel and accessories retail sector, according to Deloitte (2015), is the fastest growing in South Africa, enjoying a 5.8% composite revenue growth. Flanders Investments and Trade (2016:3) reports that households in South Africa spend an average of R582 or 5.3% of monthly household income on clothing and footwear – 56% more than what is spent on education (R373). This, amidst rising food prices and high unemployment rates, continues to place pressure on consumers' disposable income (Euromonitor International, 2019; Euromonitor International, 2017a).

The athletic wear category (which includes apparel or clothing, shoes, etc.) grew by 6% in 2016 and is predicted to reach R70 billion by 2021 (Euromonitor International, 2017b). Athletic apparel specifically represents 54% of this category, equating to R38 billion (Euromonitor International, 2017b). This is mainly due to the athleisure trend's impact on the industry. Athleisure originated as a simple preference for casual, comfortable exercise wear and proceeded to becoming a full-scale trend between 2013 and 2014, with more and more consumers taking up this distinctive look (Khawtom, 2017).

Along with the growth of the athleisure trend, the continued growth in eCommerce and mCommerce presented the biggest opportunity to the fashion sector in 2016 (Amed *et al.,* 2017:18). Many large retailers in the apparel space as well as smaller local entrepreneurs have launched online, mobile and social media presences through which to communicate with their consumers (Euromonitor International, 2017a; Flanders Investments & Trade, 2016:6). This allows them to browse and purchase their products and services in-store, online and via their mobile phones (Groß, 2015:221).

Globally, clothing and accessories form the second most-purchased type of product via mobile apps (Kahn, 2015; Baymard Institute, 2013; ComScore.com, 2011), however, in South Africa, this is far from being the case. A study conducted by Goldstuck (2014:27) reveals that the majority of South African consumers' average mobile spend is allocated to the purchase of mobile apps (34%), music downloads (32%), movie tickets (15%), computer software (13%) and online gaming products and services (11%). Clothing and accessories do not feature in the top ten. Another study by Effective Measure in 2017 shows that only 7% of surveyed South Africans purchase clothes, fashion items or beauty products using their mobile phones, compared to 47% who purchase airtime, for example (Erken, 2017). This study seeks to understand this phenomenon by identifying the constructs that influence consumers' acceptance and use of mCommerce apps to purchase athleisure apparel in South Africa.

1.7.4 Research constructs and relationships between variables

The purpose of technology acceptance theories and models is to identify the various constructs that predict behavioural intention or acceptance and adoption or actual use (Agudo-Peregrina *et al.,* 2014:301). Adoption, according to Kaldi, Aghaie and Khoshalhan (2008:38) and Renaud and van Biljon (2008:1-2), refers to the stage where an individual selects a technology for use. It is therefore synonymous with actual use.

Ratten (2011:40) states that the adoption or actual use of new technological innovations such as mCommerce is dependent upon consumers' behavioural intentions. Within each of the aforementioned studies referenced in the background section of this study (section 1.2), behavioural intention consistently features as a central concept. The intention of a user to use a certain technology is a strong predictor and determining factor of the user actually using the technology (Miladinovic & Xiang, 2016:12; Persson & Berndtsson, 2015:28; Venkatesh *et al.,* 2012:157). Previous literature concerned with the acceptance of technology refers to behavioural intention as an individual's willingness to use a technology system (Miladinovic & Xiang, 2016:12). This willingness means that a user is willing to accept the technology, therefore the terms 'behavioural intention' and 'acceptance' are often used interchangeably (Cigdem & Ozturk, 2016). Kaldi *et al.* (2008:38) and Renaud and van

Biljon (2008:2) refer to acceptance as changes in individuals' perceptions, attitudes and actions leading to a willingness to try new activities or innovations. Actual use refers to an individual's actual use of, in this case, mCommerce apps when purchasing athleisure apparel in South Africa. Actual use is often interchanged with the terms 'adoption' and/or 'use behaviour'.

As mentioned earlier, the proposed conceptual model and hypotheses for this study are based on the UTAUT2. Williams, Rana and Dwivedi (2015:460) researched the relationship between the behavioural intention and actual use constructs of this model and found that, out of 102 studies, behavioural intention had a predictive weighting of 0.82 on actual use (with a score of 1 indicating a significant relationship between constructs) (Williams *et al.,* 2015:456). An adaptation of this model is proposed for testing in this study. This study is conducted in two phases. Phase 1 (using Model A in Figure 1.9) tests the influence of specific constructs on behavioural intention to determine consumers' acceptance of mCommerce apps to purchase athleisure apparel. Phase 2 (using Model B in Figure 1.9) tests the influence of specific constructs on actual use to determine consumers' use of mCommerce apps to purchase athleisure apparel. The details of this are elaborated on below.

Firstly, the seven original UTAUT2 constructs – performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value and habit and their influence on behavioural intention – are determined. Secondly, the model also shows the constructs of facilitating conditions and habit influencing actual use in addition to behavioural intention. This also forms part of this study. Thirdly, an eighth added construct is tested – that of perceived risk – and its influence on both behavioural intention and actual use. Studies by Farivar *et al.* (2017:597) and Wu and Wang (2005:726) show that perceived risk significantly influences consumers' intention to use mobile shopping. In addition, Farivar *et al.* (2017:597) found that perceived risk also reduces actual purchase while Lim (2003:218) contends that as risk increases, the likelihood of consumers purchasing decreases. The relationship between these two constructs is therefore also tested and determined. Amoroso and Hunsinger (2009:25) observe that diminished trust heightens perceived risk, which ultimately diminishes intention (Lim, 2003:218). Therefore, this study also examines whether trust mediates the influence of perceived risk on behavioural intention and actual use. Trust has also been found to directly influence behavioural intention; thus this is also tested (Farivar *et al.,* 2017:597; Çelik & Yilmaz, 2011:155). Finally, the influence of behavioural intention on actual use will be tested. A number of researchers have tested the relationship between these two constructs in the fields of mobile payments, mobile Internet, mobile banking research and mobile shopping (Tarhini, El-Masri, Ali & Serrano, 2016:842; Persson & Berndtsson, 2015:61; Wu & Wang, 2005:726). These researchers found behavioural intention to be an adequate predictor of actual use. The following sections elaborate on each of the constructs.

1.7.4.1 Performance expectancy

Performance expectancy, according to Venkatesh *et al.* (2012:159), is described as the extent to which the usage of a specific technology will provide a benefit to the consumer who performs specific activities. In the context of mCommerce, this refers to the consumers being able to shop via their mobile device at any time and in any location (Hyben, Mladenow, Novak & Strauss, 2015:3; eMarketer, 2013). Apps also eliminate waiting time. The consumer does not have to open their mobile browser, type in the website address, wait for the website to load, etc. Mobile apps are opened and immediately provide the consumer with access to what they are looking for (Graybill, 2015). This construct has been proven to affect the behavioural intention of consumers, encouraging them to engage in mCommerce and mobile Internet browsing (Miladinovic & Xiang, 2016:21). Alkhunaizan and Love (2012:85) concur, adding that performance expectancy has the strongest influence on behavioural intention compared to the other constructs of the UTAUT2.

The following hypothesis is therefore proposed:

> *H_1 (Phase 1 and 2, Models A and B): Performance expectancy has a positive influence on the behavioural intention of consumers to use mCommerce apps to purchase athleisure apparel.*

1.7.4.2 Effort expectancy

Effort expectancy refers to the level of ease associated with consumers' use of a specific technology (Venkatesh *et al.,* 2012:159). In the context of mCommerce and app engagement, this firstly refers to the ease of use afforded by a touchscreen when using an app. Apps designed to leverage the benefits of a touchscreen are not only intuitive to use, but also help the user operate the app faster, leading to less effort required (Sky Technology, 2016). It is secondly more efficient, which has been found to be a strong motivator, inciting consumers to shop via their mobile phones (Parker & Wang, 2016:490). Miladinovic and Xiang (2016:22) report that this construct has been shown to impact the behavioural intention of consumers to use a variety of new technologies, including wireless Internet, eCommerce and mCommerce. Parker and Wang (2016:491) maintain that ease is an important enabler in mCommerce engagement. Alkhunaizan and Love (2012:86) agree, stating that effort expectancy forms should be a fundamental consideration whenever mCommerce tools are designed and implemented.

The following hypothesis is therefore proposed:

> *H_2 (Phase 1 and 2, Models A and B): Effort expectancy has a positive influence on the behavioural intention of consumers to use mCommerce apps to purchase athleisure apparel.*

1.7.4.3 Social influence

The construct of social influence refers to consumers' beliefs that their family and friends believe they should use a particular technology (Venkatesh *et al.,* 2012:159). Alkhunaizan and Love (2012:86) state that social influence not only influences consumers' acceptance of mCommerce, but their intention to use it as well. Fai (2011:121) supports this argument, claiming that social influence has the most significant influence on the acceptance of mCommerce compared to all other constructs. Yang (2010:267) also reports that social influence significantly influences behavioural intention, indicating the importance of other's opinions in consumers' acceptance of mCommerce.

The following hypothesis is therefore proposed:

H_3 (Phase 1 and 2, Models A and B): Social influence has a positive influence on the behavioural intention of consumers to use mCommerce apps to purchase athleisure apparel.

1.7.4.4 Facilitating conditions

Venkatesh *et al.* (2012:159) describe facilitating conditions as a consumer's perception of the available resources and support when performing a specific behaviour. Facilitating conditions, in the context of mCommerce and app engagement, according to Miladinovic and Xiang (2016:22), refer to the availability of online customer support and an Internet connection. Venkatesh *et al.* (2012:162) add that if consumers have the necessary support at their disposal, they will be more willing to use the technology in question and will be more likely to proceed to actually use it. Yang (2010:267) agrees, indicating that facilitating conditions are critical in consumers' acceptance and use of mCommerce.

The following hypotheses are therefore proposed:

H_4 (Phase 1 and 2, Models A and B): Facilitating conditions have a positive influence on the behavioural intention of consumers to use mCommerce apps to purchase athleisure apparel.
H_5 (Phase 2, Model B): Facilitating conditions have a positive influence on consumers' actual use of mCommerce apps to purchase athleisure apparel.

1.7.4.5 Hedonic motivation

Hedonic motivation is described as the enjoyment associated with using a specific technology (Venkatesh *et al.,* 2012:161). Miladinovic and Xiang (2016:23) state that if a consumer's engagement with technology kindles feelings of pleasure, the consumer gains enjoyment from that engagement, which in turn influences their behavioural intention to further pursue that technology. Parker and Wang (2016:495) found that browsing mCommerce apps and sites is regarded as a stress reliever by many participants in the United Kingdom (UK) and is often used in leisure and relaxation. This construct was found to be a critical determinant of behavioural intention by Venkatesh *et al.* (2012:171).

The following hypothesis is therefore proposed:

> *H_6 (Phase 1 and 2, Models A and B): Hedonic motivation has a positive influence on the behavioural intention of consumers to use mCommerce apps to purchase athleisure apparel.*

1.7.4.6 Price value

Venkatesh *et al.* (2012:161) describe price value as the cognitive trade-off between the perceived benefit afforded by the technology and the monetary cost of using it. The prices charged for items on mCommerce apps have the potential to influence consumers' decision-making process as they are often lower in comparison to prices charged in-store as mCommerce app owners save on overhead costs such as monthly salaries to salespeople, rent for physical stores, etc. These savings are then passed on to the consumer. Alkhunaizan and Love (2012:85) affirm that cost forms a fundamental part of a consumer's decision-making process when deciding whether or not to use mCommerce – so much so that it is recognised as one of the strongest deterrents of intention to use (Wu & Wang, 2005:726). According to Venkatesh *et al.* (2012:161), however, if the perceived benefit of using the technology outweighs the monetary cost of using it, this construct will have a positive effect on a consumer's behavioural intention to use.

The following hypothesis is therefore proposed:

> *H_7 (Phase 1 and 2, Models A and B): Price value has a positive influence on the behavioural intention of consumers to use mCommerce apps to purchase athleisure apparel.*

1.7.4.7 Habit

Habit refers to consumers' automatic execution of specific behaviours due to prior learning (Venkatesh *et al.,* 2012:161). Miladinovic and Xiang (2016:24) describe it as the extent to which a consumer will make automatic use of mCommerce apps. The usage of smartphones today occurs at a very habitual, almost unconscious level (Lipsman, 2015). This same phenomenon occurs with various other types of technology (Venkatesh *et al.,* 2012:161). Chou, Chiu, Ho and Lee (2013:4) for example, state that using apps encourages the formation of new habits, mainly as apps are fun and make the consumer's life more convenient. The more a certain behaviour is repeated, the more habitual it becomes. Miladinovic and Xiang (2016:24) state that if an activity or task is habitual in nature, people rely less on other external factors and choice strategies. The UTAUT2 shows that the construct of habit influences both behavioural intention and actual use (Venkatesh *et al.,* 2012:160). This is supported by Chopdar, Korfiatis, Sivakumar and Lytras (2018:117; 119) who found habit to have a direct influence on behavioural intention and a direct effect on actual behaviour.

The following hypotheses are therefore proposed:

> *H_8 (Phase 1 and 2, Models A and B): Habit has a positive influence on the behavioural intention of consumers to use mCommerce apps to purchase athleisure apparel.*
>
> *H_9 (Phase 2, Model B): Habit has a positive influence on consumers' actual use of mCommerce apps to purchase athleisure apparel.*

1.7.4.8 Perceived risk

Perceived risk is described as the nature and amount of risk, as assessed by a consumer in planning a purchase decision (Chen, 2013:316; Forsythe & Shi, 2003:869). Suh, Ann, Lee and Pedersen (2015:133) describe the construct as consumers' perceptions surrounding possible negative outcomes they may be exposed to as a result of transacting online. The concept of perceived risk, according to Farivar *et al.* (2017:590), is multifaceted, accounting for a number of context-specific risks. Forsythe *et al.* (2006:57) define four types of perceived risk that exist in an online or mobile shopping context, namely, financial risk, product performance risk, privacy risk and time/convenience risk. A study conducted by Wu and Wang (2005:722) supports these types of perceived risks from a mobile shopping point of view, as do Dai, Forsythe and Kwon (2014:15). Each of these four risk types is elaborated on below.

Forsythe and Shi (2003:869) define financial risk as "a net loss of money to a customer" arising from online shopping. Product performance risk refers to the lack of physical interaction with the item of interest which may result in it being unsuitable (Chen, 2015:62; Dai *et al.,* 2014:15; Ruane & Wallace, 2013:318; Forsythe *et al.,* 2006:57; Forsythe & Shi, 2003:869). Privacy risk refers to frustration or disappointment experienced by the consumer as a result of their personal information being disclosed after engaging in an online transaction (Dai *et al.,* 2014:15; Forsythe & Shi, 2003:869). Perceived time/convenience risk is defined as "the possibility and the importance of losing time and convenience when shopping online" (Chen, 2015:63). Online and mobile shopping, regardless of device used, allows consumers the freedom to buy anything they want from anywhere at any time (Forsythe *et al.,* 2006:59; Huang & Oppewal, 2006:337). However, there is still a time/convenience risk at play, which includes delays in order submission and delays in product delivery (Chen, 2015:62; Forsythe *et al.,* 2006:57; Forsythe & Shi, 2003:869). Of the four risk types mentioned above, two are repeatedly highlighted in the literature on online and mobile commerce, namely, financial risk and product performance risk. This is elaborated on below.

From a financial risk perspective, Marriott and Williams (2018:134) and Hubert, Blut, Brock, Backhaus and Eberhardt (2017:186) explain that financial risk is the most significant type of perceived risk in the mobile shopping domain. Chen (2013:430) supports this, stating that financial risk is one of the top predictors of perceived risk. Yang *et al.* (2015:261) go further, asserting that financial risk is the most significant predictor of perceived risk. The seminal work by Jacoby and Kaplan (1972) titled "The components of perceived risk" also identifies financial risk as the most significant forerunner to perceived risk. From a product performance risk perspective, Marriott and Williams (2018:136) and Lee and Stoel (2014:403) state that product performance risk is heightened in online or mobile environments as the quality, size or material of products cannot be accurately judged which may result in disappointment. Chaouali *et al.* (2016:211) support this, stating that, in digital retail, there are certain “spatial and temporal separations”. This combined with a lack of physical interaction or observation, leads to a lack of trust in the environment. Forsythe and Shi (2003:871) and Dai *et al.* (2014:15) concur, affirming that product performance risk is one of the most frequently cited reasons for consumers not shopping online.

Numerous studies highlight these two risks together. Ueltschy, Krampf and Yannopoulos (2004:71) conducted a cross-country study across Canada, the UK and the US, to assess consumers’ perceived risk towards online purchasing of clothing, computers and airline tickets. The research revealed that financial risk and product performance risk were much greater in the category of clothing purchases, compared to computer purchases or the purchase of airline tickets. Marriott and Williams (2018:138; 139) explored the effects of perceived risk and trust on mobile shopping in the UK. Their model tested several types of perceived risk (financial risk, psychological risk, performance risk and time risk) and trust (m-vendor trust, m-service trust, m-device trust and disposition trust) and their influence on the behavioural intention of consumers to use mobile shopping. Their research found financial risk and product performance risk to be the most accurate predictors of perceived risk. Farivar *et al.* (2017:591) state that financial risk and product risk, also commonly referred to as product performance risk, are the two primary risk types influencing consumers’ online purchasing behaviour. This is supported by Yang *et al.* (2015:261) in China who examined the perceived risks associated with mobile payment acceptance. Their findings revealed that financial risk and product performance risk have the strongest negative impact on consumer acceptance of mobile payments. Similarly, Featherman and Pavlou (2003:460) report that financial risk and product performance risk are the two most significant predictors of perceived risk, with perceived risk subsequently having a significant influence on consumers’ behavioural intention to use eServices. These findings are corroborated by South African studies.

In the South African context, financial risk and product performance risk feature as the two most prominent types of risk influencing consumers’ acceptance and use of online and mobile commerce. Goldstuck (2014:13; 17) found that firstly, South Africans’ concerns about online security increase year on year, reflecting financial risk. Secondly, the biggest barrier to purchasing online or via mobile phone is the lack of physical interaction with the product, reflecting product performance risk. Swiegers (2018:128) concurs with Goldstuck as to financial risk, reporting that financial risk impacts South African consumers' behavioural intention to purchase online. Similarly, Beneke, Greene, Lok and Mallett (2012:8) found product performance risk to have a significant influence on South Africans' intention to purchase, again supporting Goldstuck's findings. For the purposes of this study then, the construct of perceived risk includes a specific focus on financial risk and product performance risk. This is supported by the literature, as detailed above.

The construct of perceived risk has been shown to have an effect on behavioural intention to use mobile banking services in a study conducted by Chen (2013:428). Wu and Wang also demonstrated that perceived risk significantly influences consumers' intention to use mobile shopping as well as their actual use (Holmes, Byrne & Rowley, 2013:35; Wu & Wang, 2005:726).

The following hypotheses are therefore proposed:

> *H_{10} (Phase 1 and 2, Models A and B): Perceived risk has a negative influence on the behavioural intention of consumers to use mCommerce apps to purchase athleisure apparel.*
> *H_{11} (Phase 2, Model B): Perceived risk has a negative influence on consumers' actual use of mCommerce apps to purchase athleisure apparel.*

1.7.4.9 Trust

Trust, according to Ribbink *et al.* (2004:447), in the context of online shopping is defined as "the degree of trust consumers have in online exchanges" or, in the case of this study, exchanges via a mobile phone. Kesharwani and Bisht (2012:309-310) describe it as the degree to which a trustor (for example, a consumer) feels confident about relying on a trustee (for example, an mCommerce retailer). Trust has been found to significantly influence mCommerce usage intention and it generally decreases perceived risk associated with using a product or service (Farivar *et al.,* 2017:597;

Joubert & van Belle, 2013:29; Ribbink *et al.,* 2004:446). However if trust is already impaired, risk increases (Amoroso & Hunsinger 2009:25) while the likelihood of consumers purchasing, decreases (Lim, 2003:218). Trust can therefore be seen as mediating the influence of perceived risk on behavioural intention and actual use.

The following hypotheses are therefore proposed:

> *H_{12} (Phase 1 and 2, Models A and B): Trust mediates the negative influence of perceived risk on the behavioural intention of consumers to use mCommerce apps to purchase athleisure apparel.*
> *H_{13} (Phase 2, Model B): Trust mediates the negative influence of perceived risk on consumers' actual use of mCommerce apps to purchase athleisure apparel.*
> *H_{14} (Phase 1 and 2, Models A and B): Trust has a positive influence on the behavioural intention of consumers to use mCommerce apps to purchase athleisure apparel.*

1.7.4.10 Behavioural intention and actual use

The construct of behavioural intention, according to Miladinovic and Xiang (2016:12), is described as an individual's willingness to use or accept a particular technology, for example, a mobile shopping app. Phong, Khoi and Le (2018:119) expand on this definition, stating that behavioural intention is an individual's personal evaluation of their ability to perform an online transaction by means of a mobile device through a wireless connection.

The dependent variable in this study is actual use. Actual use refers to an individual actually using, in the case of this study, mCommerce apps when purchasing athleisure apparel in South Africa (Davis, 1986:25). As mentioned in section 1.7.4, the behavioural intention of a user to use a certain technology is a strong predictor and determining factor of the user actually using the technology (Miladinovic & Xiang, 2016:12; Persson & Berndtsson, 2015:28; Williams *et al.,* 2015:464; Venkatesh *et al.,* 2012:157). Further research by Tarhini *et al.* (2016:842) and Wu and Wang (2005:726) supports, contending that behavioural intention is an adequate predictor of actual use.

The following hypothesis is therefore proposed:

> *H_{15} (Phase 2, Model B): Behavioural intention has a positive influence on consumers' actual use of mCommerce apps to purchase athleisure apparel.*

1.7.5 Proposed model for this study

The arguments outlined earlier indicate the suitability of the UTAUT2 for this study. The model has successfully explained behavioural intention in various mobile contexts, including payments, mobile Internet and banking (Marriott & Williams, 2016:264). Its application in the field of mobile shopping research, however, has been underutilised, despite the fact that it has been proven to outperform all the other TAMs (Miladinovic & Xiang, 2016:19). The model has been adapted slightly for the purposes of this study and includes two additional constructs, namely, perceived risk and trust. These constructs have been repeatedly cited as two of the main variables impacting consumers' use of mCommerce (Farivar *et al.,* 2017:597; Dai & Chen, 2015:42; Wu & Wang, 2005:726; Lim, 2003:218). The proposed model and hypotheses for this study are illustrated in Figure 1.9 below.

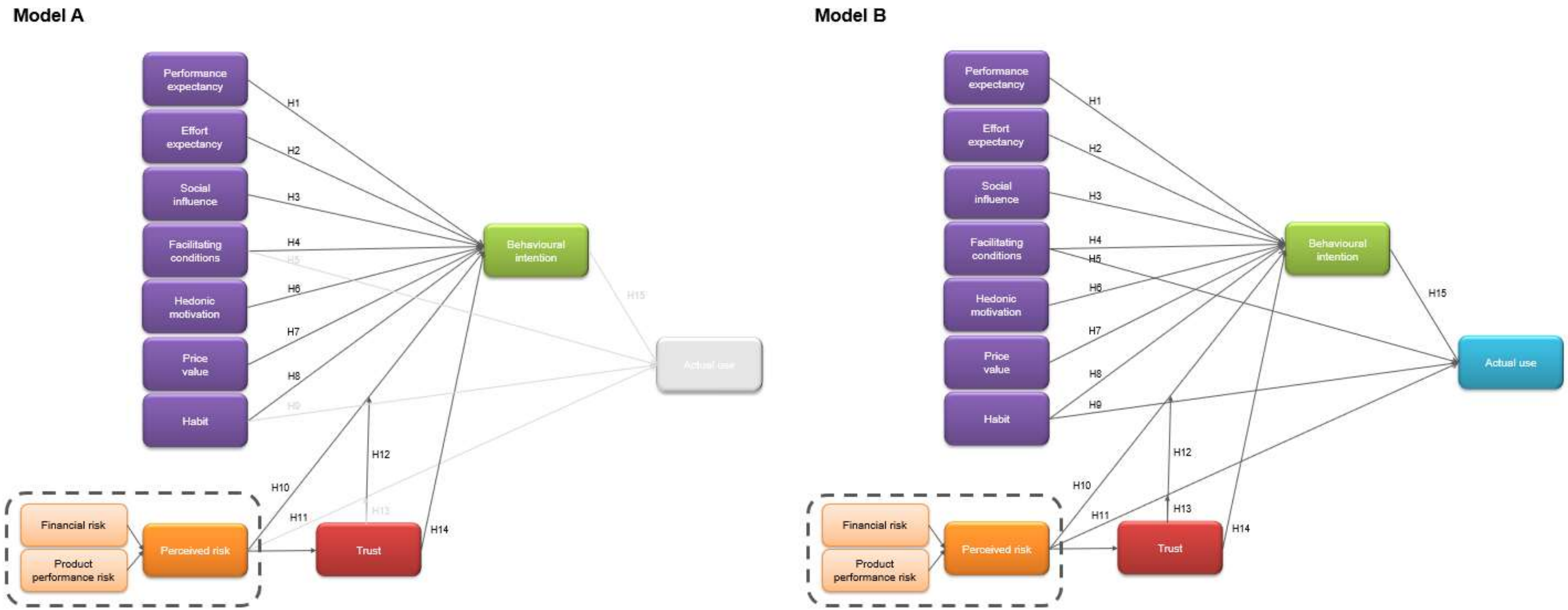


Figure 1.9: Proposed model and hypotheses for this study

***Source**: Researcher's own construct*

1.8 Research methodology

The research methodology section follows the structure of the 'research onion' conceptualised by Saunders, Lewis and Thornhill (2016:124) (refer to Figure 1.10). It commences with the selected philosophy and approach to theory development, followed by an outline of the research design and plan. Thereafter, the population and sample for the study are discussed and an outline of the sampling plan is presented. The instruments, sources and procedures for data collection are then discussed. The section concludes with the data analysis procedure.

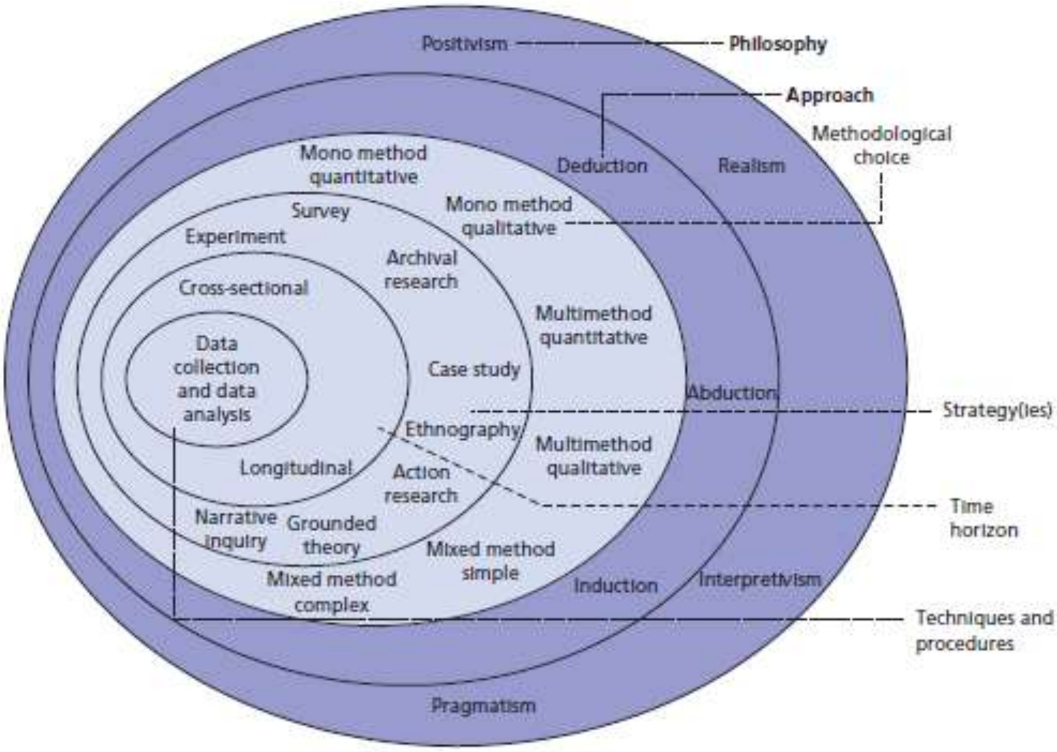


Figure 1.10: The research onion

***Source**: Saunders et al. (2016:124)*

1.8.1 Research philosophy

Research philosophy refers to "a system of beliefs and assumptions about the development of knowledge" (Saunders *et al.,* 2016:124). There are five major research philosophies: positivism, critical realism, interpretivism, postmodernism and pragmatism. The positivist research philosophy is described as the preference for collecting quantitative data through observable reality and searching for relationships and regularities in the data to arrive at generalisations (Benzo, Mohsen & Fourali, 2018:96-97; Saunders *et al.,* 2016:135-136). This research philosophy produces knowledge that is accurate and free from ambiguity; it is therefore the proposed research philosophy for this study, which seeks to determine the constructs that influence consumers’ acceptance and use of mCommerce apps to purchase fashion apparel in South Africa, with a specific focus on athleisure apparel.

1.8.2 Approach to theory development

The nature and link between theory and research can be described by clearly understanding deductive and inductive theories. Deductive theory requires the researcher to deduce a hypothesis based on what is known about a specific domain from a theoretical or practical point of view. Inductive theory, on the other hand, focuses on drawing inferences from observations (Benzo *et al.,* 2018:182; Saunders *et al.,* 2016:51; Bryman & Bell, 2011:9-11). This study is grounded in deductive theory as mCommerce and the purchase of athleisure apparel are examined to formulate a new model for testing. Fifteen proposed hypotheses have been developed for testing (refer to section 1.7.4 and Figure 1.9).

1.8.3 Research design and plan

A research design can be defined as “the overall plan of the methods used to collect and analyse the data” (Hair, Celsi, Ortinau & Bush, 2013:36). There are three distinct research designs in marketing research, namely, exploratory, descriptive and causal (often referred to as explanatory). Benzo *et al.* (2018:106) and Hair *et al.* (2013:36-37) state that exploratory research aims to gain insights into consumer attitudes or behaviours to better define the problem at hand. A descriptive research design involves the collection of quantitative data to answer specific research questions. Finally, causal research looks at cause-and-effect relationships between variables by means of data collection.

The theoretical chapters of this study (Chapters 3, 4 and 5) as well as the industry research chapter (Chapter 2), were compiled using secondary research. Secondary data is defined as “information previously collected for some other problem or issue” (Hair *et al.,* 2013:26). In this study, relevant data was gathered from sources such as academic journals which were obtained from, amongst others, the Emerald, Science Direct and SA ePublications databases. Accredited websites and academic textbooks were also consulted.

Primary data collection can be described as gathering information to answer a current research problem (Hair *et al.,* 2013:26). Benzo *et al.* (2018:49) describe it as generating and analysing new data which is unpublished. The nature of this study requires a descriptive research design in order to collect the primary data as the research problem is clear, the research objectives have been set and the hypotheses have been formulated.

As a descriptive research design was applied, a quantitative research methodology was used to examine the relationships between performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, habit, perceived risk, trust and behavioural intention. The influence of facilitating conditions, habit and perceived risk on actual use in addition to behavioural intention were also determined. Moreover, the study examined whether trust had a mediating effect on the influence of perceived risk on behavioural intention and actual use. Finally, the influence of behavioural intention on actual use was determined.

Benzo *et al.* (2018:302) state that quantitative research “collects numerical data and uses logic and statistical analysis to verify hypotheses”. Quantitative research is therefore relevant for the purposes of this study as hypotheses have been formulated for testing. In line with the positivist research philosophy, the collection of quantitative data is preferred as relationships in the collected data can be identified and generalised to the greater population (Saunders *et al.,* 2016:135-136). The proposed research design therefore also aligns well with the positivist research philosophy.

Quantitative data collection methods include questionnaires, structured interviews, observations, and the like. This study used a mono-method (quantitative) methodology; a quantitative data collection technique was used, namely, questionnaires (Saunders *et al.,* 2016:166). A survey research strategy was selected;

this can be described as a plan that the researcher will use to answer the research questions at hand (Saunders *et al.,* 2016:177). A survey strategy and questionnaire allow for the collection of standardised data from a large population, which can be used to suggest reasons for relationships between variables (Saunders *et al.,* 2016:181-182).

1.8.4 Target population and sample

The target population of this study comprises South African consumers who use or have used an mCommerce app over the last 12 months. Consumers who simply made use of an mCommerce app to browse (without making a purchase) were included in the study along with consumers who did make a purchase (i.e. they bought an athleisure apparel item using the app). The former were used to measure behavioural intention to use while the latter were used to measure actual use.

Effective Measure (2017a:2) reports that 66% of consumers purchase online or via mobile phone at most once every three months. IT News Africa (2017) states that 67% of South African shoppers who shop online or via mobile phone purchase less than ten products over a year. Therefore, the time frame of 12 months was selected as an optimal period for a sufficient sample to be drawn as the frequency of mCommerce purchases is low in South Africa.

Non-probability sampling is described as a sampling design in which the probability of each sampling unit's selection for participation in the study is unknown (Hair *et al.,* 2013:140; Zikmund & Babin, 2010:423). The sampling method in this study was a combination of two-part quota and convenience sampling. Quota sampling is based upon the premise that the sample is representative of the population being investigated as the variability in the sample for various quota variables is designed to reflect the variability of the actual population (Saunders *et al.,* 2016:299; Bryman & Bell, 2011:180; Zikmund & Babin, 2010:425). As the target population comprises South African consumers who use or have used an mCommerce app to purchase athleisure apparel over the last 12 months, as well as consumers who have purely used it for browsing purposes, the quotas were created to ensure that the data was representative of the population of South Africa (refer to Table 1.1). In addition to quota sampling, convenience sampling was also used. This sampling method allows for the research sample to be drawn at the researcher's convenience and permits a large number of respondents to be interviewed within a shorter timeframe (Hair *et al.,* 2013:145; Zikmund & Babin, 2010:424). The proposed sampling plan, as shown in Table 1.2, shows the details of the data collection. The study proposed one month within which to collect 500 questionnaire responses. Convenience sampling was therefore well-suited to this study.

To ensure that the sample was representative of the South African population, it was imperative to understand the current demographic breakdown of the country. According to the Statistics South Africa (Stats SA, 2017:1) mid-year population estimates report, the national population was estimated at 56.52 million. Of these 56.52 million, 80.8% (45.6 million) were Black, 8.8% (4.9 million) were Coloured, 8.0% (4.4 million) were White and 2.5% (1.4 million) were Indian/Asian. Approximately 51% of the population was female (28.82 million) while 49% was male (27.69 million) – a relatively even split. Approximately 25.3% (14.3 million), the majority of the population, reside in Gauteng, with KwaZulu Natal following in second place at 19.6% (11.1 million) (Stats SA, 2017:1). As the majority of the South African population resides in Gauteng, it was proposed that the sample be drawn from this province specifically. According to Effective Measure (2017a:5), Gauteng is home to the largest percentage of online shoppers in South Africa, namely a total of 43%.

The proposed quotas for this study, as depicted in Table 1.1, were compiled based on the aforementioned ethnic and gender demographics of South Africa.

Table 1.1: Quotas and questionnaires to be fielded

Ethnicity	Percentage of the population	Number of questionnaires to be fielded (equal male and female)		
		Male	Female	Total
Black	80.8%	202 101 Phase 1, Model A 101 Phase 2, Model B	202 101 Phase 1, Model A 101 Phase 2, Model B	404
Coloured	8.8%	22 11 Phase 1, Model A 11 Phase 2, Model B	22 11 Phase 1, Model A 11 Phase 2, Model B	44
Indian/Asian	2.5%	6 3 Phase 1, Model A 3 Phase 2, Model B	6 3 Phase 1, Model A 3 Phase 2, Model B	12
White	8.0%	20 10 Phase 1, Model A 10 Phase 2, Model B	20 10 Phase 1, Model A 10 Phase 2, Model B	40
Total	**100%**	**250**	**250**	**500**

Source: *Stats SA (2017)*

Table 1.2 below provides a synopsis of the sampling plan for this study.

Table 1.2: Sampling plan

Target population	South African consumers who simply made use of an mCommerce app to browse (i.e. they did not make a purchase) were included in the study along with consumers who did make a purchase (i.e. they bought an athleisure apparel item using the app)
Sampling units	• Phase 1: South African consumers who simply made use of an mCommerce app to browse (i.e. they did not make a purchase) were included in the study along with • Phase 2: consumers who did make a purchase (i.e. they bought an athleisure apparel item using the app)
Sampling elements	• Phase 1: South African consumers who simply made use of an mCommerce app to browse (i.e. they did not make a purchase) were included in the study along with • Phase 2: consumers who did make a purchase (i.e. they bought an athleisure apparel item using the app), in selected metropoles of Johannesburg and Tshwane
Sampling technique	Non-probability two-factor quota and convenience sampling
Time and period	July-August 2019
Extent	Gauteng province of South Africa
Sampling size	500 respondents with an ideal split of 50 male/50 female based in Gauteng, i.e. 250 consumers who simply made use of an mCommerce app to browse (i.e. they did not make a purchase) were included in the study along with 250 consumers who did make a purchase (i.e. they bought an athleisure apparel item using the app)

1.8.5 Data collection

The data collection instrument selected for this study was a questionnaire. A hybrid method was used to ensure that a sufficient number of respondents was reached, comprising self-completed and interviewer-administered questionnaires. Self-completed questionnaires were answered by the respondents themselves and could be distributed via the Internet (Benzo *et al.,* 2018:318; Saunders *et al.,* 2016:440). Email was used to send the questionnaire to each consumer in South Africa. Respondents were able to access the questionnaire by clicking on the link provided in the email. In addition, interviewer-administered questionnaires were leveraged to improve the response rate. These were conducted either in the respondent's home, at their place of work or via mall-intercept, which refers to the respondent being approached whilst shopping in a mall (Malhotra, 2007:187-188). Field workers from Osmoz Consulting with extensive experience in data collection were contracted to assist with this. The fieldworkers were briefed on the study prior to collecting the data to ensure they were able to answer any potential questions from respondents.

The questionnaire was targeted at specific respondent demographics, as detailed in Table 1.1 and made use of previously validated five-point Likert scales. A Likert scale requires that respondents indicate their level of agreement or disagreement with particular statements (Saunders *et al.,* 2016:457; Malhotra, 2007:274). This type of scale is classified as a rating scale and is widely used to collect opinion data, which is what this study is interested in (Saunders *et al.,* 2016:457; Malhotra, 2007:274). In addition, the scale is straightforward and respondents can easily comprehend what is expected of them, making it well-suited to questionnaires (Malhotra, 2007:275).

The survey was validated through a pilot test on a sample of 40 individuals. The results of the pilot were not included in the final results. A pilot is essential to identify potential challenges before formally collecting the data required for the study. It also assists in refining the questionnaire and addressing any possible concerns before commencing with the collection of the data. This also provides an opportunity to assess the validity of the questionnaire, as well as the expected reliability of the data that is to be collected (Saunders *et al.,* 2016:473).

1.8.6 Data entry, editing and coding

Once all the research was gathered, a consultant from Osmoz Consulting reviewed the data for completeness. The consultant then manually captured the data into the IBM Statistical Package for the Social Sciences (SPSS), version 24 to secure data analysis by the University of Johannesburg's (UJ's) Statistical Consultation Service (Statkon). All physical questionnaires (paper-based records) were kept in a steel safe during this period, with access limited to Osmoz Consulting. All online questionnaires and captured research (computer-based records) were password protected and stored in an access-controlled and password-protected cloud drive with access limited to the researcher, research supervisors and Osmoz Consulting.

1.8.7 Data analysis and procedure

Data analysis was conducted using the SPSS programme, version 24. This programme applied various statistical procedures, including descriptive statistical analyses, multiple regression modelling, factor analysis, and structural equation modelling (SEM) to test the hypotheses. This assisted in the development and delivery of accurate statistical data that contributes towards the existing research field by offering improved knowledge regarding mobile shopping via apps in emerging markets such as South Africa. Insight gathered provides South African business owners selling athleisure apparel with a more in-depth understanding of the constructs that influence both consumers' behavioural intention to use and actual use of mCommerce apps to purchase athleisure apparel. Statkon statistically analysed the data to ensure the quality and validity of the results.

1.9 Ethical considerations

Ethical clearance was obtained from UJ before commencement of this study. Research participants were fully informed of the planned research process in order to obtain informed consent. Participation in the questionnaire was at each participant's own discretion. All participants' identities were protected by replacing names with codes and all data was kept confidential and securely stored using protected by passwords (Bryman & Bell, 2011:122). Any paper-based data was also securely stored and locked away.

1.10 Layout of the study

This study comprises eight chapters, as summarised below.

Chapter 1:	This chapter contains an introduction and background to the study. The research problem, objectives and hypotheses are then presented, followed by a review of the academic literature.
Chapter 2:	This chapter contains a discussion of the evolution of the retail industry globally and in South Africa, showing how it has grown and developed over the years, including the advent of mCommerce.
Chapter 3:	This chapter contains a perspective on the foundational theories and models grounding the study.
Chapter 4:	This chapter explores the UTAUT2 with perceived risk and trust.
Chapter 5:	This chapter validates the proposed model for the study.
Chapter 6:	This chapter defines the research methodology, including the design and plan, the population and sample, the sampling plan, data collection and data analysis.
Chapter 7:	This chapter analyses and interprets the data and presents the research results.

Chapter 8: This chapter provides conclusions and recommendations derived from the research findings and discusses how the primary and secondary objectives were achieved.

1.11 Discussion of terminology

Key terms are referred to throughout this study and are defined below.

Activewear: Attire designed for informal wear or recreation (Merriam Webster, 2020a).

Actual use: An individual's actual use of mCommerce apps when purchasing athleisure apparel in South Africa (Davis, 1986:25). This term is often used interchangeably with the terms 'use behaviour' and/or 'adoption'.

App: A piece of software designed to run on a mobile device such as a tablet or smartphone (Techopedia, 2020; Miladinovic & Xiang, 2016:7).

Athleisure: A term used to describe activewear that can be used both for exercising and general wear (Team, 2016).

Behavioural intention: The willingness of an individual to use a particular technology (Miladinovic & Xiang, 2016:12). This term is often used interchangeably with the term 'acceptance'.

eCommerce: The "buying and selling of goods via the Internet" (Çelik & Yilmaz, 2011:152).

Effort expectancy: The level of ease associated with consumers' use of a specific technology (Venkatesh *et al.,* 2012:159).

Facilitating conditions: A consumer's perception of the available resources and support when performing specific behaviour (Venkatesh *et al.,* 2012:159).

Habit: The extent to which a consumer makes automatic use of mCommerce apps (Miladinovic & Xiang, 2016:24).

Hedonic motivation: The enjoyment associated with using a specific technology (Venkatesh *et al.,* 2012:161).

mCommerce: A type of eCommerce by means of a wireless handheld device such as a smartphone (Bloomenthal, 2019b; Persson & Berndtsson, 2015:2).

Perceived risk: Consumers' perceptions as to potential negative outcomes as a result of transacting online (Suh *et al.*, 2015:133).

Performance expectancy: The extent to which the usage of a specific technology will provide a benefit to consumers who perform specific activities (Venkatesh *et al.,* 2012:159).

Price value: The cognitive trade-off between the perceived benefit provided by the technology in question and the monetary cost of using it (Venkatesh *et al.,* 2012:161).

Smartphone: A mobile phone built with an advanced mobile OS that allows it to run mobile apps (Cassavoy, 2017).

Social influence: Consumers' belief that their family and friends believe they should use a particular technology (Venkatesh *et al.,* 2012:159).

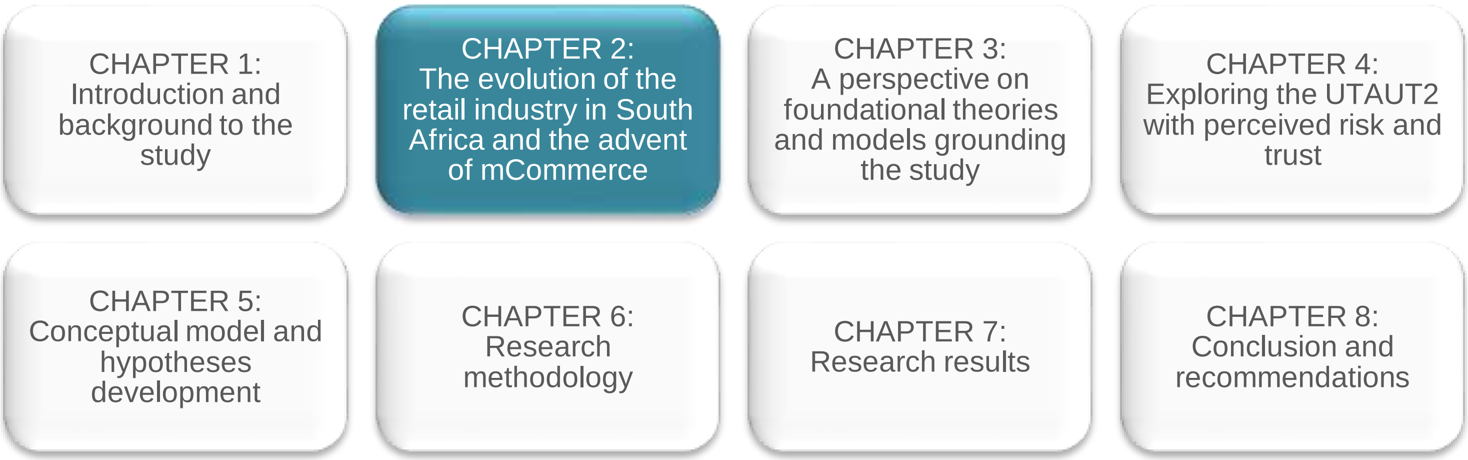
Trust: The degree to which a trustor (for example, a consumer) feels confident about relying on a trustee (for example, an mCommerce retailer) (Kesharwani & Bisht, 2012:309-310).

1.12 Conclusion

Most South Africans access the Internet via their mobile phones (Space Station, 2017) and prefer to utilise apps to shop (Business Tech, 2015). Of those who do shop via their mobile phones, however, the category of clothing and accessories does not seem to feature prominently (Erken, 2017; Goldstuck, 2014:27). Why is this? This study seeks to determine the constructs that influence consumers' acceptance and use of mCommerce apps to purchase athleisure apparel in South Africa. This study uses quantitative survey research; insights gleaned from the research will add to the existing body of knowledge. The results will also assist mCommerce business owners in South Africa selling athleisure apparel to better understand the factors that influence both consumers' behavioural intention to use, and their actual use of mCommerce apps to purchase their products, enabling them to adjust their business strategies accordingly.

CHAPTER 2

THE EVOLUTION OF THE RETAIL INDUSTRY IN SOUTH AFRICA AND THE ADVENT OF mCOMMERCE



2.1 Introduction

Chapter 2 provides a detailed account of the evolution of the retail industry in South Africa and the advent of mobile commerce (mCommerce). The chapter commences with a definition of the retail industry and retailing in South Africa, followed by a brief history of the industry and its current performance. A discussion of the changes in South African retail consumers’ buying habits is then presented, followed by a look at the emergence of electronic commerce (eCommerce) and mCommerce. The chapter then examines the athleisure apparel industry in South Africa, defining the industry and providing an overview of it. The chapter concludes with a view on mCommerce integration into the athleisure apparel industry.

2.2 A perspective on the South African retail industry

This section commences with a definition of the South African retail industry and retailing. A brief history on the industry is then provided, followed by an overview of current performance. An investigation into the changing buying habits of South African retail consumers is then presented. The section concludes with a discussion surrounding the emergence of eCommerce and mCommerce.

2.2.1 Defining the retail industry and retailing in South Africa

Commercially, retailing is vitally important to the economy as it provides consumers with an opportunity to purchase merchandise from a variety of manufacturers, specialising in different products (Vault, 2018). An end-to-end retail supply chain, as can be seen in Figure 2.1, consists of various role players, namely, the manufacturer (the entity responsible for manufacturing the product in question), the wholesaler (the entity which purchases the product in large quantities from the manufacturer and sells it to the retailer), the retailer (the entity selling the product to the public (consumers) in lower quantities and at higher prices), and the consumer (the end-user purchasing the product from the retailer for consumption) (Farfan, 2018; Vault, 2018).

Figure 2.1: The retail supply chain
Source*: Adapted from Farfan (2018)*

Retailers form the final link in the supply chain between manufacturers and consumers. It is an imperative function in the supply chain as it allows manufacturers to focus on production as opposed to interaction with consumers (Farfan, 2018). Lexico by Oxford (2020b) describes a retailer as an individual or business selling goods to the public in smaller quantities for consumption as opposed to reselling. A retail industry therefore consists of all the various retailers that sell goods to consumers for consumption (Farfan, 2018; Lucintel, 2012).

The global retail industry is mainly comprised of food, beverages, pharmaceuticals, apparel and accessories, home improvement materials, technology and others (Lucintel, 2012). According to Statista (2018a), the global retail industry is predicted to deliver sales totalling US$27.7 trillion by 2020, an increase of 11.5% from 2018. McNair and Pearl (2018) posit that the main factors driving this growth include improvements in importing/exporting, increased cross-border sales and digital retailing such as eCommerce and mCommerce. mCommerce specifically has had a profound impact on this growth, accounting for the largest share of global digital retail sales in 2017 at 58.9%. McNair and Pearl (2018) predict that mCommerce will be responsible for 72.9% of the global eCommerce market by 2021.

The above figures highlight the significance of the global retail industry to economies across the world (Ward, 2015) as well as the importance of mCommerce as a key channel in retail. This is supported by findings presented in the Euler Hermes 2018 Economic Research Report. According to this report, 2017 was a record year for bankruptcy filings from United States (US)-registered organisations. The main reason for these bankruptcy filings was due to organisations failing to remain competitive in an industry which is increasingly influenced by technology. This same report emphasises the importance of retailers understanding and implementing the latest technologies, such as mCommerce, to cement their relevance in the market in 2018 and beyond (Euler Hermes Economic Research, 2018:1).

Although the global retail industry is dominated by developed countries, emerging economies also have a role to play. Brazil, Russia, India, China and South Africa are the five countries that together, form the BRICS. These countries were grouped together based on their expanding middle classes, increasing incomes and growing economies. The BRICS countries present a lucrative opportunity to retailers facing static demand in Western countries (Euromonitor International, 2013). This particular study focuses on the emerging economy of South Africa, the smallest of the BRICS emerging countries.

Locally, in South Africa, the retail industry comprises seven retail clusters, namely, (i) general dealers, (ii) food, beverages and tobacco in specialised stores, (iii) pharmaceuticals and medical goods, cosmetics and toiletries, (iv) textiles, clothing, footwear and leather goods, (v) household furniture, appliances and equipment, (vi) hardware, paint and glass, and (vii) all other retailers (Stats SA, 2018b; Gauteng Province Quarterly Bulletin, 2012:3). As this study examines the constructs influencing South African consumers' acceptance and use of mCommerce apps to purchase athleisure apparel – a type of clothing – it focuses on the textiles, clothing, footwear and leather goods cluster specifically.

Various retail formats operate within the seven clusters highlighted above. The most prominent are department stores (selling a wide range of manufacturers' products, for example, Makro), grocery stores (selling mostly foods and beverages, but also other home products, for example, Spar or Woolworths), Internet or online retailers (retailers that do not maintain a physical, brick-and-mortar presence, but rather make their products available to consumers through a website, for example Takealot.com, Zando and Superbalist.com) as well as mobile retailers (similar to Internet retailers, but these retailers make use of smartphone apps to sell products to consumers, for example, Takealot.com, Zando and Superbalist.com) (Farfan, 2018).

The South African retail industry is dynamic (Prinsloo, 2016) and boasts a variety of different retailers operating within each of the aforementioned retail formats. Online and mobile retailers are of specific interest to this study. In order to better understand how these retailers were established, it is important to consider the history of the retail industry as discussed below.

2.2.2 A brief history on the South African retail industry

Retailing is fundamental in the evolution of modern humanity (Braun, 2015). Before the birth of currency, civilisations were already trading (Reyhle, 2014). Between 9 000 and 6 000 BC, according to Braun (2015), traders bartered animals such as sheep, cows and camels for other goods. At around 1 200 BC, traders used cowrie shells as currency for commercial transactions. Coins later replaced these shells and subsequently currency, as it is known today, was invented (Reyhle, 2014). Retail evolved alongside currency, with rapid progression in the 1900s.

In the early 1900s, local corner stores were established. People walked to and in between these different stores to source the products they required from a limited selection (Leibowitz, 2013). In South Africa, the first clothing retailer, Ackermans, opened its doors in 1916 (Maydon, 2017) followed by OK Bazaars in 1927 (SA History, 2015). In the same decade, the automobile was introduced (South African Embassy in the Netherlands, 2013), offering consumers the ability to drive to stores and purchase more than they were traditionally only able to carry. Refrigerators appeared at the same time, offering consumers the ability to purchase and stock more products at home (Leibowitz, 2013). With more purchasing came more producing. And with more producing came greater choice. Retailers noticed that consumers would often want to purchase more than the physical cash they had available, and proceeded to invent ‘charge cards’, referred to as credit cards today – a convenient payment method for consumers who did not have enough cash on hand (Braun, 2015).

Towards the 1960s, electronic cash registers were launched, with Woolworths being the first South African retailer migrating to a computerised retail system (Maydon, 2017). During this decade, convenience and speed became priorities in the retail space. Chain stores and supermarkets appeared, allowing consumers to purchase all their groceries under a single roof (OCS, 2016). Many of the large retailers, still active in South Africa today, were founded in this decade, including Spar and Pick n Pay. Some of the first malls in South Africa were also welcomed around this time, including Hyde Park Corner and Killarney Mall in Johannesburg (SA Venues, 2020).

From the 1980s to 1990s, specifically the period between 1984 and 1993, the market began slowing down and South Africa experienced its poorest decade-growth performance. This was mainly as a result of trade sanctions and opposition to the then apartheid government. However, the transition to a democratic government in 1994 brought with it a turnaround in economic performance (du Plessis & Smit, 2006:2-3). Following 1994, many retailers shifted their strategies and operations, targeting new consumer segments which had emerged – previously-disadvantaged communities (De Bruyn & Freathy, 2011:539).

Since then, the market has evolved significantly, both from an economic and infrastructure point of view (Flanders Investments & Trade, 2016:5). Economically, many South Africans have been lifted out of poverty and moved into the middle class, the country's gross domestic product (GDP) has almost doubled and access to services has expanded greatly (Leke, Fine, Dobbs, Magwentshu, Lund, Wu & Jacobson, 2015). From an infrastructural perspective, the retail industry has benefitted significantly due to increased distribution opportunities to urban and rural areas around the country (Gauteng Province Quarterly Bulletin, 2012:4). The post-apartheid era furthermore brought with it unprecedented growth in urbanisation which led to a significant increase in mall development (Brand South Africa, 2014). South Africa is currently home to over 2 000 malls, equating to 23 million square metres – the sixth highest number in the world. Its retail industry has advanced to becoming the largest in sub-Saharan Africa and occupies the 20th position globally (University of Pretoria, 2016:50). In 2017, the industry hit a record high, generating R1 trillion in sales revenue (Business Tech, 2018b). The following section provides an overview of the current performance of the South African retail industry.

2.2.3 A current overview of the South African retail industry

The South African retail industry employs over 800 000 South Africans (Stats SA, 2018a). The economy is becoming increasingly consumer-driven, with the retail industry playing a key role in this growth (South African Market Insights, 2017; Gauteng Province Quarterly Bulletin, 2012:4). As mentioned in section 2.2.1, the South African retail industry comprises seven retail clusters, with the general dealers' cluster (inclusive of supermarkets) contributing the largest percentage to total retail sales in 2017 at 44% (refer to Figure 2.2) (Stats SA, 2018a). Textiles, clothing, footwear and leather goods retailers contributed 15.7% while the cluster for all other retailers contributed 11.9% to total retail sales in 2017 (Stats SA, 2018b:2).

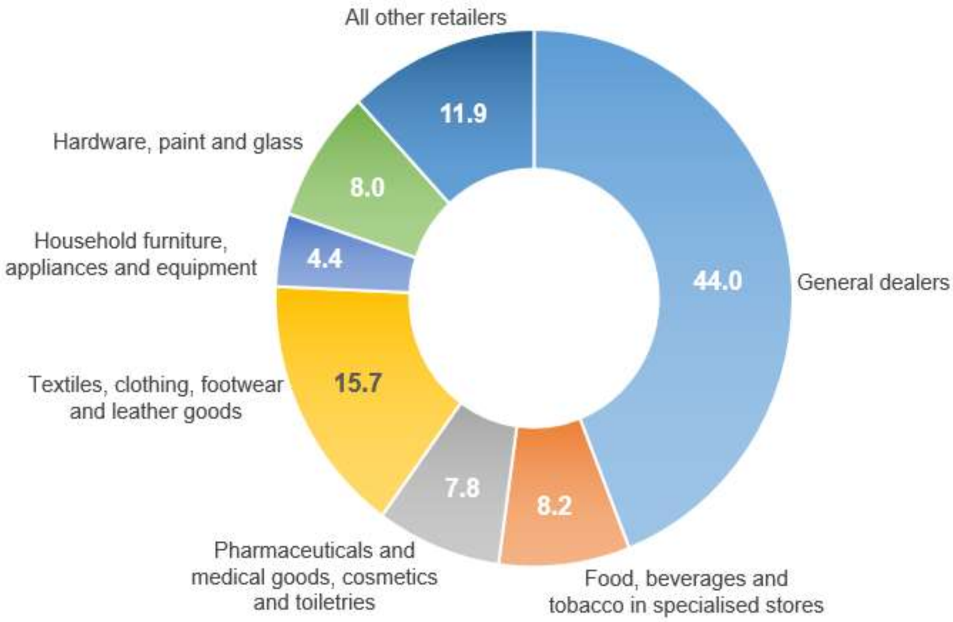


Figure 2.2: Percentage of total retail sales in 2017 by retail cluster

***Source**: Adapted from Stats SA (2018b:2)*

In 2016, consumer spend only increased by 1.7% from 2015 (Business Tech, 2018b; Stats SA, 2018a) – the weakest growth experienced by the retail industry in seven years. This was mainly due to poor economic growth along with a number of other factors, including political instability, the drought experienced across the country as well as low credit growth (Omarjee, 2017). Household expenditure was also under increased pressure as a result of rising costs of fuel and utilities, inflation, the introduction of new taxes and the increase of sin taxes (Flanders Investments & Trade, 2016:6). Consumers in South Africa face continued financial pressures as a result of these factors, alongside low growth in wages. Towards the fourth quarter of 2016, however, a good recovery on sales was shown (Omarjee, 2017) and this extended into 2017. By the end of 2017, the South African retail industry closed off at R1 trillion (March 2018 prices) in retail trade sales (Business Tech, 2018b; Stats SA, 2018a). Consumer spend increased by 2.9% in 2017, resulting in an overall marginally improved performance compared to 2016. However, this growth was still not on par with growth experienced in 2015 at 3.3% (Business Tech, 2018b; Stats SA, 2018a).

For the first quarter of 2018 (i.e. January to March 2018) total retail trade sales increased by 4.1% compared to the same period in 2017, as can be seen in Table 2.1. The main contributors to this change were, firstly, a 1.3% contribution by textile, clothing, footwear and leather goods retailers as a result of an increase of 8.1% in sales. Secondly, the general dealers cluster enjoyed a 2.2% increase in sales, contributing 1%. Lastly, household furniture, appliances and equipment retailers contributed 0.7% thanks to a 16.3% increase in sales (Stats SA, 2018b:2).

Table 2.1: Retail trade sales in South Africa for the period Jan-Mar 2018

Type of retailer	**Retail trade sales Jan-Mar 2017 (R mil)**	**Weight**	**Retail trade sales Jan-Mar 2018 (R mil)**	**% change**	**Contribution (% points) to the total % change**
General dealers	91 022	44.0%	92 986	2.2%	1.0%
Food, beverages and tobacco in specialised stores	17 061	8.2%	17 508	2.6%	0.2%
Pharmaceuticals and medical goods, cosmetics and toiletries	16 223	7.8%	17 119	5.5%	0.4%
Textiles, clothing, footwear and leather goods	32 527	15.7%	35 164	8.1%	1.3%
Household furniture, appliances and equipment	9 034	4.4%	10 505	16.3%	0.7%
Hardware, paint and glass	16 652	8.0%	16 522	-0.8%	-0.1%
All other retailers	24 549	11.9%	25 783	5.0%	0.6%
Total	**207 068**	**100%**	**215 587**	**4.1%**	**4.1%**

Source*: Stats SA (2018b:2)*

Overall, 2018 looked more promising to economists. The election of new President Cyril Ramaphosa brought with it positive sentiments that have had a positive impact on the South African economy (Business Tech, 2018a). Even though growth experienced over the first quarter of 2018 was positive, economic realities in South Africa such as high unemployment rates, rising inflation, a volatile Rand and land reform issues had the potential to drastically change expected performance (Business Tech, 2018a; Omarjee, 2017). However, the South African Treasury's Budget Review (2019:11) reported that the South African economy started gaining lost ground in 2019. Economists are cautiously optimistic, expecting growth to rise to 2.1% in 2021.

There are still significant challenges. Another dynamic factor posing a challenge is changing consumer behaviour (Omarjee, 2017). South African consumers' shopping habits have evolved considerably over the last few years, according to Dicey (2017), mainly due to consumer spend being placed under continued pressure. Consumers have started comparing options to find the best price, have decreased spending and have started delaying purchasing (Hattingh, Magnus & Ramlakan, 2016). A study conducted by BMi Research revealed that consumers nowadays plan their shopping trips more carefully, researching and comparing prices online and searching for specials before finalising shopping lists (Dicey, 2017). The following section explores these changes in greater depth.

2.2.4 Changes in the buying habits of South African retail consumers

A survey conducted by McKinsey in 2016 reveals several shifts in consumer behaviour among South Africans. As depicted in Figure 2.3, 79% of South Africans remain brand-loyal, despite economic challenges, but are keenly searching for their favourite brands at lower prices. The remaining 21% report that they started purchasing brands that were more affordable instead of their brands of choice. The majority (57%) of the 21% intend to remain with the new, more affordable brand (Hattingh *et al.,* 2016). These behavioural changes have had a significant impact on the textile, clothing, footwear and leather goods cluster with a number of clothing retailers reportedly feeling the effects of household consumption slowing down in the midst of economic uncertainty, including the Foschini Group (TFG), Edcon and the Mr Price Group (Goko, 2017). Overall, however, the textile, clothing, footwear and leather goods cluster has enjoyed good growth since 2005 thanks to market demand for apparel in South Africa being on a consistent increase (PwC, 2012:27). Over the last decade alone, the top six retailers, i.e. Truworths, TFG, Edcon, Woolworths, Pepkor, and the Mr Price Group, have grown their combined market share from 62% to 73% (City Press, 2017).

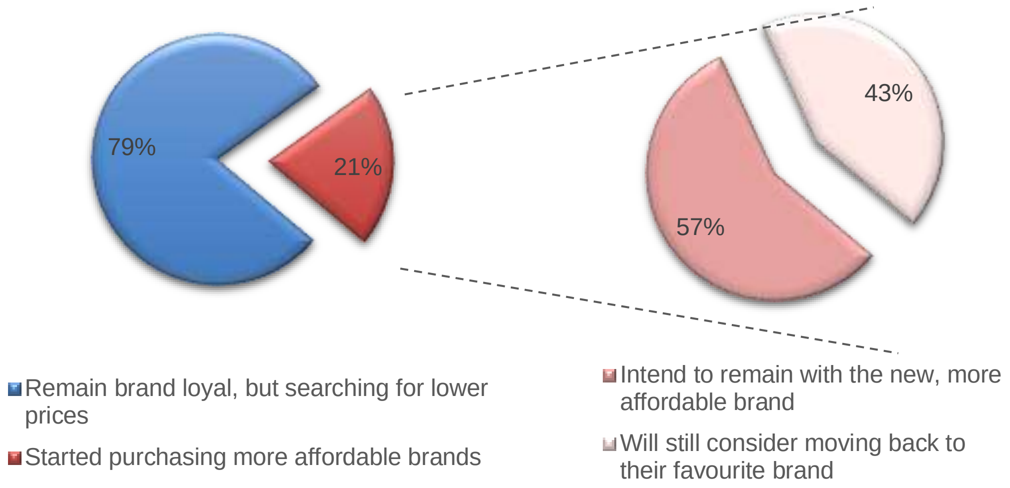


Figure 2.3: McKinsey survey results surrounding consumer behaviour changes
***Source**: Adapted from Hattingh et al. (2016)*

In addition to these shifts in consumer behaviour, Hattingh *et al.* (2016) report that South Africans have started shopping across various channels. As shown in Figure 2.3, 79% of South African consumers are actively searching for techniques to save money, and shopping across channels provides them with room for saving (Hattingh *et al.,* 2016). Retailers are, however, quite well equipped to adapt in this space. Over many years within the retailing industry, businesses have developed different strategies in response to evolving competitive environments and customer needs and wants (Miotto & Parente, 2015:242). For example, retailers that own and maintain outlets in South Africa leverage different retail formats such as general stores, retail chains, wholesale and/or retail outlets, specialty stores as well as more exclusive boutiques (Gauteng Province Quarterly Bulletin, 2012:4). The focus, however, has shifted from traditionally opening up new stores to increasing distribution and accessibility as well as launching online shopping facilities, which provides retailers with a faster route to market while reducing risk (Deloitte, 2014:3).

Argyros (2017) affirms that ensuring the continued existence and success of the retail industry is heavily dependent on how retailers implement new technologies into their approaches. South African consumers are becoming more technologically-savvy and expect their retailer of choice to offer them multiple channels through which they can engage and purchase from the retailer. A digital retailing channel such as eCommerce or mCommerce therefore complements an existing physical presence and offers the retailer another means through which to drive sales and meet steep growth targets (Deloitte, 2014:3).

The South African market, according to Nielsen (2017), is not a ‘bricks or clicks’ environment, i.e. one or the other, but rather a ‘bricks and clicks’ environment, where one form complements the other. Bricks refers to, for example, physical retail stores, whereas clicks refers to a digital retailing channel such as an online shop or mCommerce app. The consumers of today are more contemporary or modern, and are becoming increasingly savvy with technology (Amed, Andersson, Berg, Drageset, Hedrich & Kappelmark, 2018:16; Evans & Schmalensee, 2016). The consumer market has changed from a linear model to a multifaceted journey across a number of different touch points, both in the offline (bricks) and online (clicks) environments. These consumers expect retailers to take the advantages of both bricks and clicks environments, and combine them, to create a better experience and a more meaningful relationship with the consumer (Evans & Schmalensee, 2016; Jao, 2015).

Traditionally, bricks and clicks have competed with each other as opposed to complementing one another, however, this trend is changing. Many online fashion retailers have realised the value consumers assign to being able to see, touch and feel clothing items or try on shoes instead of trusting photographs displayed on online or in mobile stores. They have subsequently launched physical locations. An example of this is Bonobos, a US-based menswear digital retailer. They created physical stores, referred to as ‘guideshops’, to allow consumers try on, touch and feel items before purchasing. This approach seems to be the key to success – a bricks and clicks shopping experience that seamlessly integrates offline and online elements to offer the customer the best possible experience (Jao, 2015). Euler Hermes Economic Research (2018:2) supports this, stating that more and more eCommerce companies are launching physical stores, reaffirming the importance of this dual bricks-and-clicks approach to retailing. Herhausen, Binder, Schoegel and Herrmann (2015:310) concur, stating that the integration of bricks-and-clicks environments is becoming a necessity in order to remain competitive. Other advantages associated with integrating bricks-and-clicks includes the prevention of customer frustration or confusion as well as enriching the value proposition for the customer (Herhausen *et al.,* 2015:310). One particular challenge, however, is the maintenance of both these bricks-and-clicks environments. For example, one of the biggest drawcards of digital retailing (clicks) is the lower cost of products, mainly due to the fact that digital retailers do not need to maintain physical stores, hire and pay salespeople, pay rent, etc. Now that these digital retailers are moving into physical spaces (bricks), financials need to be restructured to allow for the ownership and maintenance of physical spaces, which will affect the pricing (Jao, 2015).

In an attempt to combat some of these challenges, South African retailers are putting a number of initiatives in place. Many retailers are endeavouring to move with the times through various strategies that leverage the opportunities provided by digital retailing. For example, 'showrooming' involves displaying goods but allowing consumers to buy it online for later delivery while 'click-and-collect' allows consumers to purchase their products online and collect them in-store (Noble, 2017). South African retailers, according to Cooke (2018), are seeing an increase in the 'click-and-collect' method of shopping with more and more consumers starting their shopping journey online, and finishing it in-store. This method of shopping allows consumers the ability to browse online, at their convenience, and collect in-store where they can try on different sizes or choose alternative styles.

In addition to this, digital retailers have introduced a variety of different payment methods such as credit cards, debit cards, electronic funds transfers (EFTs), loyalty points purchasing as well as integration into digital payment apps such as Snapscan and Zapper to allow consumers the convenience of a preferred and trusted payment method when shopping online or via their mobile phones (Euromonitor International, 2017). Finally, retailers are actively trying to embrace eCommerce and mCommerce by launching online shops and mCommerce apps to capitalise on consumers' increased acceptance and use of new technologies (Groß, 2015:221). These changes are not expected to slow down. Globally, retailers reported that investment into digital retailing such as eCommerce and mCommerce was a top priority in 2018 (Amed *et al.,* 2018:24).

2.2.5 The emergence of eCommerce and mCommerce

The term ‘online shopping’, often referred to as electronic commerce or eCommerce, is described by Bloomenthal (2019a) as a business model that permits an organisation or individual the ability to do business via an electronic medium, such as the Internet. Çelik and Yilmaz (2011:152) support this definition, stating that eCommerce is defined as the “buying and selling of goods via the Internet”. eCommerce was first founded in 1979, almost 40 years ago, by Michael Aldrich, an innovator in the United Kingdom (UK). His invention was called a Videotex. This was essentially a television (TV) that displayed interactive information (Wood, 2015; Netonomy, 2013). The first order was placed by an elderly woman, Jane Snowball, in May 1984 using a remote, TV and Videotex. She was among the first to officially shop online. This was six years before the World Wide Web (WWW) was introduced (Netonomy, 2013).

In 1991, seven years after this first transaction, the Internet was commercialised and eCommerce was officially born (Wood, 2015). In 1995, Amazon was launched – initially only as a website that sold books to the public (Hartmans, 2017; Wood, 2015). By the turn of the 21st century, seven of the eight largest US retailers from the 1980s were either declared bankrupt, were acquired by another company or became irrelevant (Leibowitz, 2013). Today, Amazon is not only the leading online shopping retailer in the world, but also the leading retailer, selling almost anything, from books to clothing, fragrances, appliances, technology, etc., and it continues to grow (Debter, 2019). According to Gensler (2017), in 2017, the company became the third largest retailer globally, just behind Wal-Mart and CVS. Holder and Hem (2018) report that Amazon’s market value in 2017 was US$740 billion, more than the total combined market values of Wal-Mart (US$257.6 billion), Costco (US$85.3 billion), Target (US$37.7 billion) and ten other well-known US retailers.

Globally, the top three online stores, i.e. Amazon, Apple and Wal-Mart, accounted for US$97,888 million in revenue in 2017 (eCommerce DB, 2018). Deloitte (2017) states that in many international markets, online sales growth has surpassed physical store growth. Thanks to the availability and proliferation of digital retailing, consumers can purchase an array of products online or via their mobile phones which may not be available in-store; prices can be compared; product availability can be checked; and orders can be placed from anywhere and at any time (Fuentes & Svingstedt, 2017:137; Chen, 2015:61; Ruane & Wallace, 2013:318; Forsythe *et al.,* 2006:57; Huang & Oppewal, 2006:337). Statista (2018a) adds that in 2016, 1.61 billion people across the globe purchased goods online. Retail eCommerce sales worldwide grew by 72.5% from 2014 to 2017, amounting to US$2.3 trillion in 2017, and 53.5% from 2017 to 2019, amounting to US$3.53 trillion. This is predicted to grow by another 85.3% by 2022, amounting to US$6.54 trillion (Statista, 2019c). One of the main drivers of this growth is said to be international emerging markets, including India, Indonesia and South Africa (Statista, 2019d; Deloitte, 2014:3).

As little as two decades ago, the Internet was launched in South Africa with the first .co.za domain being registered in June 1992 (Venktess, 2016). By 2001, South Africans had started purchasing goods online and by 2003, the retail industry had made R341 million in online sales (Shop Direct, 2018). In 2016, at a constant growth rate of over 20% per annum (World Wide Worx, 2016), this figure grew to R8.1 billion (Euromonitor International, 2017c). Even though this equates to a mere 1.4% of total retail sales (World Wide Worx, 2019), it is predicted to grow exponentially over the next decade (Moneyweb, 2017).

There are 18.4 million online shoppers in South Africa, according to eShop World (2018), including consumers who purchase on desktop computers or laptops, tablets, and mobile devices. This figure is expected to grow by 34.8% by 2021, reaching 24.8 million, as depicted in Figure 2.4 below. eCommerce revenue in South Africa from purchases via desktop computers or laptops, tablets and mobile devices, across product categories, is currently US$2.69 billion. This figure is expected to grow by 57% to US$4.7 billion by 2021 (eShop World, 2018) or R68 billion based on the exchange rate in August 2018 of US$1 = R14.537. Smith (2017) predicted online expenditure of over R53 billion in 2018 alone, with mCommerce being marked as the biggest driver of this growth.

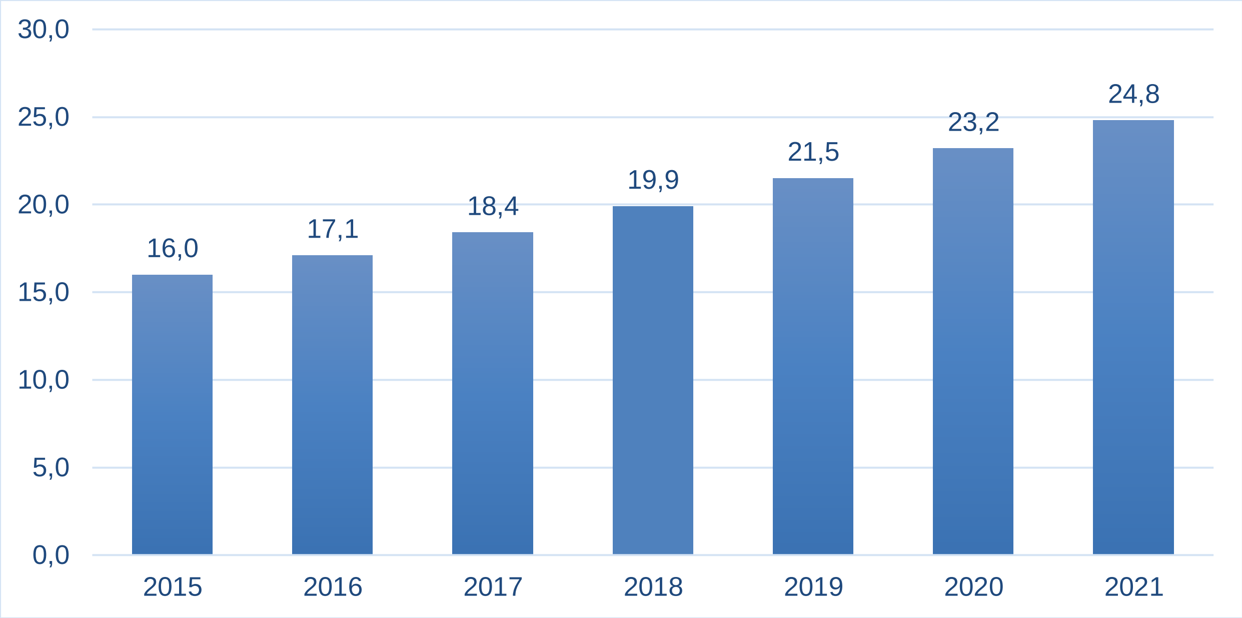


Figure 2.4: Number of online shoppers in South Africa (in millions)

Source*: eShop World (2018)*

Several definitions have been proposed for the term 'mCommerce'. According to Bloomenthal (2019b), and Persson and Berndtsson (2015:2), for example, mCommerce is described as a form of eCommerce by means of a wireless handheld device such as a smartphone. A definition by Gupta and Arora (2017:2) is closely aligned, stating that mCommerce refers to using wireless Internet services in order to shop via a mobile phone. More recently, however, this definition has begun transforming into something that covers a greater range of activities. mCommerce includes using a mobile phone to make a purchase, according to Fuentes and Svingstedt (2017:137), but also includes using the phone to check and compare products and pricing; gathering pertinent information relating to a product of interest; and reading peer reviews from consumers who have purchased the same product. For the purposes of this study, however, the definition from Bloomenthal (2019b) and Persson and Berndtsson (2015:2) is adopted, i.e. mCommerce is described as a form of eCommerce by means of a wireless handheld device, such as a smartphone.

mCommerce is predicted to grow 200 times faster than eCommerce (Kolowich, 2016). Euromonitor International (2016) concurs, stating that consumers are shifting away from eCommerce to mCommerce at a rapid pace. In South Africa, consumers are spending more on their mobile phones due to increased mobile penetration in the country, with expenditure that had been predicted to grow by 123% in 2018 (Smith, 2017). The increased penetration is as a result of more affordable smartphones being released to the South African market including, for example, Huawei, Hisense and Xiaomi (du Plessis, 2018). Erken (2017) considers that “mobile is the future of online trading”. South Africa will surpass the 21 million active smartphone mark within the next five years, meaning that that one in every 2.6 people in the country will own a smartphone (Erken, 2017).

Despite this phenomenal growth, only 1.4% of total retail sales have been made via a digital medium such as an online or mobile shop (World Wide Worx, 2019). Furthermore, research done by Euromonitor International (2017c) indicates that digital purchasing is still heavily skewed towards desktop computers or laptops, as opposed to tablets and mobile devices. This can be seen in Figure 2.5 below which indicates the significant weighting towards the use of desktop computers or laptops, averaging 84%, compared to tablets at 10% and mobile phones at 6%. Research by Effective Measure (2017a:13) supports this, confirming that 65% of South African online shoppers prefer to shop on desktop computers or laptops, as opposed to their tablets or mobile phones. Globally, however, 80% of consumers prefer to shop via their mobile phones (Kahn, 2015).

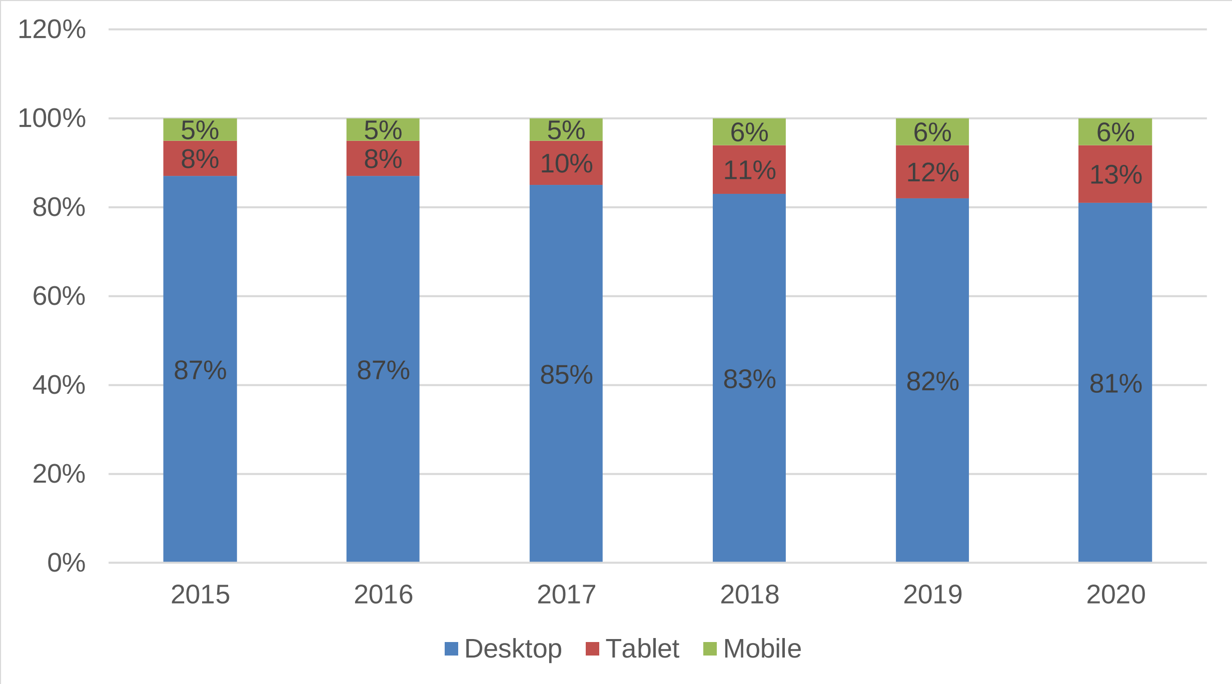


Figure 2.5: Digital purchasing by device (2015-2020)

Source*: Euromonitor International (2017c)*

Even though online and mobile shopping currently accounts for a very small percentage of total retail sales (World Wide Worx, 2019), the growth potential presented by these digital retailing channels in South Africa has not gone unnoticed. The exclusively online shopping market in South Africa is expanding at a rapid pace. According to Craig Tyson, editor of GQ, South Africa's entrepreneurial technology industry is dynamic and represents the best opportunity to the fashion industry from a growth point of view (Young, 2014). Over the last few years, the country has welcomed many new, exclusively online and mobile retailers including Takealot.com, Zando and Superbalist.com (Euromonitor International, 2017c). In addition, more traditional retailers such as Truworths, TFG, and Mr Price launched online shops in 2016, with Mr Price also offering a mobile shopping app (Euromonitor International, 2017c). Takealot.com is reportedly dominating the space with a market share of around 12.5%, compared to its closest apparel competitor, Spree (part of Superbalist.com since 2018), at 1.4% (Bratt, 2018). A more in-depth view of each of these online and mobile retailers is provided below.

In October 2010, Take2, an eCommerce business, was successfully acquired by US-based investment firm, Tiger Global Management, along with Kim Reid, current co-

CEO of Takealot.com. In June 2011, Takealot.com was officially launched. A US$100 million investment in 2014 was a pivotal year in the company's history (Takealot.com, 2020a; van Zyl, 2015). After the investment, Takealot.com acquired Mr Delivery, giving it ownership of a large logistics network of its own. Another acquisition followed – Superbalist.com – a fashion and design eCommerce business. Finally, Naspers-owned Kalahari.com was announced to be merging with Takealot.com, cementing Takealot.com's reputation. Since its inception, the business has grown to become the leading eCommerce retailer in South Africa, growing to 1,200 employees in 2018 (Takealot.com, 2020a). Transactions on Takealot.com have grown at a rate of 90% per annum since inception and gross merchandise revenue has grown by over 100% (Klein, 2017). In 2016, for example, the company's turnover was R2.3 billion, generated from 2.9 million transactions processed by one million customers (Mybroadband, 2017a).

However, as previously mentioned, online retail in South Africa equates to 1.4% of the total retail market (World Wide Worx, 2019). According to Saleh (2017), globally, the UK has the highest percentage of eCommerce sales in relation to total retail sales, at 15.6%. This was measured in 2016. The UK is followed by China at 13.8%, Norway at 11.5%, Finland at 10.8% and South Korea at 10.5%. South Korea, fifth on the list, is 650% ahead of South Africa's 1.4%. Manson (2016) states that other emerging markets are reportedly sitting at an average of 5-6%, still 300% higher than South Africa. Takealot.com has capitalised on mobile penetration in South Africa by actively working to attract app and mobile site shoppers (Mybroadband, 2017a). Most of the site's traffic is generated from mobile (Klein, 2017) and it reportedly receives in excess of 10 million visits per month (Mybroadband, 2017b).

Founded in 2012 by a German-based company called Rocket Internet, Zando has grown to become the biggest online fashion retailer in South Africa. The company is owned by The Jumia Group which operates across a number of verticals on the African continent, with fashion being but one of them. Investors in the group include MTN, Milicom and Rocket Internet (Zando, 2020b). Having the backing of a German technology company comes with a number of benefits, including leveraging existing technology. According to Manson (2012), in Germany, there are more than 80,000 eCommerce businesses, two of which, Zalando and 7trends, were influential in the creation of Zando. Today, Zando boasts over 550 brands selling fashion on its platform (Zando, 2020b).

Spree, a fashion-focused online shopping destination, was launched in April 2013 by Media24 (Media24, 2018). In 2017, Spree's daily transactions grew by 76%, with sales increasing by 88%. App sales, specifically, more than doubled (BizCommunity, 2017b). In 2018, Spree and Superbalist.com merged (ITWeb, 2018).

Originally launched as CityMob in 2011, Superbalist.com has grown to establish itself as the leading youth online fashion retailer in South Africa. Coming off a small base, the company has enjoyed 100% growth year on year with 2015 achieving 330% (Manson, 2016). As previously mentioned, Superbalist.com was acquired by Takealot.com in 2014 (Takealot.com, 2020a). In terms of the aforementioned South African online and mobile retailers, Takealot.com is the most established. The Takealot.com site is reported to receive over 10 million visits per month, far ahead of its competitors such as Zando (1.4 million), Superbalist.com (996,000) and Spree (870,000) (part of Superbalist.com since 2018) (Mybroadband, 2017b).

Many of these retailers have capitalised on the athleisure trend. Takealot.com maintains a permanent athleisure category or department on its website (Takealot.com, 2020b). Superbalist.com has blogged about the topic of athleisure and offers many athleisure apparel pieces on its site (Superbalist.com, 2020; 2016). Zando has a dedicated sports section on its site featuring many different types of athleisure apparel (Zando, 2020a).

2.3 A focus on athleisure apparel

In South Africa, the athletic wear retail category has grown by 36% over the past five years, mainly as a result of the athleisure apparel trend (Euromonitor International, 2017b). This section commences with a definition of the South African athletic apparel industry. An overview of the industry is then provided, followed by an investigation into the impacts of mCommerce on this industry.

2.3.1 Defining the South African athleisure apparel retail industry

As mentioned earlier, the South African retail industry consists of seven retail clusters (refer to section 2.2.1), one of which is textiles, clothing, footwear and leather goods retailers (Gauteng Province Quarterly Bulletin, 2012:3). This cluster encompasses all retailers selling clothing for men, women and children; accessories such as hats, caps, ties and handbags; as well as leather products and footwear (FPM SETA, 2014:5).

Athletic wear, a term including, amongst others, clothing (apparel) and shoes, is described by the Merriam Webster (2020a) dictionary as clothing intended for use during informal settings or recreational activity. The word is often interchanged with activewear or sportswear. Lexico powered by Oxford (2020a) defines activewear as "clothing designed to be worn for sports, exercise, and outdoor activities". Athleisure apparel in particular, is defined as "casual clothing that can be worn for exercising and doing (almost) everything else" (Merriam Webster, 2020b). The following section provides an overview of the athleisure apparel retail industry in South Africa.

2.3.2 An overview of the South African athleisure apparel retail industry

Globally, the athletic apparel market has enjoyed significant growth over the past few years and is expected to bring in US$184.6 billion by 2020, mainly as a result of an increase in health consciousness and fitness activity around the world, including running, swimming, yoga and aerobics (Bisht, 2017). Research by the NPD Group reveals that consumers in the US spent US$323 billion in 2014 on clothing, accessories and footwear. This was a 1% increase over expenditure in 2013. The 1%, however, equates to US$2 billion in sales, which were largely driven by athleisure purchases including apparel, performance footwear and bags (Petro, 2015). Green (2017) and Kell (2016) state that retail sales in the US were flat in 2015 for all categories except the athletic wear category, which was up by 12%, mainly due to the athleisure trend. According to Statista (2018b), the athletic apparel market is expected to grow by 21.7% over the next five years (2018-2023), reaching revenues of US$212.57 billion. Contributing to this is the athleisure trend, which has resulted in an upsurge in demand for this type of fashionable, trendy apparel that can be worn both for exercising and general wear (Bisht, 2017).

Traditionally, before the advent of athleisure, fashion and activewear were kept separate. Today, athleisure fashion has a significant impact on the fashion industry in general (Khawtom, 2017). Fashion experts have stated that athleisure is set to become one of the fastest-growing segments in the fashion industry by 2020 (Shezi, 2016). Athleisure initially started off as a preference for comfortable, casual clothing for exercise, according to Khawtom (2017), but between 2013 and 2014, it became a global trend with consumers around the world taking up this distinctive look. The exponential growth of this category is ascribed to two elements. Firstly, consumers are becoming more fitness- and health-conscious and see exercise as a lifestyle and no longer just as a hobby. And secondly, there is the need for comfortable clothing (Petro, 2015). Green (2017) supports this view, commenting that "athleisure is the new casual".

As is the case internationally, in South Africa, the combination of more active and healthy lifestyles and the athleisure trend are driving demand in the activewear retail category. Euromonitor International (2018) states that it has become commonplace to wear athleisure apparel throughout the day and not just for exercise purposes, across different ages and income groups. The fashion retail industry in South Africa was predicted to achieve a revenue figure of US$641 million in 2019 (Statista, 2019e). Based on the exchange rate in January 2020, i.e. US$1 = R14.215, this translates to over R9 billion. Over 60% of this is driven by clothing sales. An annual growth rate of 12.7% is expected, reaching US$1.167 billion or over R16 billion by 2024 (Statista, 2019e). The activewear category, which incorporates athleisure apparel, particularly, grew by 36% over the past five years, and 6% in 2016 alone. It is predicted to reach R70 billion in sales by 2021 (Euromonitor International, 2017b).

Athleisure apparel is produced and sold by a number of clothing retailers in South Africa. Many of the dominant clothing retailers still active and thriving in the South African market today, first opened their first stores at the beginning of the 20th century (Maydon, 2017). Ackermans, a clothing retailer known for stocking affordable clothing for the entire family, was founded in 1916. In 1917, Truworths followed suit as a brand that provides male and female consumers with a variety of colours and fabrics. Foschini, a female clothing brand, was founded in 1924. Edgars, South Africa's largest retailer, was founded in 1929. Woolworths, a brand passionate about delivering quality goods to South African consumers, specialising not only in clothing, but also in food and other general merchandise, was founded in 1931. In 1965, Pep, South Africa's largest, single-brand retailer followed. Like Ackermans, Pep is owned by Pepkor and provides affordable clothing for children, teens and parents. Finally, Mr Price was founded in 1986 (Maydon, 2017). Most of these retailers stock or have started stocking athleisure apparel to capitalise on market demand. At present, retail is the most common channel of sale for athleisure brands, however, future growth is expected to be driven by online and mobile channels with increased Internet penetration globally (Bisht, 2017).

In addition to the aforementioned retailers, a number of new, smaller retailers have launched their brands online in South Africa. MovePretty, an athleisure brand launched by two friends in South Africa, prides itself on creating stylish activewear with the required functional attributes (Kimani, 2017). The company maintains a mobile-optimised online shop where consumers can browse and purchase clothing as well as a physical store in Stellenbosch (MovePretty, 2020). Lorna Jane SA, a brand originally founded in Australia in 1990, was launched in South Africa several years ago, today boasting an online shop and several retail stores (Lorna Jane SA, 2020). Another brand, Boost, launched in 2003, offers consumers the ability to order custom-fit and custom-colour gym-wear via its website (Kimani, 2017). Mermaids and Unicorns, a Durban-based label, imports its fabrics and creates limited-edition activewear which is sold via its mobile-optimised website (Kimani, 2017). In addition to these smaller retailers, larger and exclusively online and mobile retailers have dedicated athleisure categories showcasing hundreds of pieces of apparel for consumers to browse and purchase, including Superbalist.com and Zando. These retailers also offer consumers mobile apps through which to purchase. Table 2.2 summarises the aforementioned South African retailers active in the athleisure space, indicating their various retail formats.

Table 2.2: South African retailers operating in the athleisure apparel industry

Retailer	Sells athleisure apparel	Physical presence (bricks)	Online / mobile shopping presence (clicks)	mCommerce app (clicks)
Ackermans	X	X		
Truworths	X	X	X	
Foschini	X	X	X	
Edgars	X	X		
Pep	X	X		
Mr Price	X	X	X	X
MovePretty	X		X	
Lorna Jane SA	X	X	X	
Boost	X		X	
Mermaids and Unicorns	X		X	
Superbalist.com	X		X	X
Zando	X		X	X
Takealot.com	X		X	X

With increased competition and increased demand, mCommerce sales will continue to grow significantly over the coming years (Smith, 2017). It is therefore important for South African fashion retailers selling athleisure apparel to understand the reasons why, at present, consumers are not purchasing clothing and accessories via their mobile phones (Erken, 2017; Goldstuck, 2014:27). A better understanding of the constructs that influence both consumers' behavioural intention to use and actual use of mCommerce apps to purchase their products, will enable these retailers to adjust their business strategies accordingly.

2.3.3 mCommerce and the South African athleisure apparel retail industry

Amed *et al.* (2018:16) state that globally, the fashion industry is finding itself in a pivotal developmental phase where digital adoption among consumers is increasing rapidly and online sales of apparel and footwear are predicted to follow suit. International digital retailers such as Amazon, Zappos and Alibaba continuously improve customer experience, raising the bar quite significantly for fashion retailers, who are expected to deliver an even more premium experience. The benefit of operating in a country that has experienced slower growth on the digital retailing front, such as South Africa, is that local retailers can learn from international retailers such as Amazon (Klein, 2017). The opportunity to learn, however, can be quick to pass given the rate of change. In South Africa, for example, mobile penetration is significant and is predicted to pass the 21 million mark by 2022 (Erken, 2017) while expenditure via mobile phones was predicted to grow by 123% in 2018 alone (Smith, 2017). It is therefore important to understand the South African online/mobile consumer better.

A total of 65% of South Africans aged 16 years and older are now active online, equating to 25 million individuals. The largest proportion of users (30%) are aged between 25 and 34. Compared to global statistics, South African online users are much younger, with 60% falling in the under-35 age bracket versus 34% globally. The male/female split is 50/50, aligned to global statistics (BizCommunity, 2017a). Access to the Internet primarily occurs via mobile devices. In South Africa, 69% of consumers access the Internet through this medium, compared to 30% globally. Of the 69%, 60% use a smartphone to access the Internet (BizCommunity, 2017a).

The Google Consumer Barometer (2017) surveyed 734 South Africans and found that their daily Internet activities include 56% visiting social networks, 32% searching for information and 13% watching videos. Only 7% responded that they purchased products or services through their browsers or apps on their mobile phones. From a purely online/mobile shopping point of view, Nielsen (2017) found that South Africans mainly spend on travel (53%), event tickets (52%) as well as books, music and stationery (45%) online. Fashion is allocated 38% while perishables and medicines are mostly purchased in-store. Fashion, however, is purchased more in-store as opposed to online. A study conducted by Goldstuck (2014:10) indicates that South African consumers' average online spend was primarily allocated to airlines (US$197), hotels (US$163), and paid-for video websites (US$123). Electronic products was allocated US$69, and clothing and accessories US$49. This can be seen in Figure 2.6 below.

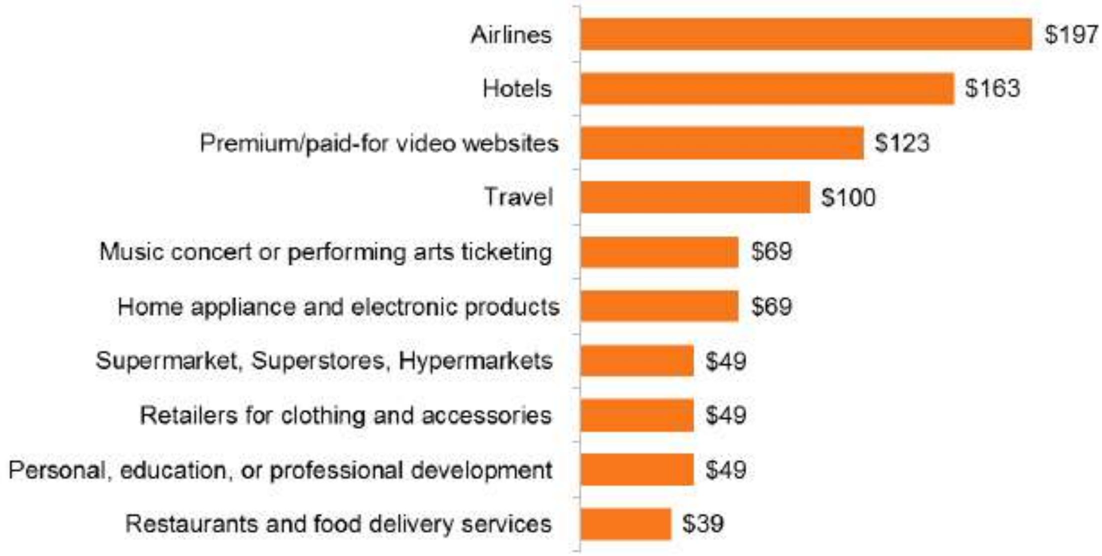


Figure 2.6: Average South African consumers' spend online
***Source**: Goldstuck (2014:10)*

When considering Figure 2.6, three of the top five categories all fall under travel and tourism, i.e. airlines, hotels and travel. Goldstuck (2014:10) advises that travel and accommodation is allocated significant average online spend as there are increasingly fewer offline or more traditional alternatives available to consumers. Research by Effective Measure (2017a:10) suggests that the most popular items purchased online are available immediately after purchase and do not require delivery. This includes travel (22%), books (10%) and tickets to events (10%). More in-depth research by Travelport South Africa revealed that 85% of South African travellers booked their travel using computers (Thebe Tourism, 2017:6).

Im and Hancer (2014:177) contend that innovations in mobile technology have greatly impacted the travel and tourism industry. These advances have addressed a pressing consumer need – being able to co-create a travel experience or being actively involved in the process. This, along with fewer offline solutions and the need for instant gratification online justifies the average online spend being allocated to this category.

Average mobile spend allocation, however, is different. Consumer preferences differ from online spend insofar as purchases seem to be driven by convenience, for example, purchasing phone apps and movie tickets or downloading music. Clothing and accessories feature in eighth position on average online spend allocation, however, it does not feature as one of the top ten categories for average mobile spend allocation (Goldstuck, 2014:27), as can be seen in Figure 2.7.

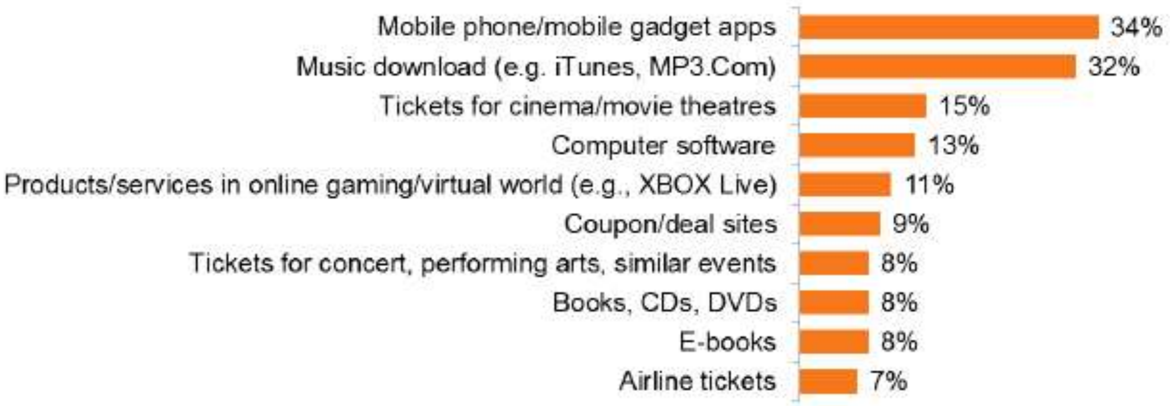


Figure 2.7: Average South African consumers' spend on mobile
***Source**: Goldstuck (2014:27)*

Research by Effective Measure in 2017 shows that 47% of South Africans purchase airtime using their mobile phones, 25% purchase apps and related in-app purchases, 33% do not purchase anything on their mobile phones and only 7% purchase clothes, fashion items or beauty products (Erken, 2017). Research conducted by Spree (before it merged with Superbalist.com in 2018) found that only 17.5% of surveyed consumers purchase clothing online or via mobile devices. This is in stark contrast to the 68.09% who purchase airline tickets. Nonetheless, the Spree site, at the point of publishing this research, saw a sharper growth in year-on-year mobile sales, compared to desktop sales (Dirk, 2015).

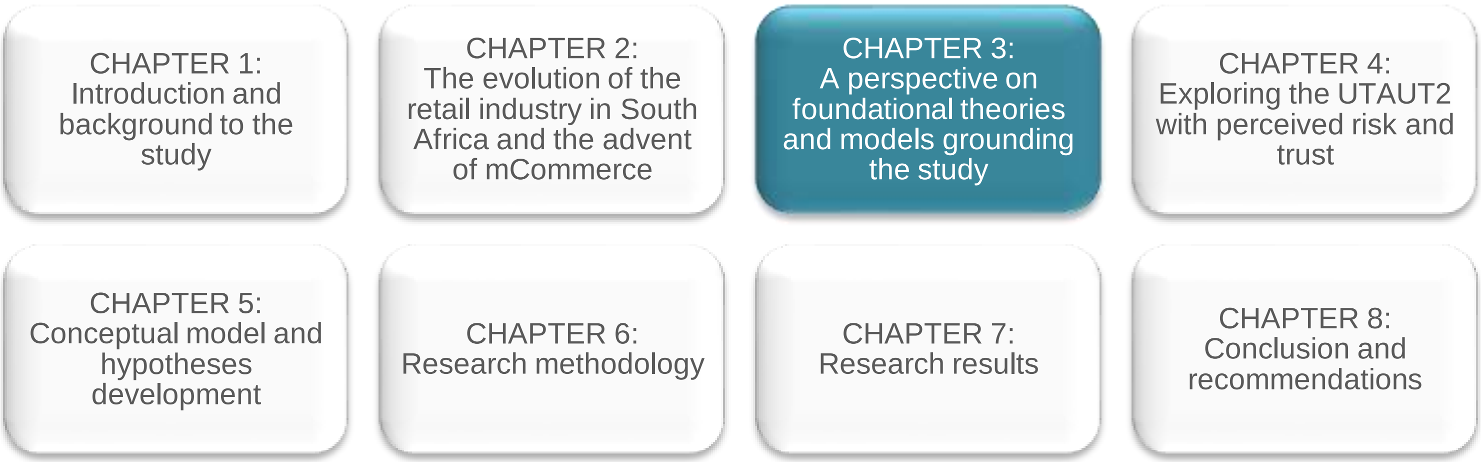
Another report by Effective Measure, the South Africa Mobile in 2017 report, indicates that 48% of South Africans do not purchase using their mobile phones when on a mobile connection (Effective Measure, 2017b:7). A mobile connection refers to being on the Internet through a mobile network such as MTN or Vodacom, as opposed to a WiFi connection. A WiFi connection refers to a wireless technology that provides connectivity between two or more devices. Many malls, airports and restaurants offer free WiFi as a means of attracting consumers (Pullen, 2015). The fact that 48% of South Africans do not purchase using their mobile phones when on a mobile connection highlights a potential concern relating to the cost of data for consumers (Du Plessis, 2018). A key question arising from these research studies is: Why do South African shoppers not use their mobile phones to purchase fashion apparel and, more specifically, athleisure apparel? This study aims to answer this question.

2.4 Conclusion

The retail industry in South Africa provides employment to over 800,000 people (Stats SA, 2018a) and is a key industry in expanding the country's economy (South African Market Insights, 2017; Gauteng Province Quarterly Bulletin, 2012:4). Therefore, 'future-proofing' this industry and ensuring its continued existence is of great importance. This is heavily dependent on how retailers implement new technologies into their approaches (Argyros, 2017). South Africans have started shopping across different channels (Hattingh *et al.,* 2016); they are becoming more technologically astute and expect their retailer of choice to offer them multiple channels through which they can engage and purchase from the retailer (Deloitte, 2014:3). Even though South African consumers are spending more on their mobile phones due to increased mobile penetration in the country, digital purchasing is still heavily skewed towards desktop computers or laptops, as opposed to tablets and mobile devices (Euromonitor International, 2017c). This is particularly the case for clothing and accessories (Goldstuck, 2014:27). This study identifies the constructs that influence why South African shoppers do not use their mobile phones to purchase fashion apparel and, more specifically, athleisure apparel.

CHAPTER 3

A PERSPECTIVE ON FOUNDATIONAL THEORIES AND MODELS GROUNDING THE STUDY



3.1 Introduction

Chapter 3 provides detailed information on the foundational theories and models grounding the study. The chapter commences with a perspective on the relationship-building theories such as the Theory of Social Exchange (SET) and the Transaction Cost Theory (TCT). It then moves to the technology acceptance theories and models including the Innovation Diffusion Theory (IDT), the Theory of Reasoned Action (TRA), Social Cognitive Theory (SCT), the Technology Acceptance Model (TAM), the Theory of Planned Behaviour (TPB), the Unified Theory of Acceptance and Use of Technology (UTAUT) and the UTAUT2.

The chapter provides an overview of each theory or model. The relevance of each theory in the field of technology is then discussed, followed by criticisms of the theories and models and the importance of each in the present study. The chapter concludes with the relevance of the selected foundational theories and models to the field of mCommerce.

3.2 A perspective on relationship-building theories grounding the study

When people started exchanging goods and services by bartering in 9 000 to 6 000 BC, they also started interacting in relationships (Gummesson, 2017:17; Braun, 2015). Barter exchanges were personal, two-party relationships which rapidly grew and expanded to relationships beyond neighbours, family and friends (Gummesson, 2017:17). From the 1950s, the concept of relationships has been studied across various disciplines, including sociology, social psychology, economics and management (Eiriz & Wilson, 2004:277). The concept of relationship marketing emerged from these research studies.

Relationship marketing first became a dominant discipline in marketing when, in 1983, Berry advised that the traditional 4 P's of marketing (price, product, place and promotion) did not include any relationships. The concept of relationship marketing was then founded, attempting to provide an all-encompassing view of relationships and their management in the field of marketing (Gummerus, von Koskull & Kowalkowski, 2017:1). The advent of relationship marketing brought about a paradigm shift in marketing, moving exchanges away from a purely transactional basis to a relational one and from focusing on customer attraction to customer retention (Gummerus *et al.,* 2017:1). Morgan and Hunt (1994:22) define relationship marketing as "all marketing activities directed toward establishing, developing and maintaining successful relational exchanges". Eiriz and Wilson (2004:276) expand this definition by including the termination of relational exchanges. There are various theoretical foundations, spanning a number of disciplines, upon which the concept of relationship marketing was built. Two, in particular, are of interest to this study. Firstly, the discipline of sociology and social psychology and secondly, the discipline of economics (Eiriz and Wilson, 2004:278). Each of these disciplines are elaborated on below.

In sociology and social psychology research, the focus is on the behavioural interactions between groups or individuals in a particular community, during an exchange. A key theory which emanated from this research is the SET (Eiriz & Wilson, 2004:277). Proposed by Homans in 1958, the SET analyses human behaviour in the process of exchanging resources (Yan, Wang, Chen & Zhang, 2016:644; Shiau & Luo, 2012:2432). The theory advances that the exchange of resources between individuals is based on the notion of reciprocity, or the expectation of getting something in return (Huang, Cheng, Huang & Teng, 2018:233). There is, therefore, a cost and reward element to each exchange. This exchange of cost and reward is not just economic in nature. Research has shown that perceptions of service quality, convenience, comfort, reliance and risk are also exchanged (Jeong & Oh, 2017:116; Devaraj *et al.,* 2006:1091).

The SET has been applied as theoretical foundation across a number of technology acceptance studies including understanding personality traits of online gamers (Huang *et al.,* 2018), understanding online health communities and knowledge sharing (Yan *et al.,* 2016), the constructs that affect consumers' adoption of online banking (Montazemi & Qahri-Saremi, 2015), mCommerce exchange perceptions (Dai & Chen, 2015), the acceptance of enterprise blogs (Wu, Kao & Lin, 2013) and online group buying intentions (Shiau & Luo, 2012). In the context of this study, the SET can be applied to better understand the cost and reward from an exchange between a buyer or consumer on the one hand and the seller on the other, as the buyer will use the seller's app to purchase athleisure apparel (Shiau & Luo, 2012:2432).

In economics research, one of the most prominent contributions to the literature surrounding relationships has been the TCT, developed by Williamson in 1981. The TCT focuses on the rationality of relationships from an economic point of view (Eiriz & Wilson, 2004:278). The theory postulates that individuals have a preference for conducting transactions in the most cost-effective way (Teo & Yu, 2004:452; Williamson, 1981:555). In the context of this study, from an online and mobile shopping point of view, the unique electronic environment in which these shopping activities occur is still perceived as uncertain and risky to consumers (Wu, Chen, Chen & Cheng, 2014:2770). Consumers' perceptions of uncertainty and risk in the digital retail environment lead to increased transaction cost, which has been proven to be a predictor of consumer acceptance and adoption (Che *et al.,* 2015:589-590).

These two foundational theories of relationship marketing, the SET and TCT, ground this study from a relationship-building perspective. The following section provides a more in-depth look at these theories in order of foundation year – first the SET, founded in 1958, followed by the TCT, founded in 1981.

3.2.1 Social Exchange Theory (SET)

The SET postulates that buyers and sellers interact with one another in order to minimise cost while exploiting reward. This theory can therefore be applied to this study to better understand the cost and reward derived from an mCommerce exchange between a buyer and a seller (Shiau & Luo, 2012:2432).

This section commences with an overview of the SET. The relevance of the SET in the field of technology is then discussed, including key findings from studies using this theory. Criticisms of the theory are then presented. The section concludes with the importance of the SET to this study.

3.2.1.1 An overview of the SET

The SET was established by Homans in 1958 with the intent of analysing human behaviour. It was later applied in organisational structures to better understand organisational behaviour (Shiau & Luo, 2012:2432). Rooted in behavioural psychology and economics, the SET attempts to determine the complexities of social structures by analysing human behaviour and relationships (Yan *et al.,* 2016:644; Tanskanen, 2015:579; Shiau & Luo, 2012:2432). The SET describes social exchange as a tangible or intangible exchange of activity between a buyer and seller based on a trade-off between cost and reward (Jeong & Oh, 2017:116; Dai & Chen, 2015:44). The relationship between the two parties is the unit of analysis (Tanskanen, 2015:579). These exchanges are voluntary or non-contractual in nature and, importantly, create value for both parties. The non-contractual and value-creating nature of the exchange emphasises the importance of reciprocity and trust in the relationship (Huang *et al.,* 2018:233; Tanskanen, 2015:578). The SET postulates that, during these exchanges, individuals will always attempt to maximise positive response and minimise negative response, based on past experiences and lessons learnt.

In a marketplace exchange environment, the SET posits that consumers make decisions to buy or not buy, to use or not use and to adopt or not adopt, based on an evaluation of cost versus reward (Dai & Chen, 2015:45). From an mCommerce perspective, Zafirovski (2005:4) explains that the cost from a user's point of view involves only the economic exchange with an extrinsic reward – that of material gain.

Research has, however, shown that the cost component goes beyond that of pure economic exchange. The choices consumers make when purchasing go beyond pure monetary factors into perceptions surrounding perceived risk, service quality, comfort, convenience and reliance (Jeong & Oh, 2017:116; Devaraj *et al.,* 2006:1091). The cost therefore extends into a social exchange as users' costs involve not just the monetary component of the transaction, but also fears surrounding exploitation and the privacy and security risks associated with the platform (Dai & Chen, 2015:42).

From an exploitation point of view, according to Montazemi and Qahri-Saremi (2015:212), trust assists in decreasing consumers' fears of being exploited, whilst at the same time increasing their perceptions surrounding certainty that the other party will behave a certain way. These fears and perceptions are heightened in an online or mobile environment such as an mCommerce app as consumers are required to pay for their goods before receiving them. As the reward of the exchange cannot be guaranteed in a social exchange, trust becomes an essential component of the exchange, as it governs a consumer's expectations.

Perceived risk such as privacy and security risks are greater within the field of mobile computing as more personal data is collected from users compared to eCommerce (e.g. the collection of a user's location via his/her mobile device) (Dai & Chen, 2015:42). Therefore, perceived risk, in the context of this study, represents the cost component of the transaction (Chen, 2013:1221). According to Matikiti *et al.* (2016:30), Chen (2013:1223) and Posey, Lowry, Roberts and Ellis (2010:190), perceived risk deters consumers from using new technologies.

A study by Dai and Chen (2015:50) tested privacy and security concerns in mCommerce using the SET as foundation theory. Their model hypothesised cost as a security concern. The results indicated that this construct had a significant negative influence on attitude which, in turn, influenced behavioural intention. This confirms the findings of the original SET which holds that social exchange costs are a deterrent to the exchange itself. From a reward point of view, Dai and Chen's (2015:45) model hypothesised perceived usefulness as the reward component. This is similar to the construct of performance expectancy in the proposed model for this study (refer to Chapter 1, Figure 1.9). Perceived usefulness from the TAM was used to create performance expectancy in the UTAUT2. Performance expectancy refers to the degree to which the usage of a specific technology will provide a benefit to consumers who perform specific activities (Venkatesh *et al.,* 2012:159). Dai and Chen's (2015:45) findings showed perceived usefulness to have a significant influence on consumer attitude, with attitude having a significant influence on behavioural intention.

This above example is but one technology acceptance study that has used the SET as theoretical foundation. Advancements in technology in recent years have cast new light on the domain of social engagement and social exchange, with the SET being applied more frequently to technology behaviour studies (Shiau & Luo, 2012:2432). The following section explores the relevance of this theory to the field of technology, referencing further research studies.

3.2.1.2 The relevance of the SET to the field of technology

With the rapid proliferation of technology, digital retailing and social networking over the last decade, greater emphasis is being placed on interactions among individuals, the concept of exchange and sharing (Shiau & Luo, 2012:2432). As such, the SET is being applied more frequently to studies in the technology domain. Huang *et al.* (2018:233) observe that the SET has proven to be a valuable theory in explaining consumer behaviour in online environments. These researchers, along with a number of others in the technology and information systems domains, have applied the SET to understand user behaviour (Huang *et al.,* 2018:233; Yan *et al.,* 2016:644).

Huang *et al.* (2018:239) used the SET as theoretical foundation to understand the personality traits of online gamers in Taiwan. The study demonstrates that gamers' personality traits are important in online social exchanges. In China, Yan *et al.* (2016:644-650) used the SET to investigate online health communities and knowledge-sharing. The researchers specifically selected this theory as it has been applied extensively to studies exploring individual behaviours. Both Huang *et al.* (2018) and Yan *et al.* (2016) proved the SET to be comprehensive enough to explain relationships between constructs in new research domains, such as the building of relationships online or the sharing of knowledge online. Further research are elaborated on below.

Matikiti *et al.* (2016:30) used the SET to understand the drivers behind making travel arrangements through social networking sites. Their research revealed that trust positively influenced the use of social networking sites while perceived risk negatively influenced it. Chen (2013:1223) corroborates this finding, stating that perceived risk negatively influences the use of social networking sites.

According to Liu, Deligonul, Cavusgil and Chiou (2018:172), the SET considers trust to be fundamental in stabilising an exchange relationship; the presence of trust means that individuals will collaborate more and manipulate less in order to achieve mutual goals. Montazemi and Qahri-Saremi's (2015:220) research examined the constructs that affect consumers' adoption of online banking. Their research proved that trust is an essential component of an exchange that takes place in an online environment, such as online banking, or online or mobile shopping, seeing that a reward cannot be guaranteed in a social exchange. Shiau and Luo (2012:2438-2439) investigated the constructs that affect online group buying intentions and resultant satisfaction. Their research also proved that trust had a significant influence on both satisfaction and behavioural intention. These findings are supported by Liébana-Cabanillas *et al.* (2017:16), who state that trust is one of the most vital constructs in digital retailing such as eCommerce and mCommerce. Consequently, a lack of trust is regarded as one of the main reasons why consumers refrain from purchasing via such digital retailing channels. The true value of the SET to this research study therefore lies in the constructs of trust and perceived risk, as elaborated on in section 3.2.1.4.

Although the above studies prove the relevance of the SET in the field of technology and cement its inclusion in this study, the theory is not without criticism, as discussed in the following section.

3.2.1.3 Criticisms of the SET

The SET has had a number of criticisms levelled against it. Firstly, the two central concepts of the theory – cost and reward – are not clearly defined. According to West and Turner (2018), making an operational distinction between how people behave, what they value and what they find rewarding, is very difficult. It becomes an impossible task to find a situation in which a person does not act in a specific way with the intention of obtaining a reward. A second concern raised with the SET is that consumers or individuals are regarded to be calculative and rational in their approach. The theory assumes that individuals go through a significant amount of cognitive activity when engaging in a behaviour. The reality, however, is that the amount of cognitive processing allocated to a particular behaviour is based on context and individual difference (West & Turner, 2018). Jeong and Oh (2017:115) continue that, thirdly, the capability of the SET to explain certain phenomena is indefinite and may depend on the type of relationship being examined. Fourthly, these researchers further state that the SET's constructs are often abstruse, lacking in empirical and conceptual support. There is also limited literature that assesses the theoretical roles of these constructs, for example, trust. This view is supported by Cropanzano, Anthony, Daniels and Hall (2016:2), who maintain that the lack of empirical and conceptual support limits the utility of the theory.

Even though the aforementioned criticisms have been raised, the SET continues to be applied to studies internationally, across a broad spectrum of disciplines, with technology being but one (Huang *et al.,* 2018; Matikiti *et al.,* 2016; Yan *et al.,* 2016; Dai & Chen, 2015; Montazemi & Qahri-Saremi, 2015; Chen, 2013; Shiau & Luo, 2012). The following section elaborates on the importance of the SET in this study.

3.2.1.4 Importance of the SET in the present study

As mentioned in section 3.2.1, the SET can be applied to better understand the cost and reward from an exchange between two parties (Shiau & Luo, 2012:2432). In the context of this study, the exchange between the buyer or consumer on the one hand and the seller on the other, is of interest, specifically to better understand the value derived for both parties from using the seller's mCommerce app.

Research by Matikiti *et al.* (2016), Chen (2013) and Posey *et al.* (2010) proves that perceived risk has a significant influence on actual use, reinforcing the argument that perceived risk has a negative influence on consumers' actual use of mCommerce apps to purchase athleisure apparel (refer to Chapter 5, section 5.4.4). In addition, Matikiti *et al.* (2016), Montazemi and Qahri-Saremi (2015) and Shiau and Luo (2012) establish that trust has a significant influence on behavioural intention, supporting the argument that trust has a positive influence on the behavioural intention of consumers to use mCommerce apps to purchase athleisure apparel (refer to Chapter 5, section 5.4.7).

The aforementioned studies demonstrate the relevance of the SET in the field of technology, thereby justifying the inclusion of the constructs of perceived risk and trust in the model proposed in this study (refer to Chapter 1, Figure 1.9).

The following section discusses the next foundational theory used in the formulation of relationship marketing, the TCT. The TCT is completely separate from the SET.

3.2.2 Transaction Cost Theory (TCT)

The TCT is rooted in economics and explains why one particular transaction subject favours a specific form of transaction over another. The essence of the theory is that individuals have a preference for conducting transactions in the most cost-effective way (Teo & Yu, 2004:452; Williamson, 1981:555). In the context of this study, electronic environments such as an online or mobile shop is perceived as uncertain and risky to consumers (Wu *et al.,* 2014:2770). This perception results in an increased transaction cost. The TCT is therefore relevant to this study as it assists in better understanding the transaction costs present in an mCommerce exchange.

This section commences with an overview of the TCT. The relevance of the TCT in the field of technology is then discussed, including key findings from studies using this theory. Criticisms of the theory are then presented. The section concludes with the importance of the TCT in this study.

3.2.2.1 An overview of the TCT

Developed by Williamson in 1981, the TCT posits that individuals prefer to conduct transactions in a way that is most cost-effective. Three dimensions underpin each transaction: frequency, uncertainty and asset specificity. Transactions can be either frequent or rare, have high or low levels of uncertainty and involve either specific assets or non-specific assets (Akbar & Tracogna, 2018:94, 96; Teo & Yu, 2004:452; Williamson, 1981:555).

From a digital retailing point of view, transactions are described as the transfer of goods or services across technological interfaces that are distinguishable (Williamson, 1981:552). In order for a consumer to conduct a transaction, they will have to search for the required information, perform the actual transaction and monitor the fulfilment process (Teo & Yu, 2004:452). The costs assigned to completing the digital retail activity of purchasing via an online or mobile medium are referred to as transaction costs (Che *et al.,* 2015:589; Wu *et al.,* 2014:2770). Consumers still perceive digital retail as an uncertain, risky space due to its unique electronic environmental context, which leads to an increase in transaction cost (Wu *et al.,* 2014:2769). This transaction cost includes uncertainty and asset specificity, elaborated on in the following section. Research has found these costs to be accurate predictors of consumers' acceptance of digital retailing channels (Che *et al.,* 2015:589-590).

Uncertainty refers to the consumer's doubt as to the product itself as well as the outcome of online or mobile buying (Che *et al.,* 2015:589, 591; Liang & Huang, 1998:29). If a consumer is uncertain about an online transaction, they can incur high transaction costs, which may discourage them from entering into the transaction (Akbar & Tracogna, 2018:96). Wu *et al.* (2014:2769) highlight two aspects leading to uncertainty – information irregularities and behavioural assumptions. Information irregularities refer to the fact that suppliers, i.e. eCommerce or mCommerce business owners, may not disclose information in an accurate or complete manner to buyers. For example, delivery charges may not be disclosed upfront (Wu *et al.,* 2014:2769; Devaraj *et al.,* 2006:1092).

Behavioural assumptions comprise bounded rationality and opportunism (Wu *et al.,* 2014:2770). It is impossible for consumers shopping on digital retail platforms to gather any and all sources of information before making a decision. The consumer therefore behaves under bounded rationality and this leads to uncertainty (Devaraj *et al.,* 2006:1092). From an opportunist point of view, this refers to the fact that individuals participating in a transaction could falsify information in order to gain an unfair advantage from the transaction (Alaghehband, Rivard, Wub & Goyette, 2011:127). Combining information irregularities with the behavioural assumptions bounded rationality and opportunism leads to consumers' cognitive evaluations becoming more complex in an online shopping environment as opposed to offline. Ensuring information is less complex and accurate will enable consumers to make the right decisions (Wu *et al.,* 2014:2770). In addition, trust can act as a means of alleviating uncertainty. Research has suggested that this is key in reducing perceived risk and, in turn, transaction cost (Akbar & Tracogna, 2018:96; Che *et al.,* 2015:591). Asset specificity refers to the money, time and effort required to be invested into the transaction (Che *et al.,* 2015:590; Liang & Huang, 1998:29).

Teo and Yu (2004) used the TCT to investigate consumers' online purchasing behaviour. The results showed that the willingness of consumers to purchase online was strongly influenced by frequency, uncertainty and trust. This is an example of a technology acceptance study that has used the TCT as theoretical foundation. The following section examines the relevance of the TCT to the field of technology, referencing further research studies.

3.2.2.2 The relevance of the TCT to the field of technology

A number of researchers, referenced in this section, have proven the applicability of the TCT to explain specific behavioural aspects displayed by consumers in areas such as eCommerce and mCommerce (Devaraj *et al.,* 2006:1099).

In Taiwan, Wu *et al.* (2014) used the TCT to examine how specific transaction costs, i.e. information searching costs, moral hazard costs and specific asset investment, influenced consumers' repurchase intentions in online shopping environments. The findings revealed that information searching costs and moral hazard costs had a significant negative influence on repurchase intention, whereas specific asset investment showed a positive influence. Yen, Hsu and Chang (2013:229) reaffirm the findings of Wu *et al.* (2014). These researchers created a combined model using the TCT and the Expectancy Confirmation Theory (ECT) to investigate the repurchase intention of bidders in online auctions. Uncertainty and asset specificity were shown to significantly influence transaction cost, while transaction cost was shown to have a significant negative influence on repurchase intention.

Devaraj, Fan and Kohli's (2002) study supports the findings of Teo and Yu (2004) on uncertainty. They used the TCT to better understand satisfaction and preference in eCommerce. The study looked at the history of business-to-consumer (B2C) satisfaction and preference, specifically in relation to eCommerce. A number of different models was tested, including the TAM, TCT and service quality (SERVQUAL) framework. The findings revealed that uncertainty and asset specificity, from a TCT point of view, have an impact on the ease and efficiency of the eCommerce process for consumers.

Liang and Huang (1998:37) explored consumers' acceptance of five different products within an electronic market. The model was based on the TCT. The study proved that uncertainty and asset specificity determine consumers' choices when shopping online. Of the five products tested, i.e. books, shoes, toothpaste, a microwave oven and flowers, the products requiring examination or trial prior to purchase, such as shoes, were considered to be less appropriate for an electronic market.

The majority of the aforementioned studies indicate the influence of uncertainty on consumer acceptance, purchase intention or behavioural intention. The true value of the TCT in this study lies in the construct of trust and its impact on uncertainty, as well as its ability to reduce perceived risk (Akbar & Tracogna, 2018:96). This is elaborated on in section 3.2.2.4.

The above studies demonstrate the relevance of the TCT to the field of technology, however, the theory is not without criticism. The following section elaborates on this.

3.2.2.3 Criticisms of the TCT

Since the inception of the TCT in 1981, several researchers have criticised it. Ghoshal and Moran, for example, as early as 1996, criticised the TCT for classifying opportunism as being both a behaviour and an attitude. This means that opportunism was classified as a behaviour as well as an outcome of that behaviour, which critics argued was due to the fact that the construct was not properly defined (Ghoshal & Moran, 1996:18).

Hodgson (2010:2) states that the concept of transaction cost and its measurement has also proven cumbersome to some researchers, stating that the construct is difficult to observe and measure. He adds that the TCT does not take context into account. This is essential as outcomes are dependent on context. Foss and Klein (2010:263) concur, stating that considerations such as market process are overlooked. Other researchers focusing on more specialised technological arenas such as information technology outsourcing (ITO), contend that the TCT has become obsolete (Lacity, Willcocks & Khan, 2011:148).

Despite these criticisms, the TCT continues to be applied across a broad spectrum of disciplines, including technology (Wu *et al.,* 2014; Yen *et al.,* 2013; Teo & Yu, 2004; Devaraj *et al.,* 2002; Liang & Huang, 1998). The following section elaborates on the importance of the TCT in this study.

3.2.2.4 Importance of the TCT in the present study

As mentioned in section 3.2.2, consumers regard digital retail as uncertain and risky due to its unique electronic environment. This leads to greater transaction costs (Wu *et al.,* 2014:2769). The TCT's importance to this study lies in that fact. These transaction costs are proven to be accurate predictors of consumers' acceptance of digital retailing channels (Che *et al.,* 2015:589-590). The TCT is therefore relevant to this study as it assists in understanding the transaction costs present in an mCommerce exchange.

The transaction cost referenced most often in the studies discussed in section 3.2.2.2 is uncertainty and its impact on behavioural intention (Wu *et al.,* 2014; Teo & Yu, 2004; Devaraj *et al.,* 2002; Liang & Huang, 1998). The value of the TCT in this study therefore lies in what influences uncertainty and that is the construct of trust. The influence of trust in reducing uncertainty and perceived risk (Akbar & Tracogna, 2018:96) reinforces the argument that trust mediates the negative influence of perceived risk and consequently, on behavioural intention to use mCommerce apps to purchase athleisure apparel. Trust also mediates the negative influence of perceived risk on consumers' actual use of mCommerce apps in this regard (refer to Chapter 5, sections 5.4.5 and 5.4.6).

The studies mentioned above justify the inclusion of the construct of trust in the model proposed in this study (refer to Chapter 1, Figure 1.9). In addition, the aforementioned theories ground the study from a relationship-building perspective. The following section discusses the technology acceptance theories and models grounding the study.

3.3 A perspective on technology acceptance theories and models grounding the study

The adoption or use of technological innovations such as mCommerce depends on consumers' behavioural intentions. Consumers can learn how to use such innovations by applying a behavioural or cognitive learning model. With behavioural learning models, the consumer learns through observation, in response to an external stimulus. With cognitive learning models, the consumer learns by handling and processing information; learning is therefore not just a response to an external stimulus (Ratten, 2011:40).

A number of theories have been developed over the years in an attempt to better understand and explain cognitive learning models. Within the technological innovation field, since as early as the 1980s, researchers have been attempting to explain consumers' acceptance and use of new technologies (Rondan-Cataluña *et al.,* 2015:788). This is evident when considering the various technology acceptance theories and models in existence today, as can be seen in Chapter 1, Figure 1.1.

In 1962, for example, Rogers developed the IDT, a theory on the communication and adoption process a new technology or technological innovation follows (Hoffmann *et al.,* 2007:37; Rogers, 2003:1). Fishbein and Ajzen developed the TRA in 1975, which holds that an individual's intention to complete a behaviour is determined by their attitude and subjective norm. In 1986, Bandura developed the SCT, a theory that depicts a reciprocal relationship between cognitive and situational factors on the one hand and an individual's behaviour on the other (Ratten, 2011:41). In the same year, Davis added to the TRA, developing the TAM. This model shows perceived usefulness and perceived ease of use and how these constructs influence attitude which, in turn, influences behavioural intention. Ajzen, in 1991, enhanced the TRA and developed the TPB, which incorporates a third construct not included in the original TRA – perceived behavioural control. Finally, Venkatesh *et al.* (2003:428-432) developed the UTAUT, which consolidated and unified the multitude of technology acceptance theories and models into one single model.

The next section provides a more in-depth look at each of the aforementioned technology acceptance theories and models. The discussion follows the foundation year of each theory.

3.3.1 Innovation Diffusion Theory (IDT)

The IDT attempts to explain a user's adoption of innovative technologies and their decision-making process (Chung & Holdsworth, 2012:226-227; Khalifa & Shen, 2008:111; Wu & Wang, 2005:721; Rogers, 2003:1). This study examines the constructs that influence consumers' acceptance and use of mCommerce apps to purchase athleisure apparel. According to Natarajan, Balasubramanian and Kasilingam (2017:10), mCommerce apps are considered an innovative technology, therefore the IDT is well-suited to this study.

This section commences with an overview of the IDT. The relevance of the IDT in the field of technology is then discussed, including key findings from studies using this theory. Criticisms of the theory are then presented. The section concludes with the importance of the IDT in this study.

3.3.1.1 An overview of the IDT

Innovation is described as an object or idea that is perceived as something new by an individual (Wang *et al.,* 2018:238; Hoffmann *et al.,* 2007:37; Rogers, 2003:1). Diffusion refers to the process through which an innovation is communicated (Hoffmann *et al.,* 2007:37; Rogers, 2003:1). The IDT was developed by Rogers in 1962. The theory postulates that innovations in the field of technology are communicated by members of a social system over a period of time, through a number of channels. The information moves through a series of stages, namely, knowledge, persuasion, decision, implementation and confirmation. Rogers further outlines five innovation characteristics perceived by individuals at the persuasion stage that can result in either a positive or negative attitude towards the innovation. These characteristics are compatibility, complexity, observability, trialability and relative advantage (Oturakci & Yuregir, 2018:53; Chung & Holdsworth, 2012:226-227; Khalifa & Shen, 2008:111; Wu & Wang, 2005:721; Rogers, 2003:1). Each of the aforementioned stages and innovation characteristics is elaborated on below.

During the knowledge stage, often referred to as the awareness stage, individuals are first exposed to the existence of the innovation and start understanding its functions. During the persuasion stage, individuals start formulating an attitude towards the innovation. The individual's interest is piqued and they begin to find out more about the new innovation. The five perceived innovation characteristics influence this stage, i.e. compatibility, complexity, observability, trialability and relative advantage (Oturakci & Yuregir, 2018:53; Chung & Holdsworth, 2012:227). Compatibility refers to the extent to which the new innovation is aligned with an individual's past experiences, values and needs. An innovation compatible with these criteria is adopted at a faster rate than an incompatible one. Complexity considers whether the innovation is difficult to understand and use. Simpler innovations are adopted faster than those which are perceived to be more complex (Oturakci & Yuregir, 2018:53; Wu *et al.,* 2013:266; Chung & Holdsworth, 2012:227). This specific characteristic is similar to perceived ease of use, which features in the TAM (Wu & Wang, 2005:721). Observability refers to the degree to which the benefits of the innovation's adoption and use are noticeable to others, assisting in its uptake. Trialability is concerned with the extent to which the innovation can be experimented with. An innovation that allows an individual the opportunity to trial it for a limited period of time reduces uncertainty. Finally, relative advantage refers to whether an innovation is regarded as better than ideas that came before it. If an innovation is considered to have greater perceived relative advantage, its rate of adoption will be faster (Oturakci & Yuregir, 2018:53-54; Wu *et al.,* 2013:266; Chung & Holdsworth, 2012:227). This characteristic is similar to perceived usefulness, which appears in the TAM (Wu & Wang, 2005:721). After the persuasion stage comes the decision stage.

At the decision stage, the individual starts comparing the pros and cons of the innovation and makes a decision as to whether to adopt it or not. Innovation decisions can also be reached collectively, i.e. amongst all members of a particular social system; or authoritatively, i.e. where an individual in power makes the decision for their social system and imposes it on them (Chung & Holdsworth, 2012:227). A correlation between this stage and the constructs of subjective norm or social influence can be drawn here. These constructs, both referring to the idea of external influence, feature in a number of technology acceptance theories and models, discussed in sections hereafter, including the TRA and TPB, as well as the UTAUT and UTAUT2. All the aforementioned theories and models posit that such external influence plays an important role in an individual's ultimate decision to use a new technology or not (Lin & Lu, 2015:109). Once the decision has been reached, the implementation stage is entered.

During the implementation stage, the practicalities of the innovation are assessed. Additional information may be sought at this stage in an effort to bolster knowledge. As it is an innovation that is being communicated, there is a degree of perceived risk and uncertainty in the process. This can be reduced by obtaining information on the innovation (Hoffmann *et al.,* 2007:37; Rogers, 2003:1). Lastly, at confirmation stage, individuals cement their decision to continue using the innovation (Chung & Holdsworth, 2012:227).

The IDT led to the development of the innovation adoption curve, as depicted in Chapter 1, Figure 1.2. The curve shows the various classifications of members within a social system based on their adoption speed (Hoffmann *et al.,* 2007:44). The curve includes innovators, early adopters, early majority, late majority and laggards (Lai, 2017:23). According to Su, Wang and Yan (2018:187), the IDT is the most appropriate model to use when studying consumer adoption of innovative technologies. The following section considers the relevance of the IDT to the field of technology, referencing a number of research studies.

3.3.1.2 The relevance of the IDT to the field of technology

Slade, Williams and Dwivedi (2013:7-8) state that various researchers, referenced in this section, have used the IDT as a foundation theory in technology-related studies and more specifically, mobile payment and mobile banking adoption research. Some of these studies are elaborated on below. Oliveira, Thomas, Baptista and Campos (2016:410) conducted a study in Portugal on constructs that determine consumers' acceptance and use of mobile payments as well as their intention to recommend the technology. The study proposed a model rooted in the UTAUT2 and IDT. The results indicated that compatibility was the most important construct in explaining behavioural intention. Compatibility was used in the formulation of the construct of facilitating conditions in the UTAUT2 (Alkhunaizan & Love, 2012:83; Venkatesh *et al.,* 2003:453).

Chen (2013:425) investigated the influence of perceived risk and the characteristics of the IDT, i.e. compatibility, complexity, observability, trialability and relative advantage, on consumers' attitude towards mobile banking services. The findings revealed that compatibility, observability, trialability and relative advantage all showed significant positive influence over attitude. Complexity was shown to have a significant negative influence over attitude.

In China, Wu *et al.* (2013:279-280) explored the acceptance of enterprise or corporate blogs in the services industry. Their model included a test component for three of the five characteristics of the IDT, namely, complexity, trialability and relative advantage. Their findings showed that, firstly, complexity had a significant negative influence on attitude towards adopting enterprise blogs, indicating that corporates were unlikely to accept enterprise blogs into their businesses if complex operations were involved. Secondly, their research uncovered that corporate businesses showed a willingness to trial an enterprise blog before adoption. Lastly, relative advantage was found to have a significant effect on the intention towards adopting enterprise blogs. Relative advantage was used in the formulation of the construct of performance expectancy in the UTAUT2 (Persson & Berndtsson, 2015:16; Alkhunaizan & Love, 2012:83; Venkatesh *et al.,* 2003:447).

Zhang *et al.* (2012:1909) examined the moderating effects of culture on mCommerce adoption. They tested the influence of the specific innovation characteristic, compatibility, on behavioural intention and found it to be significant, supporting the findings of Oliveira *et al.* (2016:410). This indicates that the alignment of a technology such as mCommerce to an individuals' past values or past experiences is important and influences the individual's behavioural intention to use the technology. The value of the IDT to this research study is the role it played in the formulation of key constructs in the UTAUT2; the model of focus for this particular study. This is elaborated on in section 3.3.1.4.

Although the aforementioned studies prove the relevance of the IDT in the field of technology, validating its inclusion in this study, the theory is not without criticism. The following section elaborates on this.

3.3.1.3 Criticisms of the IDT

IDT research describes an innovation as something that has separate and quantifiable features. However, not all technological innovations can be classified this way. For example, a digital television (TV) will not have the same quantifiable features as a smart watch, virtual reality (VR) or mCommerce. The theory has further been criticised due to the various meanings that each of the characteristics can carry at different stages of the adoption process, for example, compatibility may mean something different for an innovator compared to a laggard (Lyytinen & Damsgaard, 2001:6-7). Wells and Nieuwenhuis (2018:445) agree, stating that the theory treats consumers across the spectrum, from early adopters to laggards, in an equal way. Shaikh and Karjaluoto (2015:136) add that the IDT does not successfully explain how a consumer's attitude forms to ultimately lead to either accepting or rejecting the innovation. It also fails to explain how the different innovation attributes fit into the process.

Nonetheless, the IDT continues to be applied to technology-related studies internationally (Oliveira *et al.,* 2016; Chen, 2013; Wu *et al.,* 2013; Zhang *et al.,* 2012). The following section elaborates on the importance of the IDT in this study.

3.3.1.4 Importance of the IDT in the present study

The IDT was a key model used in the compilation of the UTAUT2 – the model of focus for this study. Relative advantage was used in the creation of the construct of performance expectancy; complexity was used to inform effort expectancy; observability was used to inform social influence; and compatibility was used to inform facilitating conditions (Venkatesh *et al.,* 2003:447-453).

Wu *et al.* (2013) proved that relative advantage (represented by performance expectancy in this study) had a significant influence on behavioural intention, supporting the argument that performance expectancy has a positive influence on the behavioural intention of consumers to use mCommerce apps to purchase athleisure apparel (refer to Chapter 5, section 5.4.1.1). Research by Oliveira *et al.* (2016) and Zhang *et al.* (2012) proved that compatibility usefulness (represented by facilitating conditions in this study) had a significant influence on behavioural intention, supporting the argument that facilitating conditions have a positive influence on the behavioural intention of consumers (refer to Chapter 5, section 5.4.1.4).

The following section discusses the next technology acceptance theory grounding the study, the TRA. The TRA is completely separate from the IDT.

3.3.2 Theory of Reasoned Action (TRA)

Developed in 1975 by Fishbein and Ajzen, the TRA posits that there is a direct association between an individual's environment and attitude and their intention and behaviour (Liao, Huang, To & Lu, 2017:585). This theory was fundamental in the formulation of the construct of social influence in the UTAUT2 used in this study (Venkatesh *et al.,* 2003:447-451). In addition, both the TRA and the UTAUT2 depict behavioural intention as having a direct influence on ultimate behaviour, reinforcing another proposed hypothesis of this study (Rondan-Cataluña *et al.,* 2015:794).

This section commences with an overview of the TRA. The relevance of the TRA in the field of technology is then discussed, including key findings from studies using this theory. Criticisms of the theory are then presented. The section concludes with the importance of the TRA in this study.

3.3.2.1 An overview of the TRA

Developed in 1975 by Fishbein and Ajzen, the TRA is rooted in the field of social psychology. It is a theory of human behaviour that considers the relationships between a human being's beliefs system, attitudes, intentions and ultimate behaviour. It is based on the assumption that human beings process information rationally, in a systematic way. This systematic way of processing is strongly influenced by the individual's underlying belief system. The theory states that humans can arrive at the same behavioural decision but from different belief systems (Fishbein & Middlestadt, 1987:362).

As shown in Chapter 1, Figure 1.3, the theory posits that an individual's intention to complete a specific behaviour is determined by a personal factor (their attitude) and a social factor (the subjective norm) (Mou, Shin & Cohen, 2017:126; Yap & Gaur, 2016:168; Nasri & Charfeddine, 2012:3; AlHinai, 2009:61; Khalifa & Shen, 2008:113; Fishbein & Middlestadt, 1987:362). The TRA holds that actual behaviour is chiefly determined by an individual's behavioural intention or "the extent to which an individual intends to perform a specific behaviour" (Mou *et al.,* 2017:126; June, 2014:137).

The personal factor, attitude, refers to an individual's positive or negative feelings towards carrying out a specific behaviour, such as shopping online or via a mobile phone (Otieno, Liyala, Odongo & Abeka, 2016:3; Al-Debei *et al.,* 2015:207; AlHinai, 2009:61; Khalifa & Shen, 2008:113; Fishbein & Middlestadt, 1987:363). The social factor, subjective norm, refers to an individual's perceived level of influence of significant others in their life, for example, peers, family and friends, the media, as well as figures of authority (Otieno *et al.,* 2016:3; Yap & Gaur, 2016:170; Khalifa & Shen, 2008:113; Fishbein & Middlestadt, 1987:363). More specifically, it is the individual's perception of the social pressures applied by these significant others to perform or decline to perform a specific behaviour. When confronted with a new behaviour, such as shopping online or via a mobile phone, the individual might refer to their group of significant others for an opinion on the matter, or will check their decision against the group to ensure approval (Mou *et al.,* 2017:128; AlHinai, 2009:61-62).

As can be seen in Chapter 1, Figure 1.3, subjective norm is shown to have two routes of influence. Firstly, it influences attitude, thereby affecting behavioural intention; and secondly, it has a direct influence on behavioural intention. The influence on attitude is present in the theory as the individual's evaluation of the behaviour will include soliciting opinions from their significant others (Mou *et al.,* 2017:128; AlHinai, 2009:62). The influence of subjective norm has been extensively studied in the technology acceptance domain. Its influence on technology adoption is also supported by the IDT; Rogers states that social pressure influences the rate at which an innovation is adopted (Yap & Gaur, 2016:168; Kim, Ma & Park, 2009:218). Furthermore, the construct of subjective norm has had a significant influence on the formation of the construct of social influence, one of the key constructs of focus in this study (June, 2014:139). Attitude and subjective norm are shown to have an influence on behavioural intention. Behavioural intention is described as a measurement of the strength of an individual's intent to perform a specific behaviour. It is intended as a measure to anticipate an individual's voluntary act (Persson & Berndtsson, 2015:10; Davis, 1986:16). Behavioural intention is then shown to influence behaviour. The causal order in which attitude, subjective norm, behavioural intention and behaviour are linked indicates that an individual's actual behaviour is influenced by their intent to display that same behaviour (Mou *et al.,* 2017:128; Kim *et al.,* 2009:217). Davis (1986:25) describes behaviour as an individual's actual use of the technology in question. For example, in the instance of this study, behaviour refers to an individual actually purchasing athleisure apparel by means of mCommerce. Each of the aforementioned core constructs of the TRA, i.e. attitude, subjective norm, behavioural intention and behaviour and their associated definitions, are summarised in Table 3.1.

Table 3.1: Core constructs of the TRA

Construct	Definition	Reference
Attitude	An individual's positive or negative feelings towards carrying out a specific behaviour, such as shopping online or via a mobile phone.	Otieno, Liyala, Odongo & Abeka (2016:3); Al-Debei *et al.* (2015:207); AlHinai (2009:61); Khalifa & Shen (2008:113); Fishbein & Middlestadt (1987:363)
Subjective norm	An individual's perceived level of influence of significant others in their life, for example, peers, family and friends, the media, as well as figures of authority.	Otieno *et al.* (2016:3); Yap & Gaur (2016:170); Khalifa & Shen (2008:113); Fishbein & Middlestadt (1987:363)
Behavioural intention	A measurement of the strength of an individual's intent to perform a specific behaviour. It is intended as a measure to anticipate an individual's voluntary act.	Persson & Berndtsson (2015:10); Davis (1986:16)
Behaviour	An individual's actual use of the technology in question.	Davis (1986:25)

The following section considers the relevance of the TRA to the field of technology, referencing a number of studies.

3.3.2.2 The relevance of the TRA to the field of technology

The TRA has been applied in many studies on technology acceptance (Mou *et al.,* 2017:126; Otieno *et al.,* 2016:1; Ratten, 2011:40). Some of these studies are elaborated on below. The theory lends itself well to the conceptualisation of human behaviour and the approach to decision-making when it comes to utilising a new technology or innovation. The TRA is used to explain whether an individual's behaviour is as a result of their behavioural intention. Furthermore, it is used to determine whether the behavioural intention is a function of the individual's attitude towards the behaviour or the subjective norms that surround it (Otieno *et al.,* 2016:3). The theory is, however, mostly applied in support of other theories such as the IDT, TAM and TPB (Otieno *et al.,* 2016:1-2).

In Taiwan, Liao *et al.* (2017:595) used the TRA to examine constructs driving digital music purchasing. The findings revealed that subjective norm and attitude both positively influenced consumers' intention to purchase digital music. Subjective norm was a key construct used in the formulation of social influence, one of the constructs of interest in this study (Persson & Berndtsson, 2015:16; Alkhunaizan & Love, 2012:83; Venkatesh *et al.,* 2003:451). Yap and Gaur's (2016:174) research supports Liao *et al.*'s (2017) findings. They conducted a study to explain online social networking usage; their proposed model comprised constructs from the TRA, TAM and SCT. The findings revealed that attitude had a significant positive influence on behavioural intention.

Mou *et al.* (2017:126; 132) investigated consumers' acceptance of e-services, using the TRA as foundation theory. The study hypothesised that the construct of trust was an important behavioural belief that was thought to significantly influence consumers' acceptance of e-services. The findings revealed that trust and subjective norm both positively influenced behavioural intention while behavioural intention was shown to positively influence actual usage. This study proved the TRA to be a suitable model for examining online behaviour. This is confirmed by Sanne and Wiese (2018:8), who found the TRA to accurately explain online behaviour on a social network, as well as Otieno *et al.* (2016:7) who state that the theory is useful when studying consumer adoption or use of technological innovations.

Lin and Chang (2011:435) explored the role of technology readiness in the self-service technology industry. Part of the model tested the influence of attitude on behavioural intention and a significant positive relationship was found. The TRA has also proven to be a successful model in predicting and explaining individual behaviour. AlHinai (2009:178), for example, conducted a study in Australia to understand individuals' adoption or use of advanced mCommerce services. The study found that a higher subjective norm had a significant positive impact on attitude and behavioural intention. This reinforces the findings of Liao *et al.* (2017). Positive attitude was also found to have a significant impact on behavioural intention.

The above studies demonstrate the relevance of the TRA in the field of technology, however, the theory is not without criticism. The following section elaborates on this.

3.3.2.3 Criticisms of the TRA

Some researchers have criticised the TRA for failing to take choice into account. In many instances, at the point of making a decision, an individual is faced with a number of alternatives – a scenario which the theory does not allow for (Persson & Berndtsson, 2015:11). The TRA has also been criticised for not taking into account when an individual's behaviour is not under their direct control, which is the primary reason for Ajzen extending the model into the TPB (as discussed in section 3.3.5) (Belkhamza & Niasin, 2017:181; Miladinovic & Xiang, 2016:13; Ratten, 2011:40; Ratten & Ratten, 2007:91). Furthermore, the TRA adds all beliefs of an individual together, whereas with the TAM, for example, beliefs are seen as individual constructs. Demonstrating each belief independently allows researchers to better trace different influences on individualised beliefs (Pikkarainen, Pikkarainen, Karjaluoto & Pahnila, 2004:226).

Despite these criticisms, the TRA continues to be applied to technology-related studies internationally (Liao *et al.,* 2017; Mou *et al.,* 2017; Yap & Gaur, 2016; Lin & Chang, 2011; AlHinai, 2009). The following section elaborates on the importance of the TRA in this study.

3.3.2.4 Importance of the TRA in the present study

The TRA was a fundamental theory used in the formulation of the UTAUT2, the model of focus for this study, and specifically for the construct of social influence (Venkatesh *et al.,* 2003:447-451). As evident from the findings of the above studies (Liao *et al.,* 2017; Mou *et al.,* 2017; AlHinai, 2009), the subjective norm construct (represented by social influence in this study) was found to have a significant influence on behavioural intention, confirming that social influence has a positive influence on the behavioural intention of consumers to use mCommerce apps to purchase athleisure apparel (refer to Chapter 5, section 5.4.1.3). Mou *et al.* (2017) also proved that behavioural intention has a significant influence on actual use, thereby highlighting that behavioural intention has a positive influence on consumers' actual use of mCommerce apps to purchase athleisure apparel (refer to Chapter 5, section 5.4.8).

The following section discusses the next technology acceptance theory grounding the study, the SCT. The SCT is completely separate from the TRA.

3.3.3 Social Cognitive Theory (SCT)

The SCT was developed by Bandura in 1986 to offer a more holistic understanding of an individual's behavioural intention to adopt new technologies. Understanding an individual's adoption behaviour is imperative with the release of new technologies and innovations, such as mCommerce (Ratten, 2011:27; 41). This theory was fundamental in the formulation of the construct of performance expectancy in the UTAUT2 (Venkatesh *et al.,* 2003:447). The SCT is therefore well-suited to this study.

This section commences with an overview of the SCT. The relevance of the SCT in the field of technology is then discussed, including key findings from studies using this theory. Criticisms of the theory are then presented. The section concludes with the importance of the SCT to this study.

3.3.3.1 An overview of the SCT

Conceptualised by Bandura in 1986, the SCT considers the interactions between individuals and their behaviours within their environments. Rooted in psychology, the theory is widely accepted as it examines the reasons for people adopting specific behaviours (Ratten, 2011:41). At its core, the SCT centres on learning and suggests that individuals learn (cognitive factors) by being exposed to diverse information in their environment (situational factors). As can be seen in Chapter 1, Figure 1.4, the SCT posits that a reciprocal relationship exists between the cognitive and situational factors, as well as the individual's behaviour (Chou & Hsu, 2018:243; Ifinedo, 2017:190; Boateng, Adam, Okoe & Anning-Dorson, 2016:469; Ratten, 2011:41). According to the SCT, an individual's behaviour is regulated by their cognitive factors and by the environment they find themselves in, through situational factors (Boateng *et al.,* 2016:469).

From a cognitive point of view (cognitive factors), the theory postulates that an individual's behaviour is shaped by their expectations, perceptions and beliefs. Essentially, how the particular individual thinks and feels will ultimately shape their behaviour. Moreover, depending on the situation, skills, abilities and knowledge can influence certain behaviours. From an environmental point of view (situational factors), the SCT states that physical and social factors within the environment can influence a person's behaviour. Physically, for example, natural objects; and socially, for example, relationships, peer influence or people surrounding the individual (Chou & Hsu, 2018:244; Boateng *et al.,* 2016:469).

Honing in on cognitive factors, Bandura's research centres on two sets of outcomes – outcome expectations and self-efficacy – which cognitively guide an individual's behaviour (Compeau & Higgins, 1995:191). Outcome expectations are described as an individual's anticipated outcomes of their actions (Ifinedo, 2017:191; Lim & Noh, 2017:251). Individuals embark on specific behaviours that they expect will result in value-adding outcomes as opposed to behaviours that will not result in favourable outcomes (Compeau & Higgins, 1995:191). Self-efficacy is described as an individual's judgement regarding how well they can execute a specific course of action to deal with a specific situation (Bandura, 1989:59). This influences an individual's choice regarding which behaviour to undertake (Compeau & Higgins, 1995:191). The construct of outcome expectations is of interest to this study as it was vital to the development of the construct of performance expectancy, a key construct in the UTAUT2 (Venkatesh *et al.,* 2003:447). Outcome expectations have a marked influence on consumer behaviours including the use of computers, the Internet or new technologies such as mCommerce and knowledge sharing (Kwahk, Ahn & Ryu, 2018:65). The following section elaborates on this.

3.3.3.2 The relevance of the SCT to the field of technology

As the SCT focuses on the continuous changes in human behaviour, the theory has the ability to adapt dynamically. It is therefore well-suited to the constantly evolving technological industry, as new innovations occur on an ongoing basis (Ratten, 2011:41). Understanding an individual's adoption behaviour is imperative with the release of new technologies and innovations, such as mCommerce. Some technological advancements take time to learn and can often involve a more complex process. In such instances, environmental factors assist researchers to better understand future behavioural intention. The SCT is therefore well-suited to this study (Ratten, 2015:27). Studies in support of this view are discussed below.

Kwahk *et al.* (2018:69) conducted a study on mandatory information systems (IS) use behaviour. The SCT formed the foundation for their research model. The findings revealed that personal outcome expectations had a significant influence on use behaviour. Similarly, Lim and Noh (2017:254) investigated the mediating role of self-efficacy and outcome expectations on exercise. Their findings support those of Kwahk *et al.* (2018:68), indicating that outcome expectations have a positive influence on use behaviour.

In Ghana, Boateng *et al.* (2016:470; 475) used the SCT to examine the determinants of Internet banking adoption intention. The researchers hypothesised that trust is imperative where a technology such as mCommerce is concerned as it controls relationships and minimises uncertainty (Boateng *et al.,* 2016:470). Their research supports the argument that trust has a significant influence on behavioural intention (Boateng *et al.,* 2016:475).

Zhu *et al.* (2017:2232-2233) conducted a study in Beijing on individuals' motivations behind adopting or using mobile applications for ride-sharing. A ride-sharing application refers to a service that consumers can use to order a car ride online, for example, Uber, Lyft or Taxify (Zhu *et al.,* 2017:2219). The study was grounded in the SCT and tested whether self-efficacy influenced behavioural determinants. The influence of self-efficacy was tested on perceived value, attitude and adoption intention. The study found that self-efficacy strongly influenced perceived value and attitude, but not adoption intention. Perceived value, however, was found to have a strong influence on attitude and, in turn, attitude was found to have a strong influence on adoption intention. This indicates that self-efficacy does not have a direct influence on adoption intention, but an indirect influence, via the constructs of perceived value and attitude (Zhu *et al.,* 2017:2232-2233).

Yap and Gaur (2016:174) researched social network usage based on a model incorporating the TAM, the TRA and the SCT. The findings revealed that self-efficacy, a component of the SCT, had a significant positive influence on attitude and attitude, in turn, had a significant influence on consumers' use of social networking.

In Australia, Ratten and Ratten (2007:94-95) looked at youth's behavioural intention to use wireless application protocol (WAP) banking. The study, which was grounded in the SCT, discovered that the greater the outcome value of WAP banking, the greater the behavioural intention to use WAP banking. The study also found that higher levels of self-efficacy did not lead to an increase in behavioural intention.

The majority of the above studies prove the relevance of the SCT to the field of technology and depict the influence of self-efficacy or outcome expectations on behavioural intention to use or actual use. The value of the SCT in this study lies in the outcome expectations construct and its influence on the development of the construct of performance expectancy (Venkatesh *et al.,* 2003:447). This is elaborated on in section 3.3.3.4. The theory, however, is not without criticism. The following section elaborates on this.

3.3.3.3 Criticisms of the SCT

The SCT has been criticised for its excessive focus on the situation as opposed to an individual's emotions, which are left out of the relationship completely. In addition, it has also been stated that the theory focuses on the cognitive too much, as opposed to understanding biological influences (Weebly.com, 2018; Learning Theories, 2014). According to Lumen Learning (2018), the theory does not accommodate development as it does not take into account how an individual's personality changes over time.

Furthermore, researchers have criticised social cognitive theorists for not effectively clarifying the difference or relationship between self-efficacy and other constructs for expectancy, such as outcome expectations, stating that these constructs are not clearly defined and oversimplified (Pajares, 1997:24; 26). Despite these criticisms, however, the SCT continues to be applied to technology-related studies internationally (Kwahk *et al.,* 2018; Lim & Noh, 2017; Boateng *et al.,* 2016; Zhu *et al.,* 2017; Yap & Gaur, 2016; Ratten & Ratten, 2007).

The following section elaborates on the importance of the SCT in this study.

3.3.3.4 Importance of the SCT in the present study

The SCT was a fundamental theory used in the formulation of the UTAUT2, specifically for the construct of performance expectancy (Venkatesh *et al.,* 2003:447). As demonstrated in the aforementioned studies (Kwahk *et al.,* 2018; Lim & Noh, 2017:254), the outcome expectations construct (represented by performance expectancy in this study) was found to have a significant influence on behavioural intention, supporting the argument that performance expectancy has a positive influence on the behavioural intention of consumers to use mCommerce apps to purchase athleisure apparel (refer to Chapter 5, section 5.4.1.1).

The following section discusses the next technology acceptance theory grounding the study, the TAM. The TAM is completely separate from the SCT.

3.3.4 Technology Acceptance Model (TAM)

Conceptualised in 1986 by Davis, the TAM is the most universally-applied model in technology acceptance research (Zhu *et al.,* 2017:2220; Ratten, 2015:27). The model centres on the fact that an individual is motivated to accept and use a new technology based on three elements – perceived ease of use, perceived usefulness and attitude (Dlodlo & Mafini, 2013:2; Pinho & Soares, 2011:119). The TAM was a key theory in the formulation of the UTAUT2, specifically the constructs of performance expectancy and effort expectancy (Venkatesh *et al.,* 2003:447; 450). Furthermore, according to Miladinovic and Xiang (2016:14), the TAM proves that actual use can be predicted from behavioural intention, reinforcing another proposed hypothesis of this study.

This section commences with an overview of the TAM. The relevance of the TAM in the field of technology is then discussed, including key findings from studies using this theory. Criticisms of the theory are then presented. The section concludes with the importance of the TAM to this study.

3.3.4.1 An overview of the TAM

Built on the TRA (van Slyke, 2008:xi; Davis, 1986:13), the TAM is based on the premise that a consumer's motivation to acceptance and use a new technology is influenced by three elements, namely, perceived usefulness, perceived ease of use and attitude toward use (Dlodlo & Mafini, 2013:2; Pinho & Soares, 2011:119). As shown in Chapter 1, Figure 1.5, the model highlights that attitude is a function of perceived usefulness and perceived ease of use and is a determinant of behavioural intention. In turn, behavioural intention is predictive of actual use (Faqih & Jaradat, 2015:41-42; Wu & Wang, 2005:720). Perceived ease of use is shown to have a causal effect on perceived usefulness (Faqih & Jaradat, 2015:42; Davis, 1986:24).

Perceived usefulness is described as an individual's belief that using a specific technology or system will enhance the performance of their job (Liébana-Cabanillas *et al.,* 2017:15; Miladinovic & Xiang, 2016:14; Persson & Berndtsson, 2015:13; Davis, 1986:26). Judgements about the usefulness of a technological innovation are often made by individuals when initial assessments are made (Ratten, 2015:27). Generally, individuals will not use a specific technology or system if it does not offer a benefit for what they wish to accomplish (Persson & Berndtsson, 2015:13). This construct can be compared to the performance expectancy construct from the UTAUT and UTAUT2 (Persson & Berndtsson, 2015:16; Alkhunaizan & Love, 2012:83; Venkatesh *et al.,* 2003:447). According to Liébana-Cabanillas *et al.* (2017:15), this construct has a stronger influence on the acceptance and use of new technologies, such as mCommerce, compared to perceived ease of use.

Perceived ease of use refers to the extent to which an individual believes that using the new technology or system will be free of any effort (Miladinovic & Xiang, 2016:14; Persson & Berndtsson, 2015:13; Davis, 1986:26). Researchers have found that technologies that are easier to use are generally adopted faster. In addition, a key determinant of an individual's ease when using a new technology, is their ability to actually understand the technology. mCommerce is a technological innovation that is constantly evolving. It is therefore important to understand consumers' ease of using it (Ratten, 2015:28). Faqih and Jaradat (2015:42) concur, stating that mCommerce involves a number of complicated processes and therefore ease of use is imperative in ensuring its adoption or use. This construct can be compared to the effort expectancy construct from the UTAUT and UTAUT2 (Alkhunaizan & Love, 2012:83; Venkatesh *et al.,* 2003:450).

As can be seen in Chapter 1, Figure 1.5, perceived ease of use has an influence on perceived usefulness. Davis (1986:26) hypothesises this as technologies or systems that are easy to use, will result in greater usefulness for the individual using it. Attitude is also shown to be a function of perceived usefulness and perceived ease of use. Attitude refers to the positive and/or negative evaluations of an individual's performance of a specific behaviour (Ifinedo, 2017:190; Shanmugam, Savarimuthu & Wen, 2014:239).

The TAM has also proved that technology use can be predicted from user intention, which reinforces the findings of the TRA (Miladinovic & Xiang, 2016:14). The TRA shows that behavioural intention is the main determining construct in actual behaviour. This is also in alignment with the UTAUT2 which indicates that behavioural intention directly influences ultimate behaviour.

Each of the aforementioned core constructs of the TAM, i.e. perceived usefulness, perceived ease of use, attitude, behavioural intention and actual use and their associated definitions are summarised in Table 3.2.

Table 3.2: Core constructs of the TAM

Construct	**Definition**	**Reference**
Perceived usefulness	An individual's belief that using a specific technology or system will lead to the enhanced performance of their job.	Liébana-Cabanillas *et al.* (2017:15); Miladinovic & Xiang (2016:14); Persson & Berndtsson (2015:13); Davis (1986:26)
Perceived ease of use	The extent to which an individual believes that using the new technology or system will be free of any effort.	Miladinovic & Xiang (2016:14); Persson & Berndtsson (2015:13); Davis (1986:26)
Attitude	The positive and/or negative evaluations of an individual's performance of a specific behaviour.	Ifinedo (2017:190); Shanmugam *et al.* (2014:239)
Behavioural intention	As per the definition in Table 3.1	
Actual use	As per the definition in Table 3.1	

The following section examines the relevance of the TAM to the field of technology, referencing a number of research studies.

3.3.4.2 The relevance of the TAM to the field of technology

Zhu *et al.* (2017:2220) and Ratten (2015:27) maintain that TAM is the single, most widely used model in technology acceptance research (refer to section 3.3.4). It has been adopted and tested in various scenarios due to its sturdiness, simplicity and explanatory power (Agrebi & Jallais, 2015:16).

Liébana-Cabanillas *et al.* (2017:18) conducted a TAM-based study in Serbia to understand the antecedents of mCommerce acceptance. The findings revealed that perceived usefulness had a significant positive influence on behavioural intention, however, this was not the case for perceived ease of use. The construct of trust was also found to have a significant influence on behavioural intention. Agrebi and Jallais (2015:21) researched consumer intention to use smartphones for shopping based on a TAM model. Their findings support those of Liébana-Cabanillas *et al.* (2017:18) insofar as perceived usefulness positively impacted behavioural intention whereas perceived ease of use did not. In Jordan, Faqih and Jaradat (2015:46) investigated the adoption or use of mCommerce technology using a TAM3 model which incorporated the same constructs of perceived usefulness and perceived ease of use. Their findings corroborate those of Liébana-Cabanillas *et al.* (2017:18) and Agrebi and Jallais (2015:21) with regard to perceived usefulness. In contrast, however, they found that perceived ease of use also had a significant positive influence on the behavioural intention of Jordanian consumers to use mCommerce. The study further found behavioural intention to have a significant influence on actual use (Faqih & Jaradat, 2015:46). Ratten (2015:29-30) reported similar results to those of Faqih and Jaradat (2015:46) in a cross-cultural study in China and Australia. The study examined the influence of online behavioural advertising knowledge, online privacy concerns and social networking on the adoption of cloud computing. The model tested comprised TAM and SCT constructs. The results revealed that both perceived usefulness and perceived ease of use were important influencers of behavioural intention for consumers in both countries.

Zhang *et al.* (2012:1909) conducted a study on mCommerce adoption using the TAM, TPD and IDT as foundational theories. The findings demonstrated that perceived usefulness did not have a significant influence on behavioural intention, but both attitude and perceived ease of use did. The study also tested the effect of perceived risk and trust on behavioural intention and both these relationships were found to be significant. Behavioural intention was also found to positively influence actual use. Wu and Wang (2005:725-726) conducted a study in Taiwan to understand mCommerce adoption using an adapted TAM. The findings revealed that perceived usefulness had a strong influence on behavioural intention, but perceived ease of use did not. The researchers do, however, state that due to the strong influence of perceived ease of use on perceived usefulness, it does have an indirect influence on behavioural intention. Perceived risk was also tested and was found to have a significant influence on behavioural intention. Finally, behavioural intention was shown to have a strong influence on actual use. These findings are validated by those of Khalifa and Shen (2008:118) who conducted a cross-sectional survey in Hong Kong. The study looked at consumers' adoption of transactional B2C mCommerce, revealing that perceived usefulness was the most important construct for predicting behavioural intention.

The aforementioned studies prove the relevance of the TAM to the field of technology and demonstrate the influence of perceived usefulness and perceived ease of use on behavioural intention to use. In addition, the studies show that behavioural intention can be used as an accurate predictor of actual use. The value of the TAM to the present study lies in these findings. This is elaborated on in section 3.3.4.4. The theory however, is not without criticism. The following section elaborates on this.

3.3.4.3 Criticisms of the TAM

Even though the TAM has been extensively applied to technology acceptance research studies, it has also been extensively criticised (Zhu *et al.,* 2017:2220; Ratten, 2015:27). A frequent criticism levelled against the TAM is that the model is incomplete. It does not take into account the influence of any external factors such as social influence or economic factors (Persson & Berndtsson, 2015:20; Shafinah, Sahari, Sulaiman, Yusoff & Ikram, 2013:129; Ratten & Ratten, 2007:91). The UTAUT model attempted to address this shortcoming with the introduction of social influence (Persson & Berndtsson, 2015:20; Ratten & Ratten, 2007:91).

The model has also been criticised for being too simple. Researchers believe that this decreases the inclusive understanding of behavioural intention (Liébana-Cabanillas *et al.,* 2017:15; Ratten & Ratten, 2007:91). For example, cost-benefit patterns in behavioural decision-making theory have been found to be significant to the constructs of perceived usefulness and perceived ease of use (Wu & Wang, 2005:721).

Faqih and Jaradat (2015:39) claim that the TAM lacks actionable guidance for researchers and businesses regarding appropriate interventions to inspire individuals to adopt or use new technologies. From a mobile technology point of view, Sair and Danish (2018:503) critique the model for its lack of explanatory power with regards to the usage of mobile technology. Slade *et al.* (2013:10) concur, stating that the TAM assumes that usage is an elected behaviour by an individual without constraint. These researchers maintain that the TAM does not take individuals' characteristics into account and assumes a deterministic approach (Slade *et al.,* 2013:10).

Despite these criticisms, the TAM is still the most universally-applied model to technology acceptance research (Liébana-Cabanillas *et al.,* 2017; Agrebi & Jallais, 2015; Faqih & Jaradat, 2015; Ratten, 2015; Zhang *et al.,* 2012; Khalifa & Shen, 2008; Wu & Wang, 2005). The following section elaborates on the importance of the TAM in this study.

3.3.4.4 Importance of the TAM in the present study

The TAM was a key model used in the creation of the UTAUT2, the model of focus for this study. The TAM constructs of perceived usefulness and perceived ease of use feature prominently in the UTAUT2 as performance expectancy and effort expectancy (Venkatesh *et al.,* 2003:447; 450). The TAM also shows behavioural intention as predicting actual use, which is supported in the UTAUT2 (Miladinovic and Xiang, 2016:14).

As demonstrated in the results of the aforementioned studies (Liébana-Cabanillas *et al.,* 2017; Agrebi & Jallais, 2015; Faqih & Jaradat, 2015; Ratten, 2015; Khalifa & Shen, 2008; Wu & Wang, 2005), perceived usefulness (represented by performance expectancy in this study) was found to have a significant influence on behavioural intention, supporting the argument that performance expectancy has a positive influence on the behavioural intention of consumers to use mCommerce apps to purchase athleisure apparel (refer to Chapter 5, section 5.4.1.1).

In addition, Faqih and Jaradat (2015), Ratten (2015) and Zhang *et al.* (2012) found perceived ease of use (represented by effort expectancy in this study) to have a significant influence on behavioural intention, reinforcing the argument that effort expectancy has a positive influence on the behavioural intention of consumers to use mCommerce apps to purchase athleisure apparel (refer to Chapter 5, section 5.4.1.2).

Research by Zhang *et al.* (2012) and Wu and Wang (2005) further proves that perceived risk has a significant influence on behavioural intention, thereby supporting the argument that perceived risk has a negative influence on the behavioural intention of consumers to use mCommerce apps to purchase athleisure apparel (refer to Chapter 5, section 5.4.3).

Furthermore, Liébana-Cabanillas *et al.* (2017) and Zhang *et al.* (2012) argue that trust has a significant influence on behavioural intention, supporting the proposition that trust has a positive influence on the behavioural intention of consumers to use mCommerce apps to purchase athleisure apparel (refer to Chapter 5, section 5.4.7).

Finally, Faqih and Jaradat (2015), Zhang *et al.* (2012) and Wu and Wang (2005) demonstrate that behavioural intention has a significant influence on actual use, supporting the argument that behavioural intention has a positive influence on consumers' actual use of mCommerce apps to purchase athleisure apparel (refer to Chapter 5, section 5.4.8).

The above studies prove the relevance of the TAM to the field of technology and warrant the inclusion of the constructs of trust and perceived risk in the model proposed for this study (refer to Chapter 1, Figure 1.9).

The following section discusses the next technology acceptance theory grounding the study, the TPB. The TPB is completely separate from the TAM.

3.3.5 Theory of Planned Behaviour (TPB)

The TPB was first conceptualised in 1991, when Ajzen extended the TRA to include the construct of perceived behavioural control (Ajzen, 1991:181). The theory postulates that an individual's behaviour is the result of a consideration of available resources, the individual's attitude as well as the opinion of others. Since its inception, the theory has been frequently applied to technology acceptance research (Cheung & To, 2017:103; Leung & Chen, 2017:1639). The TPB was a key theory in the formulation of the UTAUT2, specifically the constructs of social influence and facilitating conditions (Venkatesh *et al.,* 2003:451; 453).

This section commences with an overview of the TPB. The relevance of the TPB in the field of technology is then discussed, including key findings from studies using this theory. Criticisms of the theory are then presented. The section concludes with the importance of the TPB to this study.

3.3.5.1 An overview of the TPB

Ajzen extended the TRA in 1991 with the TPB (Ajzen, 1991:181). The TRA had been criticised for not taking into account situations where an individual's behaviour was not under their direct control. Ajzen addressed this in the TPB with the addition of behaviour that was not under voluntary control, referred to as perceived behavioural control (Belkhamza & Niasin, 2017:181; Miladinovic & Xiang, 2016:13; Ratten, 2011:40; Ratten & Ratten, 2007:91). When compared to the TRA, the TPB (see Chapter 1, Figure 1.6) therefore includes one additional construct – perceived behavioural control – which is shown to influence behavioural intention and actual behaviour (Leung & Chen, 2017:1639).

According to Belkhamza and Niasin (2017:181) and Cheung and To (2017:103), attitude refers to an individual's evaluation of a behaviour as favourable or unfavourable. In the TPB, attitude is shown to influence behavioural intention. Moreover, it is shown to have a relationship with perceived behavioural control. Subjective norm is described as an individual's perceptions regarding social pressures from family, friends or business colleagues as to whether a specific behaviour should be performed or not. In the case of this study, this refers to an individual’s perception of whether their family and friends believe they should purchase athleisure apparel via a mobile shopping app or not (Belkhamza & Niasin, 2017:181; Cheung & To, 2017:103; Wei, Marthandan, Chong, Ooi & Arumugam, 2009:383).

The construct of subjective norm informed the creation of social influence in the UTAUT2 (Venkatesh *et al.,* 2003:451). Ajzen (1991:183) describes perceived behavioural control as an individual’s perception of whether the behaviour of interest will be easy or difficult to perform. The theory posits that as perceived behavioural control increases, so too will behavioural intention, and in turn, actual behaviour (Cheung & To, 2017:103; Leung & Chen, 2017:1639; Ajzen, 1991:184).

The construct of perceived behavioural control can be compared to Bandura’s concept of self-efficacy in the SCT. An individual’s beliefs of self-efficacy can influence their choices with regards to activities, the effort involved in completing such activities, patterns of thought and emotional responses. The TPB merely places the concept of self-efficacy within a more generalised framework as perceived behavioural control (Ajzen, 1991:184). This construct was also key in the creation of facilitating conditions, one of the constructs of interest in this study (Venkatesh *et al.,* 2003:453). Finally, in the TPB, behavioural intention refers to the willingness of an individual to perform a specific behaviour, such as purchasing athleisure apparel via an mCommerce app (Cheung & To, 2017:103).

Each of the aforementioned core constructs of the TPB, i.e. attitude, subjective norm, perceived behavioural control, behavioural intention and behaviour and their associated definitions are summarised in Table 3.3.

Table 3.3: Core constructs of the TPB

Construct	Definition	Reference
Attitude	An individual's evaluation of a behaviour as favourable or unfavourable.	Belkhamza & Niasin (2017:181); Cheung & To (2017:103)
Subjective norm	An individual's perceptions regarding social pressures from family, friends or business colleagues as to whether a specific behaviour should be performed or not.	Belkhamza & Niasin (2017:181); Cheung & To (2017:103); Wei *et al.* (2009:383)
Perceived behavioural control	An individual's perception of whether the behaviour of interest will be easy or difficult to perform.	Ajzen (1991:183)
Behavioural intention	The willingness of an individual to perform a specific behaviour.	Cheung & To (2017:103)
Behaviour	As per the definition in Table 3.1	

The following section examines the relevance of the TPB to the field of technology, referencing a number of studies.

3.3.5.2 The relevance of the TPB to the field of technology

Researchers have found the TPB to better explain consumers' behavioural intention to use various technological innovations than the TRA or the TAM (Zhu *et al.,* 2017:2220). The construct of subjective norm was used to inform social influence while perceived behavioural control was used to create facilitating conditions (Venkatesh *et al.,* 2003:451-453) – the two key constructs of the UTAUT2. The TPB is therefore well-suited to this study. Research in support of this view are discussed below.

Akar and Dalgic (2018:480) examined the online purchase intentions of consumers by combining the social network theory and the TPB to create their research model. Their findings proved that attitude, subjective norm and perceived behavioural control all have a significant influence on behavioural intention. In addition, perceived behavioural control was found to have a significant influence on actual behaviour. These results are confirmed by those of Belkhamza and Niasin (2017:181) who investigated the effects of privacy concerns on smartphone app purchases using the TPB as foundation theory. They found that attitude, subjective norm and perceived behavioural control all positively influence behavioural intention (Belkhamza & Niasin, 2017:181). The same results were also reported by Cheung and To (2017:107) and Leung and Chen (2017:1644). Cheung and To (2017:107) used the TPB to analyse mobile users' attitudes towards in-app advertisements. The findings proved that attitude, subjective norm and perceived behavioural control all influenced behavioural intention positively. Behavioural intention, in turn, was also shown to positively influence actual behaviour. In addition, perceived behavioural control had a significant influence on actual behaviour. Leung and Chen's (2017:1644) Hong Kong study looked at consumers' intention to adopt mobile TV. The researchers incorporated the constructs of attitude, subjective norms and perceived behavioural control into their model and found that all three had a significant positive influence on behavioural intention.

Many other researchers have demonstrated the relevance of this model to the field of technology. Carter and Yeo (2016:752), for example, explored the adoption and usage of mobile apps by Malaysian undergraduate and postgraduate students. Their research found all three constructs – attitude, subjective norm and perceived behavioural control – to have a significant influence on the adoption or use of mobile apps by Malaysians. Javadi, Dolatabadi, Nourbakhsh, Poursaeedi and Asadollahi's (2012:89-90) research partially supports the findings of Carter and Yeo (2016:752). These researchers conducted a study in Iran to assess constructs influencing the online shopping behaviours of Iranian consumers. Their model, inclusive of the TPB constructs of attitude, subjective norm and perceived behavioural control, revealed that attitude and subjective norm had significant influence on online shopping behaviour whereas perceived behavioural control did not. The findings of Zhang *et al.* (2012:1908-1909) and Carter and Yeo (2016:752) are not in complete agreement. Zhang *et al.* (2012:1908-1909) looked at the moderating effects of culture on the adoption of mCommerce. Their model tested the effects of attitude, perceived behavioural control and subjective norm on behavioural intention and all three these constructs were found to have a significant influence on behavioural intention.

The aforementioned studies prove the relevance of the TPB to the field of technology and demonstrate the influence of attitude, subjective norm and perceived behavioural control on behavioural intention to use. The value of the TPB to this research study lies in these findings. This is elaborated on in section 3.3.5.4. The theory, however, is not without criticism. The following section elaborates on this.

3.3.5.3 Criticisms of the TPB

The TPB has been criticised for failing to include an element of cognitive learning that is adaptive. The model is based on the assumption that behaviour is not subject to change, meaning that the model does not accommodate individuals learning over time and therefore behaving differently at a later stage (Ratten, 2011:41; Ratten & Ratten, 2007:91). Leung and Chen (2017:1639) criticise the model for its assumption that the behaviour of individuals can be influenced to such an extent. They argue that human behaviour is habitual in nature, more automatic, than the TPB posits. The model has also been criticised for being too simplistic. Some researchers such as Sniehotta, Presseau and Araújo-Soares (2014:2), for example, ask whether a theory that is intended to explain all preferred human behaviour is sufficient if it only comprises four explanatory constructs.

Despite these criticisms, the TPB continues to be applied to technology acceptance research (Akar & Dalgic, 2018; Belkhamza & Niasin, 2017; Cheung & To, 2017; Leung & Chen, 2017; Carter & Yeo, 2016; Javadi *et al.,* 2012; Zhang *et al.,* 2012). The following section elaborates on the importance of the TPB in this study.

3.3.5.4 Importance of the TPB in the present study

The TPB was used in the creation of the UTAUT2, the model of focus for this study. The construct of perceived behavioural control, in particular, was combined with constructs from other models to create facilitating conditions in the UTAUT2, a construct which is hypothesised to influence both behavioural intention and actual use (Persson & Berndtsson, 2015:16).

As with the results of the aforementioned studies (Akar & Dalgic, 2018; Belkhamza & Niasin, 2017; Cheung & To, 2017; Leung & Chen, 2017; Carter & Yeo, 2016; Javadi *et al.,* 2012; Zhang *et al.,* 2012), subjective norm (represented by social influence in this study) was found to have a significant influence on behavioural intention, reinforcing the argument that social influence has a positive influence on the behavioural intention of consumers to use mCommerce apps to purchase athleisure apparel (refer to Chapter 5, section 5.4.1.3).

In addition, Akar and Dalgic (2018), Belkhamza and Niasin (2017), Cheung and To (2017), Leung and Chen (2017), Carter and Yeo (2016) and Zhang *et al.* (2012) also found perceived behavioural control (represented by facilitating conditions in this study) to have a significant influence on behavioural intention, thereby reinforcing the argument that facilitating conditions have a positive influence on the behavioural intention of consumers to use mCommerce apps to purchase athleisure apparel (refer to Chapter 5, section 5.4.1.4). Akar and Dalgic (2018) and Cheung and To (2017) further found perceived behavioural control (represented by facilitating conditions in this study) to have a significant influence on actual behaviour, thereby supporting the argument that facilitating conditions have a positive influence on consumers' actual use of mCommerce apps to purchase athleisure apparel (refer to Chapter 5, section 5.4.2.1).

Lastly, Cheung and To (2017) proved that behavioural intention has a significant influence on actual use, highlighting that behavioural intention has a positive influence on consumers' actual use of mCommerce apps to purchase athleisure apparel (refer to Chapter 5, section 5.4.8).

The following section discusses the next technology acceptance theory grounding the study, the UTAUT. The UTAUT was influenced by the TPB.

3.3.6 Unified Theory of Acceptance and Use of Technology (UTAUT)

The UTAUT was created in 2003 to consolidate the host of technology acceptance theories and models into one model. Constructs from a variety of theories and models, rooted in technology, were used to compile this model, many of which have been elaborated on earlier in this chapter (Venkatesh *et al.,* 2003:428). This model led to the development of the consumer version, the UTAUT2, the model of focus for this study.

This section commences with an overview of the UTAUT. The relevance of the UTAUT in the field of technology is then discussed, including key findings from studies using this theory. Criticisms of the theory are then presented. The section concludes with the importance of the UTAUT to this study.

3.3.6.1 An overview of the UTAUT

In 2003, Venkatesh *et al.* set out to consolidate and unify the multitude of technology acceptance theories and models into one single model, the UTAUT. The researchers combined constructs from eight theories and models, including the TRA, TAM, Motivational Model (MM), TPB, combined TAM and TPB model, the Model of Personal Computer (PC) Utilisation, the IDT and the SCT (Choudrie, Junior, McKenna & Richter, 2018:453; Sair & Danish, 2018:503; Hoque & Sorwar, 2017:77; Martins *et al.,* 2014:3; Venkatesh *et al.,* 2003:428-432). Longitudinal studies were conducted at four different organisations with a specific focus on individuals being introduced to technological innovations at work. Scales from each of the original eight theories and models were used in constructing the questionnaire. Four constructs, out of the original 32, were shown to significantly influence either behavioural intention or actual use. These include performance expectancy, effort expectancy, social influence and facilitating conditions (Choudrie *et al.,* 2018:453; Sair & Danish, 2018:503; Hoque & Sorwar, 2017:78; Martins *et al.,* 2014:3; Venkatesh *et al.,* 2003:437-446). The results were used to build the UTAUT, as shown in Chapter 1, Figure 1.7.

The four core constructs of the UTAUT include performance expectancy, effort expectancy, social influence and facilitating conditions (Choudrie *et al.,* 2018:453; Sair & Danish, 2018:503; Hoque & Sorwar, 2017:78; Martins *et al.,* 2014:3). Performance expectancy is described as the extent to which an individual believes that using a technological innovation will assist them to improve their job performance (Choudrie *et al.,* 2018:453; Sair & Danish, 2018:503; Hoque & Sorwar, 2017:78; Martins *et al.,* 2014:4; Venkatesh *et al.,* 2003:447). Five constructs from a number of different theories and models, which were used to compile the UTAUT, address performance expectancy. These include perceived usefulness from the TAM, extrinsic motivation from the MM, job fit from the model of PC utilisation, relative advantage from the IDT and outcome expectations from the SCT (Persson & Berndtsson, 2015:16; Alkhunaizan & Love, 2012:83; Venkatesh *et al.,* 2003:447). Venkatesh *et al.* (2003:447) found this construct to be the strongest predictor of behavioural intention.

Effort expectancy is described as the degree of ease expected by a consumer in using a technological innovation (Choudrie *et al.,* 2018:453; Sair & Danish, 2018:504; Hoque

& Sorwar, 2017:78; Martins *et al.,* 2014:4; Venkatesh *et al.,* 2003:450). Three constructs from theories and models used in the UTAUT capture effort expectancy, i.e. perceived ease of use from the TAM, complexity from the model of PC utilisation and ease of use from the IDT (Alkhunaizan & Love, 2012:83; Venkatesh *et al.,* 2003:450).

Social influence is described as the extent to which an individual believes that other people of importance in their life believe that they should adopt or use the new technology (Choudrie *et al.,* 2018:453; Hoque & Sorwar, 2017:78; Martins *et al.,* 2014:4; Venkatesh *et al.,* 2003:451). This construct features as subjective norm in both the TRA and TPB, as social factors in the model of PC utilisation and as image in the IDT (Persson & Berndtsson, 2015:16; Alkhunaizan & Love, 2012:83; Venkatesh *et al.,* 2003:451).

The final core construct of the UTAUT, facilitating conditions, is described as an individual's belief that the necessary organisational and technical support is available for the technological innovation (Choudrie *et al.,* 2018:453; Hoque & Sorwar, 2017:78; Martins *et al.,* 2014:4; Venkatesh *et al.,* 2003:453). Three constructs from theories and models used in the UTAUT capture facilitating conditions, i.e. perceived behavioural control featured in the TPB, facilitating conditions in the model of PC utilisation and compatibility from the IDT (Alkhunaizan & Love, 2012:83; Venkatesh *et al.,* 2003:453). It is also closely aligned to self-efficacy from the SCT (Persson & Berndtsson, 2015:16). Venkatesh *et al.* (2003:454) found that the influence of facilitating conditions on behavioural intention becomes negligible in the presence of performance expectancy and effort expectancy, although it does have a significant effect on use.

Each of these core constructs of the UTAUT, i.e. performance expectancy, effort expectancy, social influence, facilitating conditions, behavioural intention and use behaviour and their associated definitions are summarised in Table 3.4.

Table 3.4: Core constructs of the UTAUT

Construct	Definition	Reference
Performance expectancy	The extent to which an individual believes that using a new technological innovation will assist them in improving their job performance.	Choudrie *et al.* (2018:453); Sair & Danish (2018:503); Hoque & Sorwar (2017:78); Martins *et al.* (2014:4); Venkatesh *et al.* (2003:447)
Effort expectancy	The degree of ease expected by a consumer in using a technological innovation.	Choudrie *et al.* (2018:453); Sair & Danish (2018:504); Hoque & Sorwar (2017:78); Martins *et al.* (2014:4); Venkatesh *et al.* (2003:450)
Social influence	The extent to which an individual believes that other people of importance in their life believe that they should adopt or use the technological innovation.	Choudrie *et al.* (2018:453); Hoque & Sorwar (2017:78); Martins *et al.* (2014:4); Venkatesh *et al.* (2003:451)
Facilitating conditions	An individual's belief that the necessary organisational and technical support is available for the technological innovation.	Choudrie *et al.* (2018:453); Hoque & Sorwar (2017:78); Martins *et al.* (2014:4); Venkatesh *et al.* (2003:453)
Behavioural intention	As per the definition in Table 3.1	
Use behaviour	As per the definition in Table 3.1	

The following section examines the relevance of the UTAUT to the field of technology, referencing a number of studies.

3.3.6.2 The relevance of the UTAUT to the field of technology

The UTAUT has been used in many studies on technology adoption (Sair & Danish, 2018; Hoque & Sorwar, 2017; Persson & Berndtsson, 2015; Martins *et al.,* 2014; Alkhunaizan & Love, 2012; Riffai *et al.,* 2012). Researchers have stated that this model can explain up to 70% of variance in consumers' behavioural intention to use technology, making it well-suited to this study (Hoque & Sorwar, 2017:77-78; Martins *et al.,* 2014:4). Studies supporting this view are discussed below.

Sair and Danish (2018:512-513) explored the effects of performance expectancy and effort expectancy on Pakistani consumers' mobile commerce adoption intention using the UTAUT. Their findings reveal a strong, positive relationship between performance expectancy and behavioural intention and effort expectancy and behavioural intention. This is aligned with the findings of Venkatesh *et al.* (2003) and the UTAUT.

Hoque and Sorwar (2017:81) also report similar findings in a study on the constructs influencing the adoption of mobile health solutions by the elderly. Using the UTAUT, they demonstrated that performance expectancy, effort expectancy and social influence had a marked influence on behavioural intention. Behavioural intention, in turn, had an influence on actual behaviour. Facilitating conditions, however, were not found to have an influence on either behavioural intention or actual behaviour, contradicting the UTAUT and Venkatesh *et al.* (2003).

In Sweden, Persson and Berndtsson (2015:59-60) analysed the adoption or use of mCommerce, using an adapted version of the UTAUT. Additional constructs were included, notably, trust and location. The results revealed that performance expectancy did not have a significant influence on behavioural intention. This is contrary to the original UTAUT and the findings of Venkatesh *et al.* (2003:447). In accordance with the UTAUT, however, effort expectancy was found to have a significant negative influence on behavioural intention. Social influence showed a significant positive influence on behavioural intention. Trust was not found to have a significant influence on behavioural intention and location was found to have a significant positive influence on behavioural intention.

Martins *et al.* (2014:5) examined the adoption of Internet banking, using the UTAUT. In support of the UTAUT, the findings revealed that performance expectancy, effort expectancy and social influence influenced behavioural intention while behavioural intention influenced actual use. Perceived risk was found to have a significant negative influence on behavioural intention. Facilitating conditions had no influence on actual use, in accordance with Hoque and Sorwar (2017:81), but contradicting the UTAUT. Similar results were also found by Alkhunaizan and Love (2012:92-94) in Saudi Arabia. These researchers looked at the adoption or usage of mCommerce services. The study tested an adapted version of the UTAUT with two added core constructs – trust and cost. The results showed that performance expectancy had the most significant influence on behavioural intention, supporting the original UTAUT and Venkatesh *et al.* (2003). Effort expectancy and cost were also shown to influence behavioural intention. Social influence and trust had no significant influence on behavioural intention while facilitating conditions had no significant influence on actual use.

In Oman, Riffai *et al.* (2012:248) explored constructs influencing users' acceptance of online banking. Using an adapted version of the UTAUT, they found that performance expectancy and effort expectancy had a significant influence on behavioural intention. In contrast, social influence had no influence on behavioural intention, which contradicts the UTAUT. Trust was also found to have a significant influence on behavioural intention.

The aforementioned studies prove the relevance of the UTAUT to the field of technology and demonstrate the influence of performance expectancy, effort expectancy and social influence on behavioural intention to use. In addition, they affirm the influence of behavioural intention on actual use. The value of the UTAUT to this study lies in these findings. This is elaborated on in section 3.3.6.4. The theory however, is not without criticism. The following section elaborates on this.

3.3.6.3 Criticisms of the UTAUT

Several criticisms have been levelled against the UTAUT. According to Venkatesh *et al.* (2012:157), one of the biggest shortcomings of the UTAUT is that it is only relevant when applied within organisational contexts and is therefore irrelevant to consumer adoption of technological innovation. Hence the reason for the development of the UTAUT2, used in this study.

According to Madan and Yadav (2016:230) and Shaikh and Karjaluoto (2015:136), another limitation of both the UTAUT and UTAUT2 is the fact that it bypasses culture as an important element in the adoption or use of a new technology. Im, Kim and Han (2008:1-2) add that the UTAUT overlooks two other critical factors – technology type (referring to the type of technology engaged with, for example email, voicemail, or software) and perceived risk (referring to uncertainty on a consumer's part in a purchase situation). The present study addresses this criticism by adding perceived risk as a key construct, hypothesised to influence both behavioural intention to use and actual use.

Despite these criticisms, the UTAUT continues to be applied to technology acceptance research (Sair & Danish, 2018; Hoque & Sorwar, 2017; Martins *et al.,* 2014;

Alkhunaizan & Love, 2012; Riffai *et al.,* 2012). The following section elaborates on the importance of the UTAUT in this study.

3.3.6.4 Importance of the UTAUT in the present study

The UTAUT forms the basis of the UTAUT2, the consumer version of the model. This is the model of focus for this study. It is, however, important to understand the history of the model, hence its inclusion. The UTAUT2 is introduced in the following section.

As in the aforementioned studies (Sair & Danish, 2018; Hoque & Sorwar, 2017; Martins *et al.,* 2014; Alkhunaizan & Love, 2012; Riffai *et al.,* 2012), performance expectancy was found to have a significant influence on behavioural intention, supporting the argument that performance expectancy has a positive influence on the behavioural intention of consumers to use mCommerce apps to purchase athleisure apparel (refer to Chapter 5, section 5.4.1.1).

In addition, Sair and Danish (2018), Hoque and Sorwar (2017), Persson and Berndtsson (2015), Martins *et al.* (2014), Alkhunaizan and Love (2012) and Riffai *et al.* (2012) found effort expectancy to have a significant influence on behavioural intention, reinforcing the argument that effort expectancy has a positive influence on the behavioural intention of consumers to use mCommerce apps to purchase athleisure apparel (refer to Chapter 5, section 5.4.1.2).

Hoque and Sorwar (2017), Persson and Berndtsson (2015) and Martins *et al.* (2014) also proved that social influence has a significant influence on behavioural intention, thereby confirming that social influence has a positive influence on the behavioural intention of consumers to use mCommerce apps to purchase athleisure apparel (refer to Chapter 5, section 5.4.1.3).

Martins *et al.* (2014) established that perceived risk has a significant influence on behavioural intention, reinforcing the notion that perceived risk has a negative influence on the behavioural intention of consumers to use mCommerce apps to purchase athleisure apparel (refer to Chapter 5, section 5.4.3).

Furthermore, Riffai *et al.* (2012) proved that trust has a significant influence on behavioural intention, supporting the argument that trust has a positive influence on the behavioural intention of consumers to use mCommerce apps to purchase athleisure apparel (refer to Chapter 5, section 5.4.7).

In conclusion, Hoque and Sorwar (2017) and Martins *et al.* (2014) also established that behavioural intention has a significant influence on actual use, thereby reinforcing the argument that behavioural intention has a positive influence on consumers' actual use of mCommerce apps to purchase athleisure apparel (refer to Chapter 5, section 5.4.8).

The above studies demonstrate the relevance of the UTAUT in the field of technology and validate the inclusion of the constructs of trust and perceived risk in the model proposed in this study (refer to Chapter 1, Figure 1.9).

The following section discusses the next technology acceptance theory grounding the study, the UTAUT2. The UTAUT2 is an extension of the UTAUT.

3.3.7 Unified Theory of Acceptance and Use of Technology 2 (UTAUT2)

The UTAUT2 was first proposed in 2012 by Venkatesh *et al.* in response to criticism that the UTAUT was only relevant when applied within organisational contexts. Thus, three constructs were added to the model, allowing for its application to consumer adoption of technological innovation studies. The three added constructs were hedonic motivation, price value and habit (Slade *et al.,* 2013:10; Venkatesh *et al.,* 2012:157).

This section commences with an overview of the UTAUT2. The relevance of the UTAUT2 in the field of technology is then discussed, including key findings from studies using this theory. Criticisms of the theory are then presented. The section concludes with the importance of the UTAUT2 to this study.

3.3.7.1 An overview of the UTAUT2

In response to criticisms of the UTAUT, Venkatesh *et al.* (2012:158) enhanced the model from a consumer use point of view. This resulted in the UTAUT2, an updated framework that includes key additional constructs and relationships, as shown in Chapter 1, Figure 1.8. Venkatesh *et al.* (2012:158) added three constructs to the model, namely, hedonic motivation, price value and habit. In this model, the original UTAUT constructs – performance expectancy, effort expectancy, social influence and facilitating conditions – along with the three new constructs hedonic motivation, price value and habit – are shown to have an influence on behavioural intention. Moreover, facilitating conditions are shown to influence behavioural intention, a relationship that was not present in the original UTAUT. One of the three new constructs – habit – is also shown to influence use behaviour (Miladinovic & Xiang, 2016:16-17; Oliveira *et al.,* 2016:405; Venkatesh *et al.,* 2012:160).

Hedonic motivation can be described as the enjoyment associated with using a specific technology (Alalwan *et al.,* 2018:128; Chopdar *et al.*, 2018:114; Verkijika, 2018:1668; Oliveira *et al.,* 2016:407; Venkatesh *et al.,* 2012:161). This construct was included as the researchers found that the enjoyment derived from using a specific technology, such as shopping via an mCommerce app, was a contributing factor of the individual's intention to use the technology (Verkijika, 2018:1668).

Alalwan *et al.* (2018:129), Chopdar *et al.* (2018:114), Verkijika (2018:1668), Oliveira *et al.* (2016:407) and Venkatesh *et al.* (2012:161) describe the construct of price value as the cognitive trade-off between the perceived benefit provided by the technology in question and the monetary cost of using it. If the benefit obtained from the adoption or use of a new technology outweighs the monetary cost of using it, price value will have a significant influence on the consumer's behavioural intention to use the technology (Alalwan *et al*., 2018:129). As mCommerce app owners save on monthly overheads such as rent for a physical store presence, salaries for salespeople, etc., these savings can be passed on to the consumer which can have a significant influence on their behavioural intention (Jao, 2015).

Habit refers to consumers' automatic execution of specific behaviours due to prior learning (Alalwan *et al.,* 2018:129; Chopdar *et al.,* 2018:114; Venkatesh *et al.,* 2012:161). The researchers added this construct as their findings revealed that habit not only influences behavioural intention, but also serves as a good alternative predictor of actual use (Alalwan *et al.,* 2018:129).

The UTAUT2 forms the basis of the conceptual model proposed in this study. Miladinovic and Xiang (2016:19) concur, stating that the UTAUT2 outperforms all other technology acceptance theories and models. Rondan-Cataluña *et al.* (2015:798) also concur; their research proved that the UTAUT2 has 26% better explanatory power, from a consumer use point of view, compared to other technology acceptance theories and models. This is further corroborated by Slade *et al.* (2013:11), who contend that the UTAUT2 explains up to 74% of the variance in consumers' behavioural intention to use technology – an increase on the 70% reported for the UTAUT (Hoque & Sorwar, 2017:77-78; Martins *et al.,* 2014:4). It also explains up to 52% of the variance on actual use (Slade *et al.,* 2013:11). This makes the UTAUT2 well-suited to this study.

Each of these core constructs of the UTAUT2, i.e. performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, habit, behavioural intention and use behaviour and their associated definitions, are summarised in Table 3.5.

Table 3.5: Core constructs of the UTAUT2

Construct	Definition	Reference
Performance expectancy	As per the definition in Table 3.4	
Effort expectancy	As per the definition in Table 3.4	
Social influence	As per the definition in Table 3.4	
Facilitating conditions	As per the definition in Table 3.4	
Hedonic motivation	The enjoyment associated with using a specific technology.	Alalwan *et al.* (2018:128); Chopdar *et al.* (2018:114); Verkijika (2018:1668); Oliveira *et al.* (2016:407); Venkatesh *et al.* (2012:161)
Price value	The cognitive trade-off between the perceived benefit of the technology in question and the monetary cost of using it.	Alalwan *et al.* (2018:129); Chopdar *et al.* (2018:114); Verkijika (2018:1668); Oliveira *et al.* (2016:407); Venkatesh *et al.* (2012:161)
Habit	Consumers' automatic execution of specific behaviours due to prior learning.	Alalwan *et al.* (2018:129); Chopdar *et al.* (2018:114); Venkatesh *et al.* (2012:161)
Behavioural intention	As per the definition in Table 3.1	
Use behaviour	As per the definition in Table 3.1	

The following section examines the relevance of the UTAUT2 to the field of technology, referencing a number of studies.

3.3.7.2 The relevance of the UTAUT2 to the field of technology

The UTAUT2 has been used in many studies on technology acceptance and use (Alalwan *et al.,* 2018; Chopdar *et al.,* 2018; Verkijika, 2018; Oliveira *et al.,* 2016). As explained in section 3.3.7.1, Slade *et al.* (2013:11) report that the UTAUT2 explains up to 74% of the variance in consumers' behavioural intention to use technology, an increase on the 70% reported for the UTAUT (Hoque & Sorwar, 2017:77-78; Martins *et al.,* 2014:4). It also explains up to 52% of the variance on actual use (Slade *et al.,* 2013:11). This makes the model well-suited to this study. Research supporting this view is discussed below.

Alalwan *et al.* (2018:131) used the UTAUT2 as foundation theory enhanced with the construct of perceived risk to understand the constructs influencing Jordanian consumers' intentions and adoption of Internet banking. Their findings demonstrate that performance expectancy, effort expectancy, hedonic motivation and price value all influence behavioural intention, while behavioural intention, in turn, influences use behaviour. The findings also prove that facilitating conditions influence use behaviour while habit is the second strongest predictor of use behaviour, just after behavioural intention. Social influence, however, had no influence on behavioural intention, contradicting the UTAUT2 and Venkatesh *et al.* (2012).

Chopdar *et al.* (2018:120-121) conducted a cross-country study between India and the United States of America (USA) to identify the constructs that influence the acceptance and use of mobile shopping apps. In India, performance expectancy, effort expectancy, facilitating conditions, hedonic motivation, price value and habit were all found to influence behavioural intention. Habit as well as behavioural intention were also found to influence use behaviour. Social influence had no influence on behavioural intention while facilitating conditions had no influence on use behaviour, contradicting the UTAUT2 and Venkatesh *et al.* (2012). In the USA on the other hand, performance expectancy, facilitating conditions and hedonic motivation were found to influence behavioural intention, however, effort expectancy, price value and habit had no statistically significant influence on behavioural intention. This finding contradicts the UTAUT2 and Venkatesh *et al.* (2012). In accordance with the results for India, both habit and behavioural intention had no influence on use behaviour while facilitating conditions had no influence on use behaviour either.

In Cameroon, Verkijika (2018:1672) used the UTAUT2 to investigate mCommerce app acceptance and use. The model was adapted to include additional constructs, i.e. perceived risk and perceived trust. The findings revealed that performance expectancy, effort expectancy and price value did not influence behavioural intention, contradicting the UTAUT2 and Venkatesh *et al.* (2012). Verkijika (2018) further reported that social influence, facilitating conditions and hedonic motivation all influenced behavioural intention, affirming the findings of Venkatesh *et al.* (2012) and the UTAUT2. Both perceived risk and perceived trust were proven to influence behavioural intention.

Oliveira *et al.* (2016:410) looked at the determinants of consumer acceptance and use of mobile payments based on a model which combined constructs from the UTAUT2 and the IDT. The findings revealed that performance expectancy and social influence had an influence on behavioural intention, however, this was not the case for effort expectancy, facilitating conditions, hedonic motivation and price value.

The aforementioned studies prove the relevance of the UTAUT2 to the field of technology and demonstrate the influence of performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value and habit on behavioural intention to use, as well as the influence of facilitating conditions and habit on actual use. In addition, these studies affirm the influence of behavioural intention on actual use. The value of the UTAUT2 to this study lies in these findings. This is elaborated on in section 3.3.7.4. The theory however, is not without criticism. The following section elaborates on this.

3.3.7.3 Criticisms of the UTAUT2

A key criticism of the UTAUT2, similar to its predecessors such as the TAM and the UTAUT, is that it fails to fully capture specific task environments. Consequently, many researchers add or remove constructs from the original UTAUT2 to enhance it, similarly to this study, which added trust and perceived risk (Morosan & DeFranco, 2016:19). Another criticism is that the model is too simplistic in nature and fails to adequately conceptualise performance perceptions, resulting in vague constructs (Tan & Ooi, 2018:1619; Morosan & DeFranco, 2016:19).

Despite these criticisms, the UTAUT2 continues to be applied to technology acceptance research (Alalwan *et al.,* 2018; Chopdar *et al.,* 2018; Verkijika, 2018; Oliveira *et al.,* 2016). It is also the most successful technology acceptance model when considering that it explains up to 74% of the variance in consumers' behavioural intention to use technology and 52% in actual use (Slade *et al.,* 2013:11). The following section elaborates on the importance of the UTAUT2 in the present study.

3.3.7.4 Importance of the UTAUT2 in the present study

Based on the arguments in section 3.3.7.2, UTAUT2 is deemed the best-suitable model for the purposes of this study. Moreover, Morosan and DeFranco (2016:19) state that this model has received strong empirical validation and enjoyed significant popularity in technology acceptance research. Further reasoning is provided below.

As in the aforementioned studies (Alalwan *et al.,* 2018; Chopdar *et al.,* 2018; Oliveira *et al.,* 2016), performance expectancy was found to have a significant influence on behavioural intention, reinforcing the argument that performance expectancy has a positive influence on the behavioural intention of consumers to use mCommerce apps to purchase athleisure apparel (refer to Chapter 5, section 5.4.1.1).

Alalwan *et al.* (2018) and Chopdar *et al.* (2018) also found effort expectancy has a significant influence on behavioural intention, highlighting that this construct exerts a positive influence on the behavioural intention of consumers to use mCommerce apps to purchase athleisure apparel (refer to Chapter 5, section 5.4.1.2). Verkijika (2018) and Oliveira *et al.* (2016) also proved that social influence has a significant effect on behavioural intention, affirming that this construct has a positive influence on the behavioural intention of consumers to use mCommerce apps to purchase athleisure apparel (refer to Chapter 5, section 5.4.1.3).

Chopdar *et al.* (2018) and Verkijika (2018) established that facilitating conditions have an influence on behavioural intention, confirming that this construct has a positive influence on the behavioural intention of consumers to use mCommerce apps to purchase athleisure apparel (refer to Chapter 5, section 5.4.1.4). In addition, Alalwan *et al.* (2018) proved that facilitating conditions have an influence on actual use behaviour, thereby highlighting this construct exerts a positive influence on consumers' actual use of mCommerce apps to purchase athleisure apparel (refer to Chapter 5, section 5.4.2.1).

Alalwan *et al.* (2018), Chopdar *et al.* (2018) and Verkijika (2018) further also proved that hedonic motivation has a significant influence on behavioural intention, supporting the argument that this construct has a positive influence on the behavioural intention of consumers to use mCommerce apps to purchase athleisure apparel (refer to Chapter 5, section 5.4.1.5).

Alalwan *et al.* (2018) and Chopdar *et al.* (2018) further also established that price value has an influence on behavioural intention. Their research reinforces the argument that price value has a positive influence on the behavioural intention of consumers to use mCommerce apps to purchase athleisure apparel (refer to Chapter 5, section 5.4.1.6).

In addition, Chopdar *et al.* (2018) found habit to have a significant influence on behavioural intention, thereby supporting the notion that habit has a positive influence on the behavioural intention of consumers to use mCommerce apps to purchase athleisure apparel (refer to Chapter 5, section 5.4.1.7). Alalwan *et al.* (2018) and Chopdar *et al.* (2018) also proved that habit has a significant influence on actual use, thereby emphasising that this construct has a positive influence on consumers' actual use of mCommerce apps to purchase athleisure apparel (refer to Chapter 5, section 5.4.2.2).

Research by Verkijika (2018) proved that perceived risk had a significant influence on behavioural intention, reinforcing the argument that this construct has a negative influence on the behavioural intention of consumers to use mCommerce apps to purchase athleisure apparel (refer to Chapter 5, section 5.4.3). Verkijika (2018) also proved that trust has a significant influence on behavioural intention, confirming that this construct has a positive influence on the behavioural intention of consumers to use mCommerce apps to purchase athleisure apparel (refer to Chapter 5, section 5.4.7).

In conclusion, Alalwan *et al.* (2018), Chopdar *et al.* (2018) and Verkijika (2018) proved that behavioural intention has a significant influence on actual use, confirming that behavioural intention has a positive influence on consumers' actual use of mCommerce apps to purchase athleisure apparel (refer to Chapter 5, section 5.4.8).

The above studies prove the relevance of the UTAUT2 in the field of technology, thereby justifying the inclusion of the constructs of trust and perceived risk in the model proposed in this study (refer to Chapter 1, Figure 1.9).

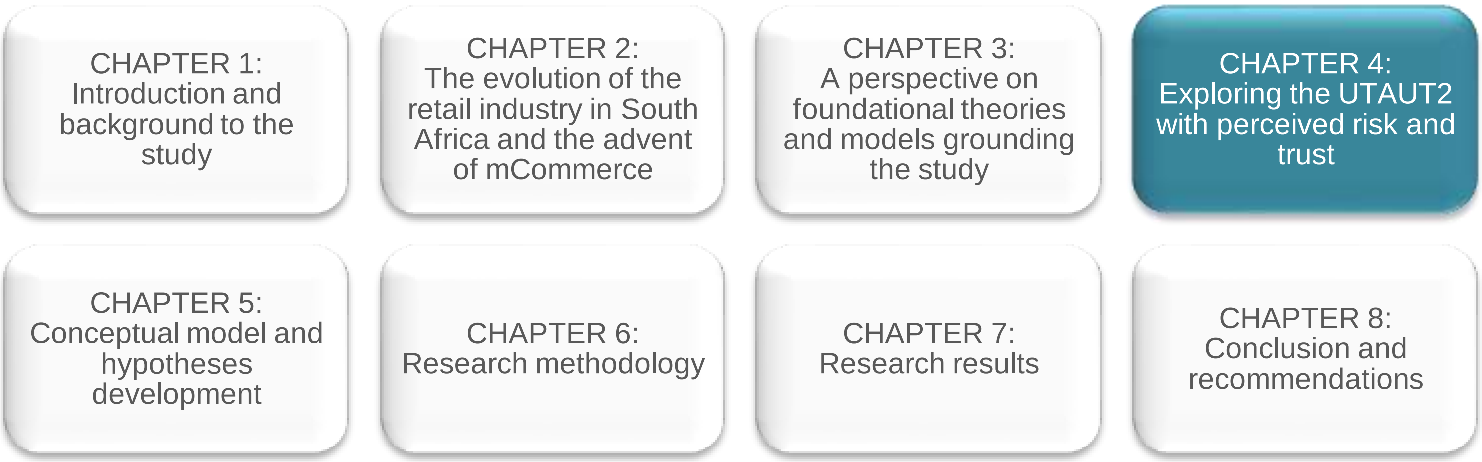
Each of the aforementioned theories and models grounds the study from a relationship building and technology acceptance perspective. A summary of these theories and models and their associated constructs is contained in Annexure 1.

3.4 Conclusion

Chapter 3 provided detailed information on various foundational theories and models, thereby creating a solid grounding for the study. From a relationship-building point of view, the SET and the TCT were discussed. From a technology acceptance point of view, the IDT, TRA, SCT, TAM, TPB, UTAUT and UTAUT2 were discussed. The model focused on in this particular study is the UTAUT2. Chapter 4 provides greater insights into this model and its various constructs, along with the additional constructs of perceived risk and trust.

CHAPTER 4

EXPLORING THE UTAUT2 WITH PERCEIVED RISK AND TRUST



4.1 Introduction

Chapter 4 builds on Chapter 3 by providing an in-depth overview of the model of focus in this particular study – the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2). Developed by Venkatesh *et al.* in 2012, this theory comprises several constructs, namely, performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value and habit. All of these have been shown to influence behavioural intention while behavioural intention has, in turn, been shown to influence use behaviour, commonly referred to as actual use.

This chapter commences with a contextualisation of the UTAUT2 with regard to the study. The chapter then focuses on each of the constructs before moving on to discuss the relevance of each construct to the UTAUT2 and the field of mCommerce as well as the relationships between the various constructs of the model. The added constructs of perceived risk and trust are then discussed, following the same approach mentioned above.

4.2 Contextualising the UTAUT2 to the study

As discussed in Chapter 3, section 3.3.6, the UTAUT was first conceptualised by Venkatesh *et al.* in 2003 in an attempt to amalgamate the different theories on technology acceptance into one consolidated model. Eight different theories and models (summarised below) were thus combined to create the UTAUT. The Theory of Reasoned Action (TRA), the Technology Acceptance Model (TAM), the Motivational Model (MM), the Theory of Planned Behaviour (TPB), the combined TAM and TPB Model, the Model of Personal Computer (PC) Utilisation, the Innovation Diffusion Theory (IDT) and the Social Cognitive Theory (SCT) were used to formulate the UTAUT model (refer to Chapter 1, Figure 1.7). This was then further transformed into the enhanced UTAUT2 (refer to Chapter 1, Figure 1.8) by Venkatesh *et al.* in 2012 (Choudrie *et al.*, 2018:453; Sair & Danish, 2018:503; Hoque & Sorwar, 2017:77; Martins *et al.*, 2014:3; Venkatesh *et al.*, 2003:428-432).

The UTAUT and UTAUT2 have been applied to numerous studies on new media or technologies, according to Lee, Park, Cho and Gin (2018:28), and have been marked as some of the most inclusive adoption theories in the field of technology. Since its inception in 2012, researchers have applied the UTAUT2 and variations of it to studies on Internet/mobile banking (Alalwan *et al.*, 2018; Chaouali *et al.*, 2016; Tarhini *et al.*, 2016; Chen, 2013; AbuShanab & Pearson, 2007), usage intention and adoption or use of mobile apps (Gupta, Dogra & George, 2018; Miladinovic & Xiang, 2016; Hew, Lee, Ooi & Wei, 2015), mCommerce acceptance and use (Madan & Yadav, 2018; Persson & Berndtsson, 2015; Alkhunaizan & Love, 2012; Fai, 2011; Yang, 2010), acceptance of mobile Internet (Wang & Wang, 2010), intention to purchase apps (Lee *et al.*, 2018), acceptance and use of information and communication technology (ICT) (Attuquayefio & Addo, 2014), acceptance and use of technology (Akbar, 2013), determining online shopping anxiety (Celik, 2016), understanding the relationship between behavioural intention and actual use (Williams *et al.*, 2015) and the adoption of mobile wallets (Madan & Yadav, 2016).

Gupta *et al.* (2018:140-141) state that recent developments in the technology acceptance literature are taken into account by the UTAUT2 through the inclusion of hedonic motivation, price value and habit. The theory therefore has better predictive capability when compared to other technology acceptance models. The UTAUT2 has been successfully applied in the aforementioned technology acceptance-related studies and is therefore well-suited to this particular study. This is supported by Rondan-Cataluña *et al.* (2015:797-798) who analysed different technology acceptance models including the TRA, TAM, UTAUT and UTAUT2 in order to determine which model had the best explanatory power for consumer use, also commonly referred to as actual use. The results of the study established that the UTAUT2 was the best model to use at it achieved 26% better explanatory power compared to all other models. Morosan and DeFranco (2016:19) concur with Gupta *et al.* (2018:140-141) and Rondan-Cataluña *et al.* (2015:797-798), stating that the UTAUT2 has enjoyed robust empirical validation, particularly in technology acceptance research. As this study aims to identify the constructs that influence consumers' acceptance and use of mCommerce apps to purchase athleisure apparel in South Africa, this model is well-suited to this research.

The UTAUT2 comprises seven constructs, namely, performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value and habit, which have all been shown to influence behavioural intention. Behavioural intention, in turn, has been shown to influence actual use. The following sections examine each of the various constructs in greater detail, commencing with a definition and overview of each and the relevance of the construct to the field of mCommerce.

4.2.1 Performance expectancy

The construct of performance expectancy is an amalgamation of five constructs from a number of different theories and models used in the compilation of the UTAUT and UTAUT2. Perceived usefulness from the TAM was merged with extrinsic motivation from the MM, job fit from the model of PC utilisation, relative advantage from the IDT and outcome expectations from the SCT (Persson & Berndtsson, 2015:16; Alkhunaizan & Love, 2012:83; Venkatesh *et al.*, 2003:447). Venkatesh *et al.* (2003:447) explain that these five constructs were merged due to the similarities in their definitions and measurement scales to create the performance expectancy construct. Perceived usefulness can be described as an individual's belief that using a specific technology or system will lead to the enhanced performance of their job, according to Liébana-Cabanillas *et al.* (2017:15), Miladinovic and Xiang (2016:14), Persson and Berndtsson (2015:13) and Davis (1986:26). Extrinsic motivation is described as a consumer wanting to perform a particular behaviour as they believe that it will allow them to achieve valuable outcomes. These outcomes are external to the behaviour itself (Mitchell, Schuster & Jin, 2018:2; Venkatesh *et al.*, 2003:428). The model of PC utilisation describes job fit as an individual's belief that the use of a particular technology will improve the performance of their job (Sharma & Mishra, 2014:22; Venkatesh *et al.*, 2003:430). Relative advantage from the IDT refers to whether an innovation is considered an improvement on ideas that preceded it (Oturakci & Yuregir, 2018:53-54; Wu *et al.*, 2013:266; Chung & Holdsworth, 2012:227). Finally, outcome expectations from the SCT are described as an individual's expected outcomes of their actions (Ifinedo, 2017:191; Lim & Noh, 2017:251).

Venkatesh *et al.* (2012:159) reviewed and compared the aforementioned five constructs and found that they could be merged and represented by a new construct termed performance expectancy. This construct is described as the extent to which an individual believes that using an innovative technology will provide them with certain benefits. Gupta *et al.* (2018:140) state that consumers are more likely to use a technology that they deem to be useful or which offers them certain benefits. The relevance of performance expectancy to this study is discussed in the following section.

In the context of this study, the construct of performance expectancy can refer to the utility value extracted by the consumer from using a mobile shopping app. This can include saving time and effort as the app allows them to shop conveniently from anywhere, at any time (Alalwan *et al.*, 2018:128; Tarhini *et al.*, 2016:834; Hyben *et al.*, 2015:3; eMarketer, 2013). It could also mean obtaining a fast response as a consumer can simply open their app and get immediate access to what they are looking for (Graybill, 2015). Lastly, the benefits could also include efficiently and effectively achieving personal objectives (Alkhunaizan & Love, 2012:86). The performance expectancy construct is therefore important to this study as it measures whether an mCommerce consumer believes that using a new technology such as a mobile shopping app, will provide them with certain benefits.

Miladinovic and Xiang (2016:21) report a definitive influence between performance expectancy and the behavioural intention of consumers to engage in mCommerce and mobile Internet browsing. The inclusion of performance expectancy in this study is supported by the fact that it has an influence on behavioural intention, reinforcing the argument that this construct has a positive influence on the behavioural intention of consumers to use mCommerce apps to purchase athleisure apparel (refer to Chapter 5, section 5.4.1.1). This argument is widely supported by researchers such as Alalwan *et al.* (2018), Chopdar *et al.* (2018) and Oliveira *et al.* (2016) (referenced in Chapter 3, section 3.3.7.2).

Given the context described above, performance expectancy is defined as follows for the purposes of this study: the extent to which an individual believes that using a new technology will provide them with certain benefits (Venkatesh *et al.*, 2012:159).

4.2.2 Effort expectancy

Effort expectancy was created from the merger of three constructs from theories and models used to compile the UTAUT and UTAUT2. Perceived ease of use from the TAM was merged with complexity from the model of PC utilisation and the IDT (Alkhunaizan & Love, 2012:83; Venkatesh *et al.*, 2003:450). Similarly to the performance expectancy construct, the aforementioned three constructs were merged into one single construct due to their similarities (Venkatesh *et al.*, 2003:450). Miladinovic and Xiang (2016:14), Persson and Berndtsson (2015:13) and Davis (1986:26) describe perceived ease of use as the degree to which an individual believes that the use of a technological innovation will not require any effort. Complexity from the model of PC utilisation refers to the extent to which an individual perceives a new technology as difficult to comprehend and use (Sharma & Mishra, 2014:22; Venkatesh *et al.*, 2003:430). Finally, Oturakci and Yuregir (2018:53), Wu *et al.* (2013:266) and Chung and Holdsworth (2012:227) examine complexity from the IDT as a way of assessing whether a technological innovation is complex or simple to comprehend and use. Innovations perceived to be more complex are adopted at a slower rate than those perceived to be simpler. Venkatesh *et al.* (2012:159) found that the aforementioned three constructs could be merged and represented by a new construct termed effort expectancy. This is described as the level of ease associated with the use of a new technology. The relevance of effort expectancy to this study is elaborated on in the following section.

In an emerging economy such as South Africa, Chaouali *et al.* (2016:212) contend that the ease of use of using a mobile shopping app will be a motivating factor for consumers to adopt or use mobile shopping. In essence, the less effort required, the easier the adoption will be. From an mCommerce perspective, effort expectancy refers to two things. Firstly, it refers to the ease of using a mobile touchscreen with an app. Apps that are created to leverage the benefits of a touchscreen provide an intuitive interface which allows the user to operate the app faster. This equates to less effort being required on the user's part (Sky Technology, 2016).

Secondly, effort expectancy addresses efficiency. This in itself has been cited by Parker and Wang (2016:490) as being a prime motivator in encouraging consumers to shop via their mobile devices. The effort expectancy construct is therefore important to this study as it measures mCommerce consumers' perception of how easy it is to use a new mobile shopping app. Alkhunaizan and Love (2012:86) posit that effort expectancy is fundamental to the successful design of mCommerce tools. Alalwan *et al.* (2018) and Chopdar *et al.* (2018), referenced in Chapter 3, section 3.3.7.2, support the inclusion of this construct in this study, with findings indicating that effort expectancy has an influence on behavioural intention. This reinforces the argument that effort expectancy has a positive influence on the behavioural intention of consumers to use mCommerce apps to purchase athleisure apparel (refer to Chapter 5, section 5.4.1.2).

Given the context described above, effort expectancy, for the purposes of this study, is defined as follows: the level of ease associated with the use of a new technology (Venkatesh *et al.*, 2012:159).

4.2.3 Social influence

The construct of social influence was created by combining subjective norm from the TRA, subjective norm from the TPB, social factors from the model of PC utilisation and observability from the IDT (Persson & Berndtsson, 2015:16; Alkhunaizan & Love, 2012:83; Venkatesh *et al.*, 2003:451). Venkatesh *et al.* (2003:451) merged these four constructs due to their similarities. According to Otieno *et al.* (2016:3), Yap and Gaur (2016:170), Khalifa and Shen (2008:113) and Fishbein and Middlestadt (1987:363), subjective norm in the TRA is described as the level of influence that an individual perceives their friends, family, peers and the media to have over their life. In essence, it refers to the perceived level of pressure applied by friends, family, peers and the media on the individual to perform or refuse to perform a specific behaviour (Mou *et al.*, 2017:128; AlHinai, 2009:61-62).

In the TPB, subjective norm, similar to the TRA definition, refers to the perceived social pressure an individual believes they are under from friends, family and peers regarding a specific behaviour (Belkhamza & Niasin, 2017:181; Cheung & To, 2017:103; Wei *et al.*, 2009:383). The model of PC utilisation explains social factors as the internalised culture and agreements an individual has made with others in a specific group. In essence, it refers to an individual's view of a particular group's culture and the relationships that the individual has built in that group (Sharma & Mishra, 2014:22; Venkatesh *et al.*, 2003:430).

Lastly, Oturakci and Yuregir (2018:53-54), Wu *et al.* (2013:266) and Chung and Holdsworth (2012:227) describe observability from the IDT as the extent to which the perceived benefit of adopting an innovation or new technology is evident to others, which assists in its adoption. Venkatesh *et al.* (2012:159) combined the aforementioned constructs into one new construct termed social influence. This has been described as an individual's belief that those close to them believe they should understand and use an innovation or new technology. The relevance of social influence to this study is elaborated on in the following section.

From a technology acceptance and adoption point of view, social influence represents the social pressures exerted on an individual to adopt a new technology, such as a mobile shopping app. In emerging economies such as South Africa, the slower-than-average penetration of the Internet and related technologies such as mCommerce means that societies will gradually increase their level of trust in these platforms as others around them do. This is linked to social influence insofar as members of societies in emerging economies wield significant influence on one another to accept and adopt or use new technologies. Therefore, social influence is expected to have an influence on consumers' behavioural intention to use a new technology such as mCommerce (Chaouali *et al.*, 2016:210). Fai (2011:121) posits that social influence has the most notable influence on consumers' acceptance of mCommerce. Verkijika (2018) and Oliveira *et al.* (2016), referenced in Chapter 3, section 3.3.7.2, support the inclusion of this construct in this study. Their findings indicate that social influence has an effect on behavioural intention, reinforcing the argument that this construct has a positive effect on the behavioural intention of consumers to use mCommerce apps to purchase athleisure apparel (refer to Chapter 5, section 5.4.1.3).

Given the context described above, social influence is defined as follows for the purposes of this study: an individual's belief that those close to them, such as family and friends, believe they should understand and use an innovation or new technology (Venkatesh *et al.*, 2012:159).

4.2.4 Facilitating conditions

The construct of facilitating conditions is the amalgamation of three constructs from several different theories and models used to compile the UTAUT and UTAUT2. Perceived behavioural control from the TPB was combined with facilitating conditions from the model of PC utilisation and compatibility from the IDT (Alkhunaizan & Love, 2012:83; Venkatesh *et al.*, 2003:453) to create this construct. Venkatesh *et al.* (2003:453) explain that these constructs overlapped with one another from a theoretical perspective and therefore the amalgamation of these constructs was warranted.

According to Ajzen (1991:183), perceived behavioural control is described as an individual's observation of whether the required behaviour will be simple or complicated to perform. As an individual's perceived behavioural control increases, their behavioural intention will follow suit and so too will actual behaviour (Cheung & To, 2017:103; Leung & Chen, 2017:1639; Ajzen, 1991:184). Facilitating conditions from the model of PC utilisation are described as the availability of support for PC users. The researchers believed that the presence of such support forms a facilitating condition that influences those individuals' use of PCs (Sharma & Mishra, 2014:22;

Venkatesh *et al.*, 2003:430). Finally, compatibility from the IDT refers to the degree to which a new technology supports the past experiences and/or values of the individual that uses it. A compatible innovation, i.e. one that supports the past experiences of the individual, is therefore adopted at a more rapid rate (Oturakci & Yuregir, 2018:53; Wu *et al.*, 2013:266; Chung & Holdsworth, 2012:227).

Venkatesh *et al.* (2012:159) combined these three constructs into one new construct termed facilitating conditions. This is described as a consumer's perception of the resources and support that are available when performing a specific behaviour. The relevance of facilitating conditions to this study is elaborated on in the following section.

In the context of mCommerce, this construct refers to online customer support being available to the consumer (for example, frequently asked questions on the company's website, an email address and/or contact number) along with an Internet connection, enabling the consumer to browse and purchase items (Miladinovic & Xiang, 2016:22). Madan and Yadav (2018:156) agree, stating that facilitating conditions in the context of mCommerce refer to a working, continuous Internet connection, a smartphone that is Internet-enabled and a working knowledge of the technology. The facilitating conditions construct is therefore important to this study as it measures mCommerce consumers' perceptions of the support on offer when using a mobile shopping app. According to research completed by Yang (2010:267), facilitating conditions have a significant influence on consumers' behavioural intention to use mCommerce.

Chopdar *et al.* (2018) and Verkijika (2018), referenced in Chapter 3, section 3.3.7.2, support the inclusion of this construct into this study. Their findings indicate that facilitating conditions have an influence on behavioural intention. This reinforces the argument that this construct has a positive influence on the behavioural intention of consumers to use mCommerce apps to purchase athleisure apparel (refer to Chapter 5, section 5.4.1.4). In addition, Alalwan *et al.* (2018), referenced in Chapter 3, section 3.3.7.2, proved that facilitating conditions have an influence on actual use behaviour, thereby highlighting that this construct has a positive influence on consumers' actual use of mCommerce apps to purchase athleisure apparel (refer to Chapter 5, section 5.4.2.1).

Given the context described above, facilitating conditions, for the purpose of this study, are defined as follows: a consumer's perception of the resources and support that are available when performing a specific behaviour (Venkatesh *et al.*, 2012:159).

4.2.5 Hedonic motivation

A number of studies in consumer behaviour and information systems (IS), according to Venkatesh *et al.* (2012:158), have highlighted hedonic motivation (or constructs related to it, such as enjoyment), as influential elements in the study of technology use. Hedonic motivation was therefore added to the UTAUT2. It is described as a consumer's level of enjoyment linked to the use of a new technology, such as shopping via a mobile app (Venkatesh *et al.*, 2012:161). Alalwan *et al.* (2018:128) further explain that hedonic motivation in the field of technology refer to feelings of joy, enjoyment, cheer or playfulness elicited from the engagement with the technology.

The construct of hedonic motivation is a significant determinant of a consumer's behavioural intention to use a technology, such as a mobile shopping app. Using mCommerce apps could lead to the perception of living a modern lifestyle, thereby eliciting feelings of joy. Verkijika (2018:1668) concurs, stating that the delight derived from the use of a new technology such as a mobile shopping app is a contributing factor to the intention to use the technology. This therefore justifies the inclusion of the construct of hedonic motivation in this study as the construct was used to measure mCommerce consumers' level of enjoyment when using a mobile shopping app to purchase athleisure apparel. Alalwan *et al.* (2018) and Chopdar *et al.* (2018), referenced in Chapter 3, section 3.3.7.2, further supports the inclusion of this construct in this study; their findings indicate that hedonic motivation has an influence on behavioural intention, reinforcing the argument that this construct has a positive influence on the behavioural intention of consumers to use mCommerce apps to purchase athleisure apparel (refer to Chapter 5, section 5.4.1.5).

Given the context described above, hedonic motivation is defined as follows for the purposes of this study: a consumer's level of enjoyment linked to the use of a new technology, such as shopping via a mobile app (Venkatesh *et al.*, 2012:161).

4.2.6 Price value

The construct of price value was added to the UTAUT2 after Venkatesh *et al.* (2012:158) found it to be an important resource consideration. The UTAUT only included the resource considerations of time and effort, however, from a consumer use point of view, price value can significantly influence behavioural intention. The construct of price value is described as the cognitive trade-off between the monetary cost and the perceived benefit of using a new technology, such as a mobile shopping app (Venkatesh *et al.*, 2012:161). The relevance of price value to this study is elaborated on in the following section.

In the context of technology acceptance and use, financial costs play a pivotal role in shaping a consumer's willingness to adopt or use the technology in question, such as mCommerce. A consumer usually determines perceived value by the cognitive comparison between the amount they will pay compared to the quality or utility they will receive in return. If the utility which can be obtained from the adoption or use of a new technology, such as mCommerce, is regarded as being of greater value than the cost, the price value will have a significant influence on the consumer's behavioural intention to use the technology (Alalwan *et al.*, 2018:129). As mCommerce app owners do not maintain a physical store presence, do not pay monthly salaries to salespeople, do not pay rent, etc., these savings can be passed on to the consumer. This can have a significant influence on the consumer's behavioural intention to use the technology (Jao, 2015). The price value construct is therefore important to this study as it measures whether the perceived benefit of using an mCommerce app outweighs the monetary cost of using it.

Alkhunaizan and Love (2012:85) and Wu and Wang (2005:726) contend that cost is pivotal in a consumer's decision-making process regarding the use of mCommerce as it is one of the main deterring factors to consumers accepting and using mCommerce. Research by Alalwan *et al.* (2018) and Chopdar *et al.* (2018), referenced in Chapter 3, section 3.3.7.2, indicates that price value has an influence on behavioural intention, reinforcing the argument that this construct has a positive influence on the behavioural intention of consumers to use mCommerce apps to purchase athleisure apparel (refer to Chapter 5, section 5.4.1.6).

Given the context described above, price value, for the purposes of this study, is defined as follows: the cognitive trade-off between the monetary cost and the perceived benefit of using a new technology, such as a mobile shopping app (Venkatesh *et al.*, 2012:161).

4.2.7 Habit

Habit predicts actual use, similarly to behavioural intention, according to Venkatesh et al. (2012:158). It is described as an individual performing a specific behaviour in an automatic fashion, based on prior learning. The concept has been operationalised in two different ways. Firstly, it is viewed as the result of prior behaviour or learning. Secondly, it is viewed as the degree to which an individual believes a particular behaviour to be automatic in nature (Venkatesh *et al.*, 2012:161). The relevance of habit to this study is elaborated on in the following section.

Habit in the context of this study refers to the extent to which a consumer will make automatic use of mCommerce apps (Miladinovic & Xiang, 2016:24). Lipsman (2015) states that in today's day and age, smartphone use is habitual in nature, occurring on an almost unconscious level. Research has also proven that the continued usage of apps leads to the formulation of new habits (Chou *et al.*, 2013:4). Therefore, this construct has a direct influence on a consumer's behavioural intention to use a new technology, such as mCommerce.

Chopdar *et al.* (2018), referenced in Chapter 3, section 3.3.7.2, state that habit has an influence on behavioural intention, reinforcing the argument that this construct has a positive influence on the behavioural intention of consumers to use mCommerce apps to purchase athleisure apparel. In addition, Alalwan *et al.* (2018) and Chopdar *et al.* (2018) established that habit does indeed have an influence on actual use, reinforcing the argument that this construct has a positive influence on consumers' actual use of mCommerce apps to purchase athleisure apparel (refer to Chapter 5, section 5.4.2.2).

Given the context described above, habit is defined as follows for the purposes of this study: the extent to which a consumer will make automatic use of mCommerce apps (Miladinovic & Xiang, 2016:24).

Sections 4.2.1 to 4.2.7 have provided a detailed account of the independent variables in this study – performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value and habit. Sections 4.2.8 and 4.2.9 which follow discuss the constructs of behavioural intention and actual use. Behavioural intention is described as an individual's willingness to use a technology system, according to Miladinovic and Xiang (2016:12). Simply put, this means that a user is willing to accept the technology, therefore the terms 'behavioural intention' and 'acceptance' are often used interchangeably (Cigdem & Ozturk, 2016). The construct of acceptance is described as changes in individuals' perceptions, attitudes and actions resulting in a willingness to try new activities or innovations (Kaldi *et al.*, 2008:38; Renaud & van Biljon, 2008:2). The adoption or actual use of a technological innovation such as mCommerce is dependent on a consumer's behavioural intentions (Ratten, 2011:40). Adoption is described as the stage where an individual selects a technology for use, according to Kaldi *et al.* (2008:38) and Renaud and van Biljon (2008:1-2). It is therefore synonymous with actual use. Actual use (discussed in section 4.2.9) refers to an individual's actual use of, in the case of this study, mCommerce apps when purchasing athleisure apparel in South Africa (Davis, 1986:25).

4.2.8 Behavioural intention

In many of the aforementioned studies referenced in Chapters 1 and 3, behavioural intention features as a dominant concept throughout. A user's intention to use a particular technology, such as mCommerce, according to Miladinovic and Xiang (2016:12), Persson and Berndtsson (2015:28) and Venkatesh et al. (2012:157), has been statistically proven to be a predicting construct of the individual actually using the technology. Miladinovic and Xiang (2016:12) describe behavioural intention as the willingness of an individual to use a particular technology, for example, a mobile shopping app. In addition, Phong *et al.* (2018:119) describe behavioural intention as an individual's personal evaluation of their ability to perform an online transaction by means of a mobile device through a wireless connection. Furthermore, research by Alalwan *et al.* (2018) and Chopdar *et al.* (2018), referenced in Chapter 3, section 3.3.7.2, also indicate that behavioural intention has an influence on actual use, reinforcing the argument that this concept has a positive influence on consumers' actual use of mCommerce apps to purchase athleisure apparel (refer to Chapter 5, section 5.4.8).

Given the context described above, behavioural intention, for the purposes of this study, is defined as follows: the willingness of an individual to use a particular technology (Miladinovic & Xiang, 2016:12).

4.2.9 Actual use

The construct of actual use, also referred to as use behaviour, is less frequently referenced in research on innovation or new technologies. This is due to the fact that these new technologies are still in the earlier stages of development and implementation and, as such, researchers have focused more on identifying barriers to acceptance, as opposed to actual use (Liébana-Cabanillas *et al.*, 2017:15). South Africans are increasingly shopping on their mobile phones through the use of apps (Business Tech, 2015), however, as can be seen in Chapter 2, Figure 2.7, the category of clothing and accessories does not feature as one of the top ten categories for average mobile spend allocation (Erken, 2017; Goldstuck, 2014:27). Therefore, this study is not only interested in behavioural intention, but also in actual use itself.

Actual use is described as an individual's actual use of mCommerce apps when purchasing athleisure apparel in South Africa (Davis, 1986:25). The relationship between behavioural intention and actual use has been widely studied and repeatedly found to be significant (Hoque & Sorwar, 2017:77; Tarhini *et al.*, 2016:842; Persson & Berndtsson, 2015:61; Williams *et al.*, 2015:465; Martins *et al.*, 2014:4; Wu & Wang, 2005:726). As mentioned in section 4.2.8 and Chapter 3, section 3.3.7.2, Alalwan *et al.* (2018) and Chopdar *et al.* (2018), have proven that behavioural intention has an influence on actual use, reinforcing the decision to include this construct.

Given the context described above, actual use is defined as follows for the purposes of this study: an individual's actual use of mCommerce apps when purchasing athleisure apparel in South Africa (Davis, 1986:25).

This section has provided a detailed account of each of the UTAUT2's constructs as well as the relevance of each construct to the field of mCommerce. Sections 4.3 and 4.4 which follow, use the same approach by discussing the added constructs of perceived risk and trust. An overview is provided of each as well as the relevance of each to the field of mCommerce. Bojang (2017:3) states that perceived risk and trust have a prominent role to play in the domain of online and mobile transacting.

4.3 The role of perceived risk in mCommerce and its relevance to the study

Perceived risk is described, according to Chen (2013:316) and Forsythe and Shi (2003:869), as the nature and amount of risk perceived by a consumer in planning a purchase decision. Suh *et al.* (2015:133) state that in the domain of online or mobile shopping, perceived risk refers to consumers' perceptions surrounding the possible negative outcomes they could be exposed to as a result of transacting online. Perceived risk is a decisive barrier for consumers purchasing a product via an online or mobile shopping channel (Kim & Koo, 2016:1020; Suh *et al.*, 2015:133).

Dai *et al.* (2014:15), Forsythe *et al.* (2006:57) and Wu and Wang (2005:722) describe four types of perceived risk that are of importance in online and mobile shopping, namely, financial risk, product performance risk, privacy risk and time/convenience risk. As discussed in Chapter 1, section 1.7.4.8, even though these four types of risks are stated to be of importance in the domain of online and mobile shopping, for the purposes of this study, only financial risk and product performance risk are focused on. This is supported by Farivar *et al.* (2017:591), Yang *et al.* (2015:261), Ueltschy *et al.* (2004:71) and Featherman and Pavlou (2003:460), all of whom found financial risk and product performance risk to be the two primary risk types influencing consumers' online and/or mobile purchasing behaviour. Each of these is discussed in greater detail below.

Financial risk refers to the loss of money on the consumer's part as a result of shopping online or via a mobile phone (Dai *et al.*, 2014:15; Forsythe & Shi, 2003:869). It is important to take note of this risk type from an mCommerce point of view as Yang *et al.* (2015:261) found that consumers have severe capital security concerns when using mCommerce. The reason for this threefold. Firstly, consumers shopping via an online or mobile shop may not necessarily be able to compare prices as easily as a consumer in a brick-and-mortar store. Researchers have suggested that this might be a reason for online or mobile shopping cart abandonment.

Secondly, credit card fraud poses a significant financial risk to consumers (Dai *et al.*, 2014:15). This is especially relevant in South Africa. South African banks saw a credit card fraud increase of 1% in 2017, according to the South African Banking Risk Information Centre's (Sabric) fraud report, amounting to R436.7 million (Rangongo, 2018). Goldstuck (2014:13) is in support, stating that South Africans' concerns about online security have increased year on year. Swiegers (2018:128) corroborates Goldstuck's findings, affirming that financial risk impacts South Africans behavioural intention to purchase online.

Thirdly, other costs such as shipping often deter consumers from purchasing via online or mobile channels. There are, for example, no shipping costs charged in brick-and-mortar stores, although the consumer does pay to get to the store and back (Dai *et al.*, 2014:15). Williamson (2014) states that, in South Africa specifically, consumers often browse for and research different products online or via their mobile devices and then proceed to purchase the actual item in-store as they are then not billed for delivery and can leave with the item there and then.

Marriott and Williams (2018:134) and Hubert *et al.* (2017:186) maintain that financial risk is the most substantial perceived risk type in the mobile shopping domain. Chen (2013:430) earlier also stated that financial risk is one of the top predictors of perceived risk, with Yang *et al.* (2015:261) and Jacoby and Kaplan (1972) asserting that financial risk is the most noteworthy predictor of perceived risk. It is important to take note of this risk type in this study as financial risk can influence a consumer to decide not to make use of mCommerce (Suh *et al.*, 2015:133).

Product performance risk refers to the lack of physical interaction with the item of interest due to the limitations of an online or mobile shopping channel. As the customer is not able to physically touch the item and, in the case of apparel, cannot try on their size, this could result in it not being suitable (Marriott & Williams, 2018:136; Chen, 2015:62; Dai *et al.*, 2014:14; Lee & Stoel, 2014:403; Ruane & Wallace, 2013:318;

Forsythe *et al.*, 2006:57; Forsythe & Shi, 2003:869). Goldstuck (2014:17) reiterates this from a South African market point of view. According to his research, the biggest barrier to South Africans purchasing online is lack of physical interaction with the product. Beneke *et al.* (2012:8) are of the same opinion, indicating that product performance risk has a significant influence on South Africans' intention to purchase. Forsythe and Shi (2003:871) also support this, stating that product performance risk is most frequently cited as consumers' main reason for refraining from online shopping. Chaouali *et al.* (2016:211) elaborate on this, by stating that digital retail comes with a lack of trust due to a lack of physical interaction with the item being purchased. It is thus important to take cognisance of this risk type in this study as this construct too, has the potential to influence a consumer to decide not to make use of mCommerce.

Based on the aforementioned arguments, the construct of perceived risk is therefore an important consideration in determining consumers' behavioural intention to use mobile shopping apps. This is supported by Alalwan *et al.* (2018:133), who note that the addition of perceived risk to the UTAUT2 improved its predictive capability of consumers' behavioural intention from 58% without perceived risk, to 64% with perceived risk. Verkijika (2018:1673), referenced in Chapter 3, section 3.3.7.2, also supports the inclusion of this construct in this study, reporting that perceived risk has an influence on behavioural intention. This reinforces the argument that perceived risk has a negative influence on the behavioural intention of consumers to use mCommerce apps to purchase athleisure apparel (refer to Chapter 5, section 5.4.3).

The influence of perceived risk on behavioural intention, however, is mediated by the construct of trust (Farivar *et al.*, 2017:597; Gao & Bai, 2014:217; Kesharwani & Bisht, 2012:315-316). Hong and Cha (2013:929) describe the relationship between these two constructs as inseparable.

Given the context described above, perceived risk, for the purposes of this study, is defined as follows: consumers' perceptions surrounding the impending negative outcomes they could be exposed to as a result of transacting in an online or mobile environment (Suh *et al.*, 2015:133).

The next section discusses the construct of trust, commencing with an overview and closing with the relevance of the construct to the field of mCommerce.

4.4 The role of trust in mCommerce and its relevance to the study

The construct of trust has been widely researched and debated across different industries including marketing, communication and information systems, to name but a few. Countless articles have been published on this construct (Gupta *et al.*, 2018; Huo, Zhang & Ma, 2018; Farivar *et al.*, 2017; Chaouali *et al.*, 2016; Wang, Min & Han, 2016; Suh *et al.*, 2015; Gao & Bai, 2014; Vasileiadis, 2014; Chong, 2013; Joubert & van Belle, 2013; Kesharwani & Bisht, 2012; Daud & Hassan, 2011; Lim, 2003).

From a digital retailing point of view, Ribbink *et al.* (2004:447) state that trust refers to the degree of confidence that the consumer has in an online or mobile exchange. Ter Huurne *et al.* (2017:486) adds that trust refers to one party's inclination to be exposed to the actions of another party, in the hope that the other party will carry out a specific action for the first party without the presence of any control over the other party. Simpler put, it is the degree to which a trustor (for example, a consumer) feels confident about relying on a trustee (for example, an mCommerce retailer) (Kesharwani & Bisht, 2012:309-310).

In transactional relationships such as Internet or mobile banking, online or mobile shopping, etc., trust plays a crucial role and can determine the ultimate failure or success of the business (Bojang, 2017:5). Trust in online or mobile domains, according to Rogers (2010:26-27), consider a consumer's hopes as to the website, mobile site, or app. It considers whether the information is believable, whether the site or app will deliver on expectations and whether it commands confidence. Trust is created once the consumer forms a positive impression of the website, mobile site, or app and is willing to accept potential exposure.

Suh *et al.* (2015:133) explain that as there is no physical interaction in a digital retailing domain, a consumer has no guarantee that the supplier will not behave in a way that is opportunistic or harmful. Bojang (2017:13) expands on this by stating that digital retailing is far more impersonal compared to traditional brick-and-mortar shopping; it does not instantly gratify like traditional brick-and-mortar shops as the item is not purchased there and then; the process is more automated, therefore allowing for greater possibility of fraud. Trust therefore becomes key critical for a consumer to decide whether or not to transact on a digital retailing channel, such as an mCommerce site (Farivar *et al.*, 2017:591). Marriot and Williams (2018:136), Bojang (2017:5) and Chaouali *et al.* (2016:211) concur, stating that trust is absolutely necessary in the digital retailing domain. Trust serves as a foundation for consumers' decisions, according to Chaouali et al. (2016:211), as to whether or not to use new technologies such as mCommerce. Many consumers are not yet familiar with mobile technologies and shopping. This means consumers may perceive these activities as risky (Gao, Krogstie & Siau, 2014:152).

There are several elements that could influence consumers' trust in mCommerce; these can be linked to the perceived risk types discussed in section 4.3, i.e. financial risk, product performance risk, privacy risk and time/convenience risk. Firstly, the financial risk posed by credit card fraud to consumers is significant, especially so in South Africa, when considering, as mentioned in section 4.3, that over R430 million in credit card fraud was committed in 2017 (Rangongo, 2018; Dai *et al.*, 2014:15). Digital retailers have attempted to address this by allowing their online purchasing processes to be verified by third-party agencies such as Thawte and Verisign. These organisations ensure data transfer security and provide consumers with assurance that a digital retailer handles all payment information securely and reliably. Moreover, consumers have been made aware of this. Posting the logos of these third-party agencies on a retailer's website therefore instils trust in the consumer, setting their mind at ease, which assists in reducing perceived financial risk (Rouibah, Lowry & Hwang, 2016:38).

Secondly, from a product performance risk point of view, Chaouali *et al.* (2016:211) state that in digital retailing environments, there are "spatial and temporal separations" along with a lack of physical interaction or observation, which further contribute to a lack of trust. As stated previously, Goldstuck (2014:17) found that the biggest barrier to South Africans purchasing online is lack of physical interaction with the product.

Thirdly, privacy and security issues also pose a threat as consumers are concerned about the security of mobile services and service providers (Gao *et al.*, 2014:152). Persson and Berndtsson (2015:26) agree, stating that consumers question the security associated with completing transactions via a mobile device and also call into question the safety of their personal privacy. Gao *et al.* (2014:152) contend that addressing security and privacy issues is pivotal in building consumers' trust in digital retailing environments.

Lastly, time/convenience risk refers to a delay in consumers receiving their online order. There is a lack of instant gratification as the customer cannot receive their order immediately after processing payment (Bojang, 2017:13; Chen, 2015:62; Forsythe *et al.*, 2006:57; Forsythe & Shi, 2003:869). It is imperative for digital retailers to educate consumers as to their order delivery policies and processes to ensure that consumers' expectations are managed upfront. This helps to build trust.

Based on the aforementioned arguments, the construct of trust is deemed an important consideration in determining consumers' behavioural intention to use mobile shopping apps. Chong (2013:1245) supports the inclusion of this construct in the present study, contending that trust is the strongest predictor of behavioural intention. This reinforces the argument that trust has a positive influence on the behavioural intention of consumers to use mCommerce apps to purchase athleisure apparel (refer to Chapter 5, section 5.4.7).

Given the context described above, trust is defined as follows for the purposes of this study: the degree to which a trustor (for example, a consumer) feels confident about relying on a trustee (for example, an mCommerce retailer) (Kesharwani & Bisht, 2012:309-310).

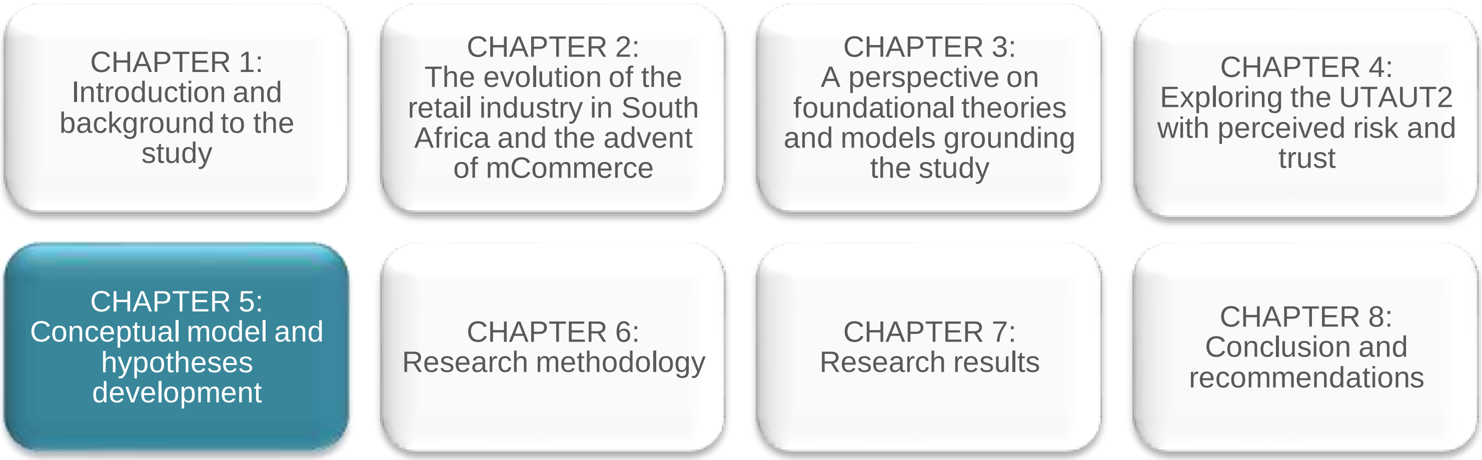
4.5 Conclusion

Chapter 4 provided an in-depth overview of the model of focus for the study, the UTAUT2, developed by Venkatesh *et al.* in 2012. The chapter described each of the model's constructs in greater detail, including performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value and habit. Behavioural intention and actual use were also discussed. An overview of each of these constructs was provided, along with the relevance of each construct to the field of mCommerce. The added constructs of perceived risk and trust were then discussed.

Chapter 5 validates the conceptual model and each of the 15 proposed hypotheses through reference to prior research. It is imperative to establish a theoretical connection for all proposed relationships and to determine whether they are likely to be accepted or rejected.

CHAPTER 5

CONCEPTUAL MODEL AND HYPOTHESES DEVELOPMENT



5.1 Introduction

Chapter 5 builds on Chapters 3 and 4 by validating the conceptual model through the theory presented in the preceding chapters. The chapter commences with an overview of the foundational theories and models grounding the study. The conceptual model and research hypotheses are then presented and each of the 15 hypothesised relationships is then validated.

5.2 An overview of the foundational theories and models grounding the study

As set out in Chapters 3 and 4, this study is grounded in relationship-building theory, i.e. the Social Exchange Theory (SET) and Transaction Cost Theory (TCT) and technology acceptance theory, i.e. the Innovation Diffusion Theory (IDT), the Theory of Reasoned Action (TRA), Social Cognitive Theory (SCT), the Technology Acceptance Model (TAM), the Theory of Planned Behaviour (TPB), the Unified Theory of Acceptance and Use of Technology (UTAUT) and the UTAUT2. The following section provides a brief overview of each of these theories and models and their relevance to this study.

From a relationship-building perspective, the first theory grounding the study is the SET. The SET was established by Homans in 1958 to analyse human behaviour during the process of resource exchange (Yan *et al.*, 2016:644; Shiau & Luo, 2012:2432). This theory assists in understanding the elements of cost and reward that are present during an mCommerce exchange as the buyer will make use of the seller's app to purchase athleisure apparel (Shiau & Luo, 2012:2432). The second relationship-building theory grounding the study is the TCT, developed in 1981 by Williamson. This theory also focuses on relationships, but from an economic point of view (Eiriz & Wilson, 2004:278). This theory assists in understanding the transaction costs present in an mCommerce exchange. Such transaction costs have been proven to be useful in predicting consumers' acceptance of digital retailing channels (Che *et al.*, 2015:589-590).

From a technology acceptance point of view, the first theory grounding the study is the IDT (refer to Chapter 1, Figure 1.2). The IDT was developed in 1962 by Rogers to determine how members of a social system adopt an innovation or new technology (Chung & Holdsworth, 2012:226-227; Khalifa & Shen, 2008:111; Wu & Wang, 2005:721; Rogers, 2003:1). Elements of this model are included in the UTAUT2, the model of focus in this study. Specific constructs from the IDT, namely, relative advantage, complexity, observability and compatibility were used to create the UTAUT2 constructs of performance expectancy, effort expectancy, social influence and facilitating conditions. A number of technology acceptance studies have proven the influence of these constructs on consumers' behavioural intention, including Oliveira *et al.* (2016:410), Chen (2013:425), Wu *et al.* (2013:279-280) and Zhang *et al.* (2012:1909), hence its inclusion as foundational theory.

The second theory grounding the study is the TRA (refer to Chapter 1, Figure 1.3). Fishbein and Ajzen developed the TRA in 1975. The theory postulates a direct association is present between an individual's attitude, the environment they operate in and their intentions and behaviour (Liao *et al.*, 2017:585). Like the IDT, the TRA is also included in the creation of the UTAUT2, and specifically, the construct of social influence (Venkatesh *et al.*, 2003:447-451). This construct has been proven to influence behavioural intention by various researchers, including Sanne and Wiese (2018:8), Liao *et al.* (2017:595), Mou *et al.* (2017:126), Otieno *et al.* (2016:7) and

AlHinai (2009:178). Additionally, Mou *et al.* (2017:126; 132) proved that behavioural intention influences actual use. The model is therefore imperative to include in this study as foundational theory.

The third theory grounding the study from a technology acceptance point of view is the SCT (refer to Chapter 1, Figure 1.4). Created by Bandura in 1986, the SCT constructs a holistic understanding of an individual's behavioural intention to adopt a new technology or innovation (Ratten, 2011:27; 41). The SCT's contribution to this study also lies in its inclusion in the design of the UTAUT2, specifically for the construct of performance expectancy (Venkatesh *et al.*, 2003:447). This construct has been proven to influence behavioural intention by, amongst others, Kwahk *et al.* (2018:69) and Lim and Noh (2017:254), hence its inclusion as foundational theory.

The fourth foundational theory and the most universally-applied technology acceptance theory is the TAM, founded by Davis in 1986 (refer to Chapter 1, Figure 1.5). The TAM posits that an individual is motivated to accept and use an innovation or new technology based on three constructs, namely, perceived ease of use, perceived usefulness and attitude (Dlodlo & Mafini, 2013:2; Pinho & Soares, 2011:119). The TAM's contribution to this study lies in it being a key theory contributing to the formulation of the UTAUT2, with specific emphasis on performance expectancy and effort expectancy (Venkatesh *et al.*, 2003:447; 450). In addition, the TAM proves that actual use can be predicted from behavioural intention (Miladinovic & Xiang, 2016:14). Several researchers have proven that performance expectancy (derived from the TAM construct, perceived usefulness) influences behavioural intention, including Liébana-Cabanillas *et al.* (2017:18), Agrebi and Jallais (2015:21), Faqih and Jaradat (2015:46), Ratten (2015:29-30), Khalifa and Shen (2008:118) and Wu and Wang (2005:725-726). Similarly, Ratten (2015:29-30) and Zhang *et al.* (2012:1909) showed that effort expectancy (created from the TAM construct, perceived ease of use) influences behavioural intention. Faqih and Jaradat (2015:46) also demonstrated that behavioural intention, in turn, influences actual use. The model is therefore imperative to include in this study as foundational theory.

The fifth theory grounding the study from a technology acceptance point of view is the TPB (refer to Chapter 1, Figure 1.6). Founded in 1991 by Ajzen, the TPB extended the

TRA to include the construct of perceived behavioural control (Ajzen, 1991:181). The TRA states that behaviour is the result of the individual's attitude, others' opinions of the individual as well as resources available to the individual (Cheung & To, 2017:103; Leung & Chen, 2017:1639). Elements of the TRA were used to formulate the specific constructs of the UTAUT2. Subjective norm from the TPB informed the construct of social influence. Perceived behavioural control from the TPB was then used to formulate the construct of facilitating conditions (Venkatesh *et al.*, 2003:451-453). A number of technology acceptance studies have proven the influence these constructs have on consumers' behavioural intention, including Akar and Dalgic (2018:480), Belkhamza and Niasin (2017:181), Cheung and To (2017:107), Leung and Chen (2017:1644), Carter and Yeo (2016:752) and Zhang *et al.* (2012:1908-1909). Furthermore, Cheung and To (2017:107) used the TPB to prove that behavioural intention influences actual use. It is thus vital to include the TPB in this study as foundational theory.

The final theories grounding the study from a technology acceptance point of view are Venkatesh *et al.*'s (2012; 2003) UTAUT and UTAUT2 (refer to Chapter 1, Figures 1.7 and 1.8). The UTAUT was created in 2003 by Venkatesh *et al.* in an effort to amalgamate the multitude of technology acceptance theories and models into a single model. It comprises constructs from the TRA, TAM, Motivational Model (MM), TPB, combined TAM and TPB model, the Model of Personal Computer (PC) Utilisation, the IDT and the SCT (Choudrie *et al.*, 2018:453; Sair & Danish, 2018:503; Hoque & Sorwar, 2017:77; Martins *et al.*, 2014:3; Venkatesh *et al.*, 2003:428-432).

The UTAUT has been applied to numerous studies on the behavioural intention to use and adopt or actual use of technology studies globally (Sair & Danish, 2018; Hoque & Sorwar, 2017; Persson & Berndtsson, 2015; Martins *et al.*, 2014; Alkhunaizan & Love, 2012; Riffai *et al.*, 2012). The relevance of the UTAUT to this study lies mainly in it forming the foundation of the UTAUT2. All the constructs of the UTAUT were included in the UTAUT2, and consequently, are included in this study as well. It is therefore imperative to include the UTAUT to understand the history of the UTAUT2.

In response to criticisms of the UTAUT, Venkatesh *et al.* created the UTAUT2 in 2012. The UTAUT, which had been criticised for its limited application within organisational contexts only, was expanded through the addition of three new constructs, namely hedonic motivation, price value and habit (Slade *et al.*, 2013:10; Venkatesh *et al.*, 2012:157). The UTAUT2 forms the basis of the conceptual model built for this study, which includes another two constructs – perceived risk and trust.

The addition of the perceived risk and trust constructs stems from a number of studies conducted in the field of mCommerce. Çelik and Yilmaz (2011:155) and Bhatnagar and Ghose (2004:1353), for example, state that the risk associated with shopping in a traditional brick-and-mortar store is significantly lower than shopping in a digital environment such as an online or mobile shop. A potential reason for this, according to Velarde (2012:22), is that in online or mobile environments definite cues that induce trust are not accessible. These cues include the characteristics of a product, being in a physical store or talking to a sales person. This then increases distrust, which increases the perceived risk of using the online or mobile shop. This study seeks to ascertain whether perceived risk has an influence on consumers' behavioural intention to use (or accept) mCommerce, as well as their actual use (or adoption) of mCommerce.

From a trust construct perspective, this is one of the most frequently cited reasons for not shopping via a digital medium (Monsuwé *et al.*, 2004:114). Trust directly and positively affects consumers' online shopping intentions (Çelik & Yilmaz, 2011:155). Farivar *et al.* (2017:591), Chaouali *et al.* (2016:211), Joubert and van Belle (2013:33) and Jarvenpaa *et al.* (2000:45) state that trust is pivotal in encouraging purchases in an online or mobile shopping environment. Amoroso and Hunsinger (2009:25) and Farivar *et al.* (2017:592) further observe that as trust diminishes, perceived risk increases and as a result, consumer intention to purchase decreases (Lim, 2003:218). This study therefore seeks to determine whether trust has an influence on consumers' behavioural intention to use (or accept) mCommerce and whether it mediates the impact of perceived risk on behavioural intention and actual use (or adoption). The following section provides an overview of the conceptual model and research hypotheses.

5.3 Conceptual model and research hypotheses

As discussed above, the UTAUT2 forms the foundation of the conceptual model built for this study, including two additional constructs of perceived risk and trust. The conceptual model and hypotheses are illustrated in Chapter 1, Figure 1.9. Based on the model, the study is conducted in two phases. Phase 1 (using Model A in Chapter 1, Figure 1.9) tests the influence of specific constructs on behavioural intention to determine consumers' acceptance of mCommerce apps to purchase athleisure apparel. Phase 2 (using Model B in Chapter 1, Figure 1.9) tests the influence of specific constructs on actual use to determine consumers' use of mCommerce apps to purchase athleisure apparel.

At this point, it is important to ensure the behavioural intention and actual use constructs are well defined. Behavioural intention is described as the willingness of an individual to use an innovation or new technology (Miladinovic & Xiang, 2016:12). A user therefore accepts the technology. Acceptance is described as a change occurring in an individual's perceptions, attitudes and actions resulting in a willingness to try a new activity or innovation (Kaldi *et al.*, 2008:38; Renaud & van Biljon, 2008:2). These two terms – behavioural intention and acceptance – are thus often used interchangeably (Cigdem & Ozturk, 2016). A consumer's actual use or adoption of a new technology or innovation is dependent on their behavioural intention or acceptance (Ratten, 2011:40). Kaldi *et al.* (2008:38) and Renaud and van Biljon (2008:1-2) describe the construct of adoption as the stage where an individual selects a specific technology for use. It can therefore be regarded as synonymous with actual use. Davis (1986:25) contends that actual use denotes an individual's actual use of, in the case of this study, an mCommerce app when purchasing athleisure apparel in South Africa.

Phase 1 (using Model A in Chapter 1, Figure 1.9) therefore tests the seven original UTAUT2 constructs, namely, performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value and habit and their influence on behavioural intention. This phase further investigates the constructs of perceived risk and trust and their influence on behavioural intention. It also examines whether trust mediates the influence of perceived risk on behavioural intention.

Phase 2 (using Model B in Chapter 1, Figure 1.9) also tests the seven original UTAUT2 and their influence on behavioural intention. It then tests whether the constructs of facilitating conditions and habit have a significant positive influence on actual use. This phase also examines the constructs of perceived risk and trust and their influence on behavioural intention, as well as the influence of perceived risk on actual use. Thereafter, it is determined whether trust mediates the influence of perceived risk on both behavioural intention and actual use. Finally, the influence of behavioural intention on actual use is tested. The following sections focus on each of the hypothesised relationships.

5.4 Hypothesised relationships between the constructs in the conceptual model

Based on the literature presented in Chapters 3 and 4 and summarised in section 5.2, this section validates the hypothesised relationships in the conceptual model (refer to Chapter 1, Figure 1.9). In the following sections, discussions on the development of each hypothesis are presented and each hypothesis is validated. The first section, section 5.4.1, commences with an overview of the relationships between the independent variables of the UTAUT2 (performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value and habit) and behavioural intention. Hypotheses 1-4 and 6-8 are validated in this section. Section 5.4.2 examines the relationships between the independent variables of facilitating conditions and habit and actual use. Hypotheses 5 and 9 are validated in this section. Sections 5.4.3 and 5.4.4 provide an overview of the relationship between perceived risk, as an independent variable and behavioural intention as well as actual use. Hypotheses 10 and 11 are validated in these sections. Sections 5.4.5 and 5.4.6 look at the relationship between perceived risk and behavioural intention as well as actual use, mediated by trust. Hypotheses 12 and 13 are validated in these sections. Thereafter, section 5.4.7 focuses on the relationship between trust, as an independent variable and behavioural intention. Hypothesis 14 is validated here. Finally, section 5.4.8 provides a view of the relationship between behavioural intention and actual use and validates hypothesis 15.

5.4.1 Relationships between the independent variables of the UTAUT2 (performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value and habit) and behavioural intention

This section provides an overview of the relationships between the independent variables of the UTAUT2 (performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value and habit) and behavioural intention (or acceptance), as depicted in Figure 5.1.

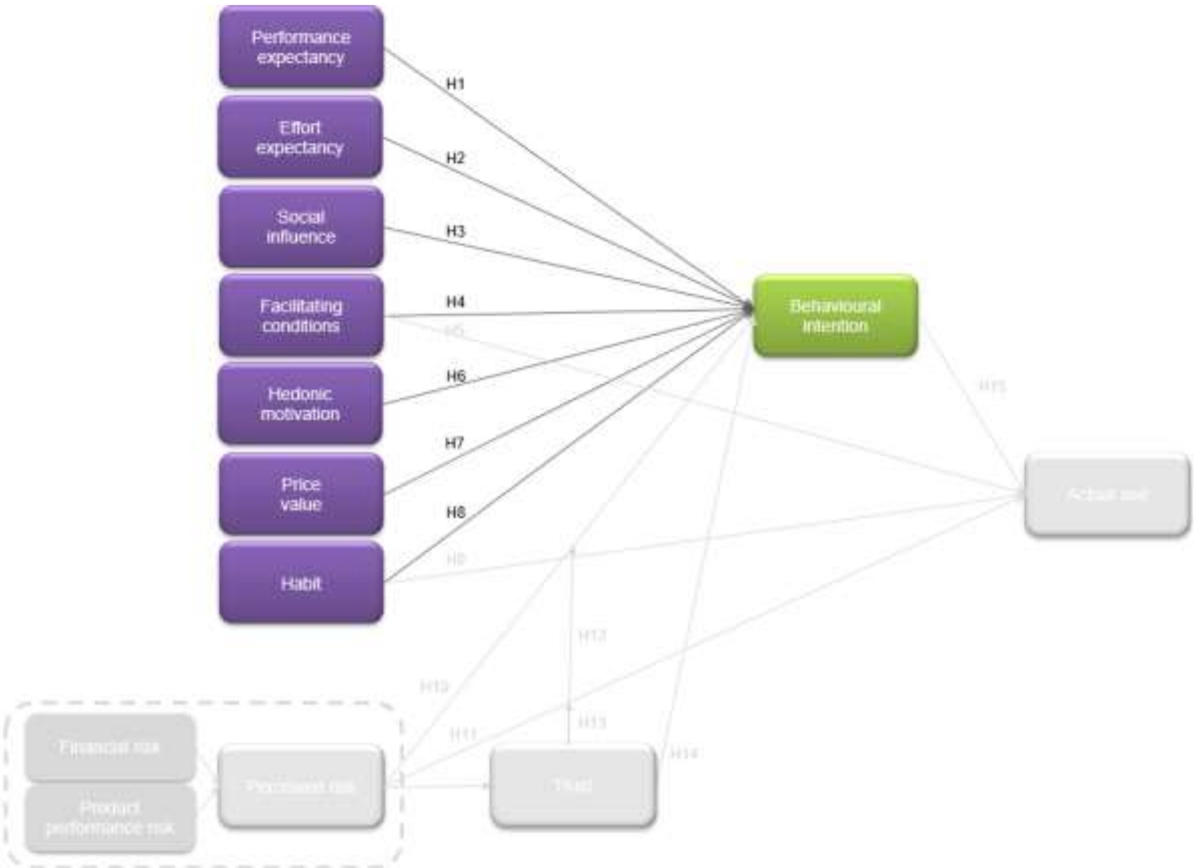


Figure 5.1: Relationships between the independent variables of the UTAUT2 and behavioural intention

***Source**: Researcher's own construct*

5.4.1.1 The relationship between performance expectancy and behavioural intention (H_1)

Performance expectancy is described, according to Venkatesh et al. (2012:159), as the degree to which an individual believes that the use of a new technology or innovation will provide them with positive benefits. From the literature reviewed in Chapter 4, section 4.2.1, five constructs from different models were combined to create the performance expectancy construct, including perceived usefulness from the TAM, extrinsic motivation from the MM, job fit from the model of PC utilisation, relative advantage from the IDT and outcome expectations from the SCT (Persson & Berndtsson, 2015:16; Alkhunaizan & Love, 2012:83; Venkatesh *et al.*, 2003:447).

The impact of performance expectancy on behavioural intention has been proven by a number of researchers. In studies by Venkatesh *et al.* (2012:159; 2003:447), the construct of performance expectancy was found to be the strongest predictor of behavioural intention. Further studies by Alalwan *et al.* (2018), Chopdar *et al.* (2018), Gupta *et al.* (2018), Chaouali *et al.* (2016), Madan and Yadav (2016), Miladinovic and Xiang (2016), Tarhini *et al.* (2016), Hew *et al.* (2015), Alkhunaizan and Love (2012), Fai (2011) and AbuShanab and Pearson (2007), which focused on new technologies or innovations in support of this view, are discussed below.

The construct of performance expectancy from the UTAUT2 and its influence on behavioural intention has been researched extensively in the Internet and mobile banking field (Alalwan *et al.*, 2018; Chaouali *et al.*, 2016; Tarhini *et al.*, 2016; AbuShanab & Pearson, 2007). Alalwan *et al.* (2018:128) conducted a study in Jordan using an adapted UTAUT2 to examine the factors influencing consumers' intentions to adopt (accept) and ultimately adopt (use) Internet banking. The researchers conceptualised performance expectancy in their study as the benefits that a consumer can attain from using Internet banking, for example, accessibility, saving time and effort and convenience. They found performance expectancy to have a significant influence on behavioural intention (Alalwan *et al.*, 2018:133). The results revealed that consumers seemed more inclined to adopt a new channel, such as Internet banking, if the channel was perceived as being useful, efficient and fruitful.

The findings of Alalwan *et al.* (2018) are supported by Chaouali *et al.* (2016:215) and Tarhini *et al.* (2016:842). Chaouali *et al.* (2016:215) conducted research in Tunisia to understand the factors influencing consumer adoption of Internet banking. Their research illustrated that performance expectancy positively and significantly influenced behavioural intention. Tarhini *et al.* (2016:842) examined consumers' acceptance and use of Internet banking in Lebanon. They tested an adapted UTAUT and also found performance expectancy to have a significant influence on behavioural intention. These researchers state that owners of new technologies or innovations, such as Internet banking facilities, should constantly work to improve their offering through a considered look at users' suggestions. This will help to better meet the users' needs (Tarhini *et al.*, 2016:842).

An earlier study by AbuShanab and Pearson (2007:90) found performance expectancy to significantly influence the behavioural intention of consumers to use Internet banking, to such an extent that it accounted for the most significant single contribution in explaining the behavioural intention discrepancy. The aforementioned studies in Internet banking indicate that performance expectancy is a strong predictor of behavioural intention. Performance expectancy and its influence on behavioural intention has also been tested in research on consumer acceptance and use of mobile apps (Gupta *et al.*, 2018; Madan & Yadav, 2016; Hew *et al.*, 2015). Madan and Yadav (2016:237) researched mobile wallet acceptance in Delhi and found performance expectancy to have the strongest influence on consumers' behavioural intention to adopt a mobile wallet. Gupta *et al.* (2018:145) report similar findings in a study on tourist acceptance of mobile apps and also found performance expectancy to have a significant influence on behavioural intention. In fact, it was the strongest determinant of behavioural intention. In Malaysia, Hew *et al.* (2015:1284) conducted a study using the UTAUT2 on catalysts of usage intention for mobile apps. They found performance expectancy to significantly influence behavioural intention, concluding that consumers will use an app if they find it useful in their day-to-day life. The results of these studies in mobile app acceptance and use support the fact that performance expectancy is a strong predictor of behavioural intention.

Numerous studies have been conducted on the acceptance and use of mobile shopping, featuring the construct of performance expectancy (Chopdar *et al.*, 2018;

Miladinovic & Xiang, 2016; Alkhunaizan & Love, 2012; Fai, 2011). Chopdar *et al.* (2018:120-121) conducted a study across two countries, the United States of America (USA) and India, to determine which factors influence consumers' acceptance and use of mobile shopping apps. The researchers found that performance expectancy, in both countries, significantly influenced behavioural intention. Miladinovic and Xiang (2016:44) explored mobile shopping app acceptance in Sweden. They tested an adapted UTAUT2 and found that performance expectancy significantly influenced behavioural intention. Alkhunaizan and Love's (2012:92) report similar findings. These researchers explored the factors that drive consumers to accept and use mCommerce in Saudi Arabia. They tested an adapted UTAUT2 and found that, out of all the constructs, performance expectancy had the strongest influence on behavioural intention. In Hong Kong, Fai (2011:113) conducted a study over a three-year period to examine negative user acceptance behaviour towards mCommerce. Three constructs of the UTAUT were tested, i.e. performance expectancy, effort expectancy and social influence. The findings of revealed that performance expectancy significantly influences consumers' behavioural intention to use mCommerce. The aforementioned studies in mobile shopping acceptance and use affirm that performance expectancy is a strong predictor of behavioural intention.

The following hypothesis is therefore proposed:

H_1: Performance expectancy has a positive influence on the behavioural intention of consumers to use mCommerce apps to purchase athleisure apparel.

5.4.1.2 The relationship between effort expectancy and behavioural intention (H_2)

Venkatesh *et al.* (2012:159) describe effort expectancy as the degree of ease a consumer associates with the use of a new technology or innovation. Based on the information provided in Chapter 4, section 4.2.2, this construct was created by amalgamating three constructs sourced from different technology acceptance models. Perceived ease of use from the TAM was combined with complexity from the model of PC utilisation as well as the IDT (Alkhunaizan & Love, 2012:83; Venkatesh *et al.*, 2003:450) to create effort expectancy.

Various studies have proven the influence of effort expectancy on behavioural intention. In both studies of Venkatesh *et al.* (2012:159; 2003:450) using the UTAUT and UTAUT2, this construct was found to significantly influence behavioural intention. Further research by Alalwan *et al.* (2018), Chopdar *et al.* (2018), Lee *et al.* (2018), Parker and Wang (2016), Hew *et al.* (2015), Persson and Berndtsson (2015), Fai (2011) and Wang and Wang (2010), which focused on new technologies or innovations in support of this view, are discussed below.

The construct of effort expectancy from the UTAUT2 and its influence on behavioural intention has been researched in the Internet, mobile banking and mobile app industries (Alalwan *et al.*, 2018; Lee *et al.*, 2018; Hew *et al.*, 2015). In Jordan, Alalwan *et al.* (2018:133) found effort expectancy to have a significant influence on the behavioural intention of consumers to adopt Internet banking, indicating that consumers are more likely to adopt a new technology if they believe that it requires little effort. Consumers cognitively trade off the effort that will be required on their part to use the technology against the advantages they can obtain from using it (Alalwan *et al.*, 2018:128). In the USA, a study by Lee *et al.* (2018:34-35) revealed that tablet users' intentions to purchase apps were influenced significantly by effort expectancy. This indicates that simple-to-use and convenient interfaces heighten the user's intention to adopt it. In Malaysia, Hew *et al.* (2015:1280) also found effort expectancy to have a significant influence on usage intention of mobile apps. According to these researchers, mobile apps must be easy to understand and work if they are to be attractive to users and positively influence behavioural intention (Hew *et al.*, 2015:1284). The aforementioned studies in Internet banking as well as mobile apps acceptance and use indicate that effort expectancy is a strong predictor of behavioural intention.

The effort expectancy construct and its influence on behavioural intention has also been tested in research on mobile shopping (Chopdar *et al.*, 2018; Parker & Wang, 2016; Persson & Berndtsson, 2015; Fai, 2011). Corroborating the findings of Hew *et al.* (2015:1284), Parker and Wang (2016:491) indicate that ease of use is an important enabler of mCommerce engagement. A study conducted in Sweden by Persson and Berndtsson (2015:60) on the acceptance and use of mCommerce, revealed that effort expectancy had a significant influence on behavioural intention, but not in a positive way. It was, in fact, found to have a negative influence. Upon further investigation, Persson and Berndtsson (2015:75) found that this negative influence only applied to smartphone shoppers who had low to moderate experience with shopping via a digital medium. When tested on more experienced shoppers, this construct was found to have a positive influence on behavioural intention. This means that the more experienced the user with shopping via a mobile device, the lesser the impact of effort expectancy on behavioural intention. Chopdar *et al.*'s (2018:120-121) cross-country research on the acceptance and use of mobile shopping apps supports Persson and Berndtsson's (2015:75) findings. Their research revealed that effort expectancy influenced behavioural intention for consumers in India, but not for those in the USA. They maintain that this can be attributed to the fact that American consumers, as compared to Indian consumers, are more technologically savvy and have more experience in using new technologies or innovations such as mobile shopping apps. Fai (2011:113) conducted a three-year study in Hong Kong in an effort to understand mCommerce acceptance and use. The findings revealed that effort expectancy significantly influenced consumers' behavioural intention to use mCommerce. In the first year, it was the strongest determinant of behavioural intention. Fai (2011:113) believes that this was due to the fact that users felt apprehensive of the ease of use of smartphones for mobile shopping purposes. By the second and third year of the study, however, effort expectancy's influence on behavioural intention was reduced, indicating that as users progress and understand mobile shopping apps, they are aware of the effort required, which therefore has less of an impact on whether they would use the app or not. The aforementioned studies in mobile shopping acceptance and use also affirm that effort expectancy is a strong predictor of behavioural intention.

The construct of effort expectancy and its influence on behavioural intention has also been researched in the field of general mobile Internet acceptance and use (Wang & Wang, 2010). Wang and Wang (2010:422) examined users' acceptance of mobile Internet using the UTAUT. They report that effort expectancy has a significant influence on behavioural intention, which reflects consumers' concerns around the time and effort required to learn about and use new technologies such as a mobile shopping app. If, for example, the app's interface is difficult to understand or slow to respond, this will decrease the benefit associated with using the app and in turn, negatively influence behavioural intention. The aforementioned research in mobile

Internet acceptance and use also confirms that effort expectancy is a strong predictor of behavioural intention.

The following hypothesis is therefore proposed:

H_2: Effort expectancy has a positive influence on the behavioural intention of consumers to use mCommerce apps to purchase athleisure apparel.

5.4.1.3 The relationship between social influence and behavioural intention (H_3)

The construct of social influence is described as the belief of an individual that those closest to them, such as family and/or friends, consider that they should try out or use a new technology or innovation (Venkatesh *et al.*, 2012:159). Based on the research in Chapter 4, section 4.2.3, the construct of social influence was created by combining subjective norm from the TRA and TPB, social factors from the model of PC utilisation and observability from the IDT (Persson & Berndtsson, 2015:16; Alkhunaizan & Love, 2012:83; Venkatesh *et al.*, 2003:451).

The influence of social influence on behavioural intention has been widely researched. In the studies by Venkatesh *et al.* (2012:159; 2003:451), this construct was found to significantly influence behavioural intention. Further studies by Gupta *et al.* (2018), Lee *et al.* (2018), Verkijika (2018), Madan and Yadav (2016), Tarhini *et al.* (2016), Persson and Berndtsson (2015), Fai (2011), Yang (2010) and AbuShanab and Pearson (2007) which focus on new technologies or innovations, and which support of this view, are discussed below.

Social influence from the UTAUT2 and its influence on behavioural intention has been researched globally with reference to Internet and mobile banking and mobile apps (Gupta *et al.*, 2018; Lee *et al.*, 2018; Madan & Yadav, 2016; Tarhini *et al.*, 2016; AbuShanab & Pearson, 2007). Tarhini *et al.* (2016:842) analysed Internet banking acceptance and use in Lebanon using an adapted UTAUT. They found social influence to have a significant influence on behavioural intention. Similarly, in Jordan, AbuShanab and Pearson (2007:93) investigated the constructs that impact the acceptance of Internet banking. They found that social influence has a significant influence on consumers' behavioural intention to use Internet banking. Consumers with a high social influence had a stronger intention to use Internet banking, indicating the impact of family and/or friends on ultimate decision-making. These findings are corroborated by Lee *et al.* (2018:34) who looked at the influences on tablet users' intentions to purchase apps. The study revealed a significant relationship between social influence and tablet users' intentions to purchase apps, illustrating the impact of perceived pressure from family or friends on decision-making (Lee *et al.*, 2018:34). Similarly, Gupta *et al.* (2018:147) report that social influence has a significant influence on tourists' behavioural intention to adopt mobile apps. The researchers state that establishing a good rapport with existing app users will assist in spreading positive word of mouth, which will encourage more consumers to accept the mobile app (Gupta *et al.*, 2018:148). Madan and Yadav (2016:237) investigated mobile wallet acceptance in Delhi and found that social influence had a significant influence on consumers' behavioural intention. These researchers observed that an individual's family, friends and peers have a significant influence on the behaviour of that individual. Individuals with a great deal of social influence are perceived as having higher credibility compared to other sources of information and thus positive word of mouth from these individuals serves as a greater persuader to drive others to test new technologies or innovations (Madan & Yadav, 2016:239). The aforementioned studies in Internet banking as well as mobile apps acceptance and use indicate that social influence is a strong predictor of behavioural intention.

The social influence construct and its effect on behavioural intention has also been tested in research on mobile shopping (Verkijika, 2018; Persson & Berndtsson, 2015; Fai, 2011; Yang, 2010). In Cameroon, Verkijika (2018:1672) analysed mCommerce app acceptance, using an adapted version of the UTAUT2. The researcher found social influence to have a marked influence on consumers' behavioural intention to use mCommerce apps. Similarly, Persson and Berndtsson (2015:68) conducted research in Sweden on consumers' acceptance and use of mCommerce and discovered that social influence has a significant influence on behavioural intention. The researchers further state that the more experienced a consumer is in using an mCommerce app, the less likely they are to believe that their family, friends or peers will have an influence over their intention to shop via their mobile phones (Persson & Berndtsson, 2015:70). Yang's (2010:266) earlier findings concur with those of Persson and Berndtsson (2015:68). Yang (2010:266) explored US consumers' acceptance of mobile shopping services. The findings established that social influence has a significant influence on behavioural intention. A three-year Hong Kong study on mCommerce acceptance and use by Fai (2011:112-113) also found social influence to have a significant influence on behavioural intention. In the first year of the study, social influence had a significant influence on behavioural intention, although this was less so than performance expectancy. In year two, social influence had the most significant influence on behavioural intention compared to performance expectancy and effort expectancy. According to the researcher, this may be as a result of smartphone users already being aware of performance and effort expectancies one year into the study and thus their behavioural intention was more affected by social influence. When all three years' data is combined though, social influence shows the most significant effect on behavioural intention. The aforementioned studies in mobile shopping acceptance and use affirm that social influence is a strong predictor of behavioural intention.

The construct of social influence and its influence on behavioural intention has also been researched in the field of general mobile Internet acceptance and use (Wang & Wang, 2010). Wang and Wang (2010:422) explored mobile Internet acceptance and found social influence to have a marked effect on behavioural intention. According to these researchers, organisations operating within the mCommerce domain should remain cognisant of the power of social influence. As users become *au fait* with mobile shopping apps, they will start talking about it, telling friends and family and persuading them to test the technology too. The aforementioned research in mobile Internet acceptance and use also affirms that social influence is a strong predictor of behavioural intention.

The following hypothesis is therefore proposed:

H_3: Social influence has a positive influence on the behavioural intention of consumers to use mCommerce apps to purchase athleisure apparel.

5.4.1.4 The relationship between facilitating conditions and behavioural intention (H_4)

The construct of facilitating conditions, according to Venkatesh et al. (2012:159), is described as an individual's perceptions regarding the resources and support available to them when performing a specific behaviour. Considering the discussion in Chapter 4, section 4.2.4, facilitating conditions was formed by uniting three constructs from three different technology acceptance models. Perceived behavioural control from the TPB was combined with facilitating conditions from the model of PC utilisation and compatibility from the IDT (Alkhunaizan & Love, 2012:83; Venkatesh *et al.*, 2003:453) to create the UTAUT2 facilitating conditions construct.

A number of studies have considered the influence of facilitating conditions on behavioural intention. Venkatesh *et al.* (2012:159) contend that this construct has a significant influence on behavioural intention; if a consumer has the necessary support at their disposal, they will show the intention to use the technology and will proceed to actually use it (Venkatesh *et al.*, 2012:162). Further research by Chopdar *et al.* (2018), Madan and Yadav (2018; 2016), Verkijika (2018), Miladinovic and Xiang (2016), Hew *et al.* (2015), Akbar (2013) and Yang (2010), which focus on new technologies or innovations, and which support this view, are discussed below.

The construct of facilitating conditions from the UTAUT2 and its influence on behavioural intention has been researched in the general technology domain, as well as mobile apps industries (Madan & Yadav, 2016; Hew *et al.*, 2015; Akbar, 2013). In Delhi, Madan and Yadav (2016:237) tested factors influencing consumers' behavioural intention to use mobile wallets. Their research indicated that facilitating conditions had a significant role to play on consumers' behavioural intention to use mobile wallets. Madan and Yadav (2016:239) further state that the necessary resources to enter into a mobile wallet transaction include knowledge on the consumer’s part, a smartphone that is Internet-enabled and a mobile network with sufficient Internet speed. All these resources combine together to create facilitating conditions which exert an influence over behavioural intention. Similar resources are required for mobile shopping. Hew *et al.*’s (2015:1280) study on mobile app acceptance by Malaysians also found facilitating conditions to have a strong influence on behavioural intention. In Qatar, Akbar (2013:22) sought to determine what affects students’ acceptance and use of technology. The original hypothesis stated that facilitating conditions would not have a significant influence on behavioural intention, however, the research proved this to be incorrect, indicating instead a significant relationship between the two constructs. The aforementioned studies in the general technology domain, as well as mobile apps industries, indicate that facilitating conditions are a strong predictor of behavioural intention.

Facilitating conditions and their influence on behavioural intention have also been tested in studies on mobile shopping (Chopdar *et al.*, 2018; Madan & Yadav, 2018; Verkijika, 2018; Miladinovic & Xiang, 2016; Yang, 2010). The study of Chopdar *et al.* (2018:120-121) in the USA and India on the acceptance and use of mobile shopping apps revealed that facilitating conditions had a significant influence on behavioural intention in both countries. The researchers state that the use of a mobile shopping app requires a number of different skills and resources to be at the disposal of the consumer including, for example, connecting the device to the Internet, installing different apps, using the apps, etc. Therefore, a complimentary set of facilitating conditions will increase the likelihood of consumers accepting and using mobile shopping (Chopdar *et al.*, 2018:113). Verkijika’s (2018:1672) research on mCommerce app acceptance in Cameroon also revealed a significant relationship between facilitating conditions and behavioural intention. This indicates that the availability of customer support and training on how to use mCommerce apps is vital to their successful acceptance. Madan and Yadav (2018:156-157) conducted a study in Delhi on the antecedents of mobile shopping acceptance and use. The findings indicated that facilitating conditions have a significant influence on behavioural intention, but that this relationship is moderated by the consumer’s age. Older consumers were inclined to require more support services compared to younger ones. Miladinovic and Xiang’s (2016:45) report similar results. They examined the constructs influencing consumer acceptance of mCommerce in Sweden and found a statistically significant relationship between facilitating conditions and behavioural intention. Miladinovic and Xiang (2016:45) further argue that consumers regard having support available while using mCommerce apps as important, thus the better the support, the more willing the consumer becomes to accepting mCommerce apps. Yang's (2010:266) study also supports this, indicating a statistically significant relationship between facilitating conditions and consumers' behavioural intention to use mobile shopping services. The aforementioned studies on mobile shopping acceptance and use affirm that facilitating conditions are a strong predictor of behavioural intention.

The following hypothesis is therefore proposed:

H_4: Facilitating conditions have a positive influence on the behavioural intention of consumers to use mCommerce apps to purchase athleisure apparel.

5.4.1.5 The relationship between hedonic motivation and behavioural intention (H_6)

The construct of hedonic motivation is described as a consumer's level of enjoyment derived from the use of a new technology or innovation, such as shopping via a mobile app (Venkatesh *et al.*, 2012:161). Alalwan *et al.* (2018:128) state that hedonic motivation in the technology industry refers to playfulness or enjoyment on the consumer's part as a result of engaging with a particular technology or innovation.

The influence of hedonic motivation on behavioural intention has been widely researched. Venkatesh *et al.* (2012:171) indicate that this construct is a critical determinant of behavioural intention. Further research by Alalwan *et al.* (2018), Chopdar *et al.* (2018), Madan and Yadav (2018), Verkijika (2018), Miladinovic and Xiang (2016) and Hew *et al.* (2015), which focus on new technologies or innovations, and which support this view, are discussed below.

Hedonic motivation from the UTAUT2 and its influence on behavioural intention has been researched in the Internet and mobile banking field as well as the mobile app industry (Alalwan *et al.*, 2018; Hew *et al.*, 2015). In Jordan, Alalwan *et al.* (2018:133-134) found that hedonic motivation plays a crucial role in enhancing consumers' behavioural intention to use Internet banking. It was, in fact, found to be the construct that exerted the most influence on behavioural intention. This view is also supported by Hew *et al.* (2015:1285) who examined mobile app acceptance in Malaysia. They found a significant influence between hedonic motivation and behavioural intention. In this particular study, hedonic motivation was the second most significant construct in the model tested. These studies on Internet and mobile banking as well as mobile apps, affirm that hedonic motivation is a strong predictor of behavioural intention.

The hedonic motivation construct and its influence on behavioural intention has also been tested extensively in mobile shopping research across the globe (Chopdar *et al.*, 2018; Verkijika, 2018; Miladinovic & Xiang, 2016). Chopdar *et al.*'s (2018:122) cross-country USA and India research on mobile shopping app acceptance and use found hedonic motivation to have a significant relationship with behavioural intention in both countries. These researchers state that app developers should endeavour to design apps that are enjoyable to use, to ensure an enhanced shopping experience. Miladinovic and Xiang's (2016:22) research shows a significant relationship between hedonic motivation and Swedish users' behavioural intention to use mobile shopping fashion apps. The researchers state that if a consumer's engagement with a specific technology kindles feelings of pleasure, the consumer will gain enjoyment from that engagement. This will, in turn, influence the consumer's behavioural intention to pursue that technology (Miladinovic & Xiang, 2016:23). Verkijika's (2018:1668) research in Cameroon on mCommerce app acceptance supports these studies. The results suggest that the enjoyment from using an innovation or new technology, such as an mCommerce app, prompts the individual's behavioural intention to use that technology and indeed, elicits a feeling of fun. The aforementioned studies in mobile shopping acceptance and use affirm that hedonic motivation is a strong predictor of behavioural intention.

The following hypothesis is therefore proposed:

H_6: Hedonic motivation has a positive influence on the behavioural intention of consumers to use mCommerce apps to purchase athleisure apparel.

5.4.1.6 The relationship between price value and behavioural intention (H_7)

Price value, according to Venkatesh et al. (2012:161), refers to the trade-off between the perceived benefit of using a new technology or innovation and the monetary expense of it. This construct was added to the UTAUT2 as the original UTAUT only included constructs that considered time and effort.

A number of studies have considered the influence of price value on behavioural intention. Venkatesh *et al.*'s (2012:161) research indicates this construct has a significant influence on behavioural intention. Further studies by Alalwan *et al.* (2018), Chopdar *et al.* (2018), Madan & Yadav (2016), Alkhunaizan and Love (2012) and Wu and Wang (2005), which focus on new technologies or innovations, and which support this view, are discussed below.

Price value from the UTAUT2 and its influence on behavioural intention, has been researched in the Internet and mobile banking, as well as mobile apps industries (Alalwan *et al.*, 2018; Madan & Yadav, 2016). In Jordan, Alalwan *et al.* (2018:133) scrutinised consumers' acceptance and use of Internet banking and found a significant positive relationship between price value and behavioural intention. This suggests that consumers are more inclined to use a new technology such as Internet banking if they perceive the utility offered by the technology to be greater than the monetary cost associated with its use. Madan and Yadav (2016:237) found similar results in their Indian study on mobile wallet acceptance. Their research revealed a positive relationship between perceived value and behavioural intention. The perceived value construct represents that of price value in their study with these two constructs carrying the same definition. These studies in Internet and mobile banking, as well as mobile apps, affirm that price value is a strong predictor of behavioural intention.

Price value and its influence on behavioural intention has also been tested in research on mobile shopping (Chopdar *et al.*, 2018; Alkhunaizan & Love, 2012; Wang, 2005). Chopdar *et al.'s* (2018:121) cross-country research in the USA and India on mobile shopping app acceptance and use discovered that price value significantly influenced behavioural intention for Indian consumers, but not for American consumers. The researchers state that this suggests Indian consumers value their money more than

American consumers, which may reflect the realities of consumers in a developing country (similar to South Africa) who value money more. In essence therefore, these developing country consumers think twice before spending. Alkhunaizan and Love (2012:85) echo Chopdar *et al.*'s (2018:121) sentiments in their research from India. According to these researchers, cost is a critical component in a consumer's decision-making process when deciding whether or not to accept and use a new technology, such as mobile shopping. Wu and Wang (2005:726) add weight to this argument, stating that cost is one of the constructs that most negatively influences consumers' behavioural intention to use a new technology. In contrast, Venkatesh *et al.* (2012:161) contend that if the perceived benefit of using the new technology overshadows the monetary cost of using it, the construct will have a positive influence on the consumer's behavioural intention to use the technology. The aforementioned studies on mobile shopping indicate that price value is a strong predictor of behavioural intention.

The following hypothesis is therefore proposed:

H_7: Price value has a positive influence on the behavioural intention of consumers to use mCommerce apps to purchase athleisure apparel.

5.4.1.7 The relationship between habit and behavioural intention (H_8)

Habit is described as performing a particular behaviour in an automated fashion based on prior conditioning (Venkatesh *et al.*, 2012:158). A number of studies have considered the influence of habit on behavioural intention. Venkatesh *et al.* (2012:161) relate that this construct has a significant influence on behavioural intention. Further studies by Gupta *et al.* (2018), Miladinovic and Xiang (2016) and Hew *et al.* (2015), which focus on new technologies or innovations, and which support this view, are discussed below.

The construct of habit from the UTAUT2 and its influence on behavioural intention has been researched in the mobile app and mobile shopping industries (Gupta *et al.*, 2018; Miladinovic & Xiang, 2016; Hew *et al.*, 2015). Miladinovic and Xiang's (2016:45) mobile shopping app acceptance study shows a statistically significant relationship between habit and behavioural intention. The researchers state that if a particular task or activity is habitual in nature, a consumer will rely less on external factors and choice strategies (Miladinovic & Xiang, 2016:24). Gupta *et al.* (2018:145) concur; their smartphone app acceptance study found habit to have a significant influence on the behavioural intention of tourists to use mobile apps. Hew *et al.*'s (2015:1280) research also found that behavioural intention to use mobile apps was significantly influenced by habit. The aforementioned studies in the mobile app and mobile shopping industries affirm that habit is a strong predictor of behavioural intention.

The following hypothesis is therefore proposed:

H_8: Habit has a positive influence on the behavioural intention of consumers to use mCommerce apps to purchase athleisure apparel.

As demonstrated in the aforementioned studies, hypotheses 1-4 and 6-8 are validated. The following section validates hypotheses 5 and 9.

5.4.2 The relationships between the independent variables of facilitating conditions and habit and actual use

This section provides an overview of the relationships between the independent variables of facilitating conditions and habit and actual use (or adoption), as depicted in Figure 5.2 below.

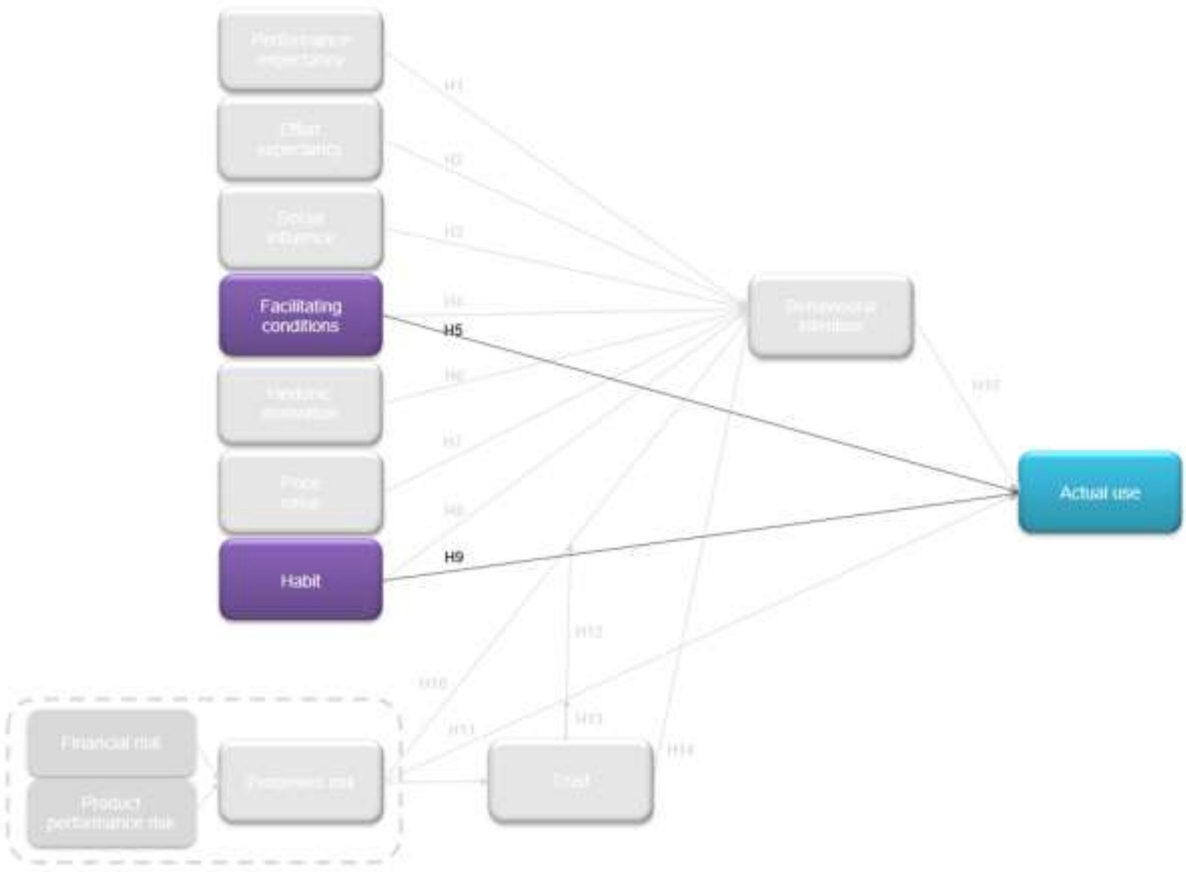


Figure 5.2: Relationships between the independent variables of facilitating conditions and habit and actual use

Source: *Researcher's own construct*

5.4.2.1 The relationship between facilitating conditions and actual use (H_5)

As discussed in section 5.4.1.4, facilitating conditions refers to the perceptions of an individual on the available resources or support when performing a specific behaviour (Venkatesh *et al.*, 2012:159). Researchers have attempted to understand the relationship between facilitating conditions and actual use, however, results have been mixed. Venkatesh *et al.* (2012:159; 2003:453) report that this construct significantly influences actual use. Further studies by Alalwan *et al.* (2018), Tarhini *et al.* (2016) and Yang (2010), which focus on new technologies or innovations, and which support this view, are discussed below.

The construct of facilitating conditions from the UTAUT2 and its influence on actual use has been researched in the Internet and mobile banking, as well as mobile shopping industries (Alalwan *et al.*, 2018; Tarhini *et al.*, 2016; Yang, 2010). Alalwan *et al.* (2018:134) found similar results to Venkatesh *et al.* (2012; 2003), maintaining that there is a statistically significant relationship between facilitating conditions and actual use of Internet banking. According to the researchers, this can be ascribed to the nature of the facilities required to conduct Internet banking such as a working Internet or Wi-Fi connection and access to a secure website or app. This is similar to some of the facilities needed to adopt mobile shopping (Miladinovic & Xiang, 2016:22). Yang (2010:267) agrees, stating that facilitating conditions are critical in consumers' adoption of mCommerce. Tarhini *et al.* (2016:842-843) also indicate that facilitating conditions are a significant determinant of consumers' actual use of Internet banking. They state that it is imperative for banks to invest more in infrastructural development and customer service enhancement to ensure the required service and/or training is delivered to the customer, as this has a significant influence on whether or not the customer will use Internet banking. The aforementioned studies in Internet and mobile banking as well as mobile shopping, indicate that facilitating conditions are a strong predictor of actual use.

The following hypothesis is therefore proposed:

H_5: Facilitating conditions have a positive influence on consumers' actual use of mCommerce apps to purchase athleisure apparel.

5.4.2.2 The relationship between habit and actual use (H_9)

As discussed in section 5.4.1.7, habit refers to an individual performing a specific behaviour in an automatic fashion based on prior learning (Venkatesh *et al.*, 2012:158). The influence of habit on actual use has been researched to a lesser extent. Venkatesh *et al.* (2012:161) indicate that this construct has a significant influence on actual use. Further studies by Alalwan *et al.* (2018) and Gupta *et al.* (2018), which focus on new technologies or innovations, and which support this view, are discussed below.

The influence of habit on actual use has been tested in research on Internet and mobile banking and mobile app adoption and use (Alalwan *et al.*, 2018; Gupta *et al.*, 2018).

Alalwan *et al.*'s (2018:129) Jordanian study on Internet banking acceptance and use found that even though behavioural intention is the most important determinant of actual use, habit has the second strongest influence on consumers' actual use of Internet banking. Gupta *et al.* (2018:146) concur, stating that habit is the only other construct besides behavioural intention that has a significant influence on tourists' actual use of mobile apps. This research affirms that habit is a strong predictor of actual use.

The following hypothesis is therefore proposed:

H_9: Habit has a positive influence on consumers' actual use of mCommerce apps to purchase athleisure apparel.

As demonstrated in the aforementioned studies, hypotheses 5 and 9 are validated. The following section validates hypothesis 10.

5.4.3 The relationship between the independent variable of perceived risk and behavioural intention (H_{10})

This section discusses the relationship between the independent variable of perceived risk and behavioural intention (or acceptance), as depicted in Figure 5.3.

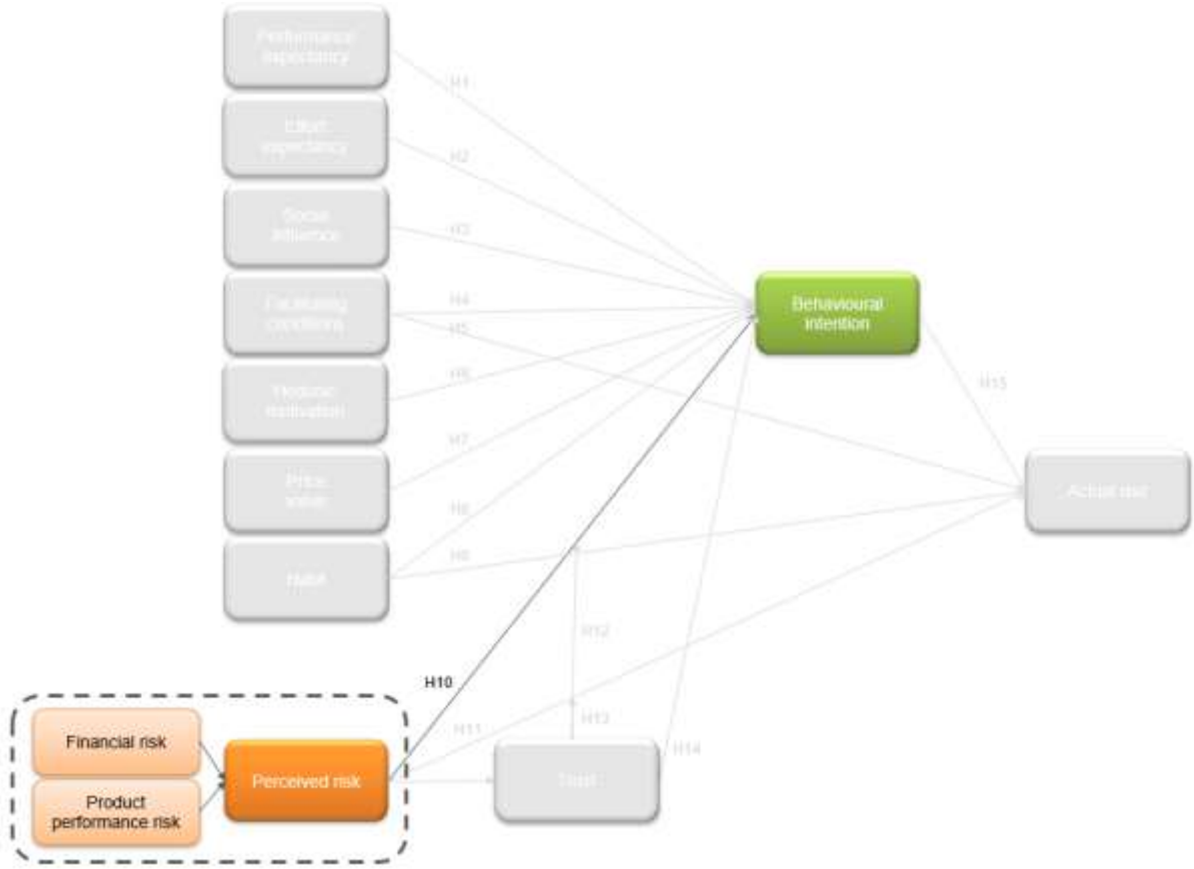


Figure 5.3: The relationship between the independent variable of perceived risk and behavioural intention

Source*: Researcher's own construct*

As discussed in Chapter 4, section 4.3, perceived risk is described as the level and type of risk, as assessed by an individual, when planning a purchase decision (Chen, 2013:316; Forsythe & Shi, 2003:869). A number of studies have considered the influence of perceived risk on behavioural intention. Alalwan *et al.* (2018:129) report that various features related to this construct have been cited as negative influences on behavioural intention. Kesharwani and Bisht (2012:307) state that perceived risk negatively influences consumers' behavioural intention to conduct transactional business with Internet retailers. Further studies by Alalwan *et al.* (2018), Gupta *et al.* (2018), Madan and Yadav (2018), Verkijika (2018), Madan and Yadav (2016), Vasileiadis (2014), Chen (2013), Thakur and Srivastava (2013), Kesharwani and Bisht (2012) and Wu and Wang (2005), which focus on new technologies or innovations, and which support this view, are discussed below.

The influence of perceived risk on behavioural intention has been tested in studies on Internet and mobile banking and mobile app adoption and use (Alalwan *et al.*, 2018; Gupta *et al.*, 2018; Madan & Yadav, 2016; Chen, 2013; Kesharwani & Bisht, 2012). Alalwan *et al.'s* (2018:134) Jordanian study tested factors influencing consumers' intention to adopt Internet banking by adapting the UTAUT2 to incorporate perceived risk. Before testing, they determined that the standard UTAUT2 was able to predict roughly 58% of the variance in behavioural intention. After the addition of perceived risk, this increased by 10.3% to 64%. The researchers concluded that the addition of perceived risk led to the model having stronger explanatory power in its prediction of behavioural intention. The results proved that perceived risk has a significant negative influence on the behavioural intention of Jordanian consumers to adopt Internet banking. Consumers are therefore less likely to use a new technology such as mCommerce if they have a higher perception of suffering a loss. These findings are supported by Chen's (2013:428) Taiwanese study on consumers' intention to use mobile banking services. The findings showed perceived risk to have a significant negative influence on consumers' behavioural intention. Madan and Yadav (2016:232; 239) explain that mobile phones store vital personal information, which leads to an increase in perceived risk on the consumer's part. Their research validates this, indicating a significant negative influence between perceived risk and the behavioural intention of consumers to use a mobile wallet. They maintain that, as with mobile shopping, a number of stakeholders are involved in a mobile wallet transaction, i.e. the consumer, the merchant, the network service provider, etc. Important information is exchanged during the transaction, therefore the various providers involved in the transaction should ensure that the necessary security is in place to minimise any potential risk to the consumer. Kesharwani and Bisht's (2012:315) study revealed similar findings, reporting a significant negative relationship between perceived risk and the behavioural intention of consumers to adopt Internet banking in India. This finding is echoed by Gupta *et al.* (2018:145) in their study on tourist acceptance of smartphone apps. The findings revealed that perceived risk has a statistically significant negative influence on behavioural intention. These studies in Internet and mobile banking as well as mobile apps, affirm that perceived risk has a strong influence on behavioural intention.

The influence of perceived risk on behavioural intention has been further tested in research on mobile shopping (Madan & Yadav, 2018; Verkijika, 2018; Vasileiadis, 2014; Thakur & Srivastava, 2013; Wu & Wang, 2010). In India, Thakur and Srivastava (2013:65) looked at consumers' intention to use mCommerce. They first tested whether perceived risk is accurately explained through security risk and privacy risk. The findings indicated that these two sub-constructs were statistically significant in predicting perceived risk. Secondly, the researchers tested whether perceived risk negatively influenced Indian consumers' behavioural intention to use mCommerce. The results indicated a statistically significant negative relationship between perceived risk and behavioural intention. mCommerce retailers' biggest challenge in ensuring the acceptance of mCommerce, according to Madan and Yadav (2018:146; 156), is to reduce the level of perceived risk and increase the level of trust in their apps. These researchers explored the antecedents of mobile shopping acceptance in Delhi and found that perceived risk has a significant negative influence on consumers' behavioural intention to use mobile shopping. Similar findings were reported by Verkijika (2018:1673) in his study on mCommerce acceptance in Cameroon. He concludes that mCommerce retailers need to actively communicate their commitment to protecting users' information (to reduce financial risk) and ensuring correct and quality product delivery (to reduce product performance risk). Vasileiadis (2014:187) concurs, stating that perceived risk has a significant negative influence on consumers' behavioural intention to adopt mCommerce. Similarly, Wu and Wang's (2005:726) research also shows a significant negative influence between perceived risk and behavioural intention to adopt mCommerce. The aforementioned studies in mobile shopping affirm that perceived risk has a significant influence on behavioural intention.

The following hypothesis is therefore proposed:

H_{10}: Perceived risk has a negative influence on the behavioural intention of consumers to use mCommerce apps to purchase athleisure apparel.

As demonstrated in the aforementioned studies, hypothesis 10 is validated. The following section validates hypothesis 11.

5.4.4 The relationship between the independent variable of perceived risk and actual use (H_{11})

This section discusses the relationship between the independent variable of perceived risk and actual use (or adoption), as depicted in Figure 5.4.

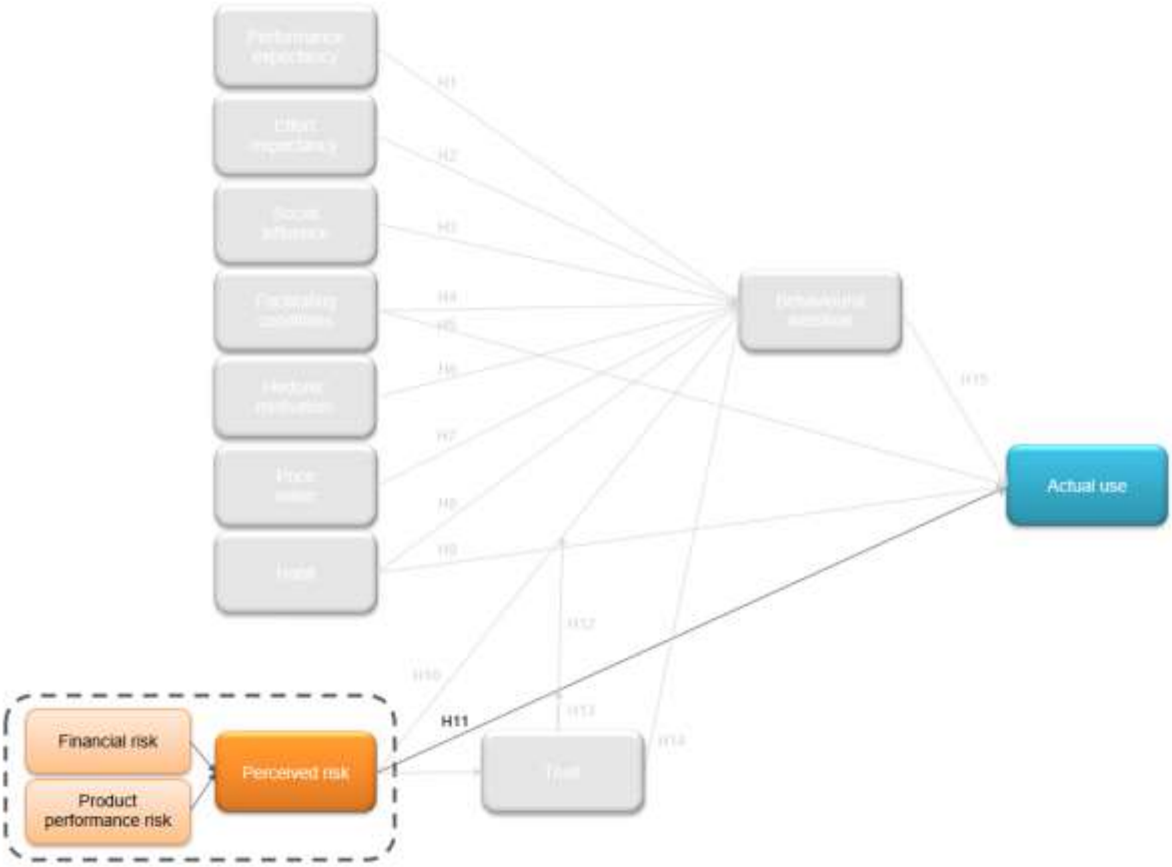


Figure 5.4: The relationship between the independent variable of perceived risk and actual use

***Source**: Researcher's own construct*

The influence of perceived risk on actual use has been researched to a lesser extent. Various features related to the construct of perceived risk, according to Alalwan et al. (2018:129), have been cited as negative influences on not only behavioural intention, but also actual use. Farivar *et al.* (2017:591), for example, state that people tend to prefer less risky behaviour over more risky behaviour. Perceived risk therefore is an inhibiting construct, deterring consumers from conducting specific actions such as actually purchasing via mCommerce channels. A study by Matikiti *et al.* (2016:30) states that perceived risk deters consumers from using new technologies, such as mCommerce. Gerber, Ward and Goedhals-Gerber (2014:105) conducted a South African study in 2014 on online shopping and found that perceived risk had an impact on online buying behaviour. To address this, mCommerce retailers should actively instil confidence in consumers, ensuring them that platforms are secure, orders are correct and delivered on time. This is supported by Wu and Wang (2005:726), who also found perceived risk to influence actual use in a study on mCommerce. Lee, Park and Ahn's (2001:117) research provides further support, with findings indicating that perceived risk negatively influences consumers' actual use of eCommerce. These researchers reiterate the importance of online and mobile shopping retailers instilling confidence in consumers to overcome perceptions surrounding risk. These studies in online and mobile shopping affirm that perceived risk has a significant influence on actual use.

The following hypothesis is therefore proposed:

H_{11}: Perceived risk has a negative influence on consumers' actual use of mCommerce apps to purchase athleisure apparel.

As demonstrated in the aforementioned studies, hypothesis 11 is validated. The following section validates hypothesis 12.

5.4.5 The relationship between perceived risk and behavioural intention, mediated by trust (H_{12})

This section discusses the relationship between perceived risk and behavioural intention (or acceptance), mediated by trust, as depicted in Figure 5.5.

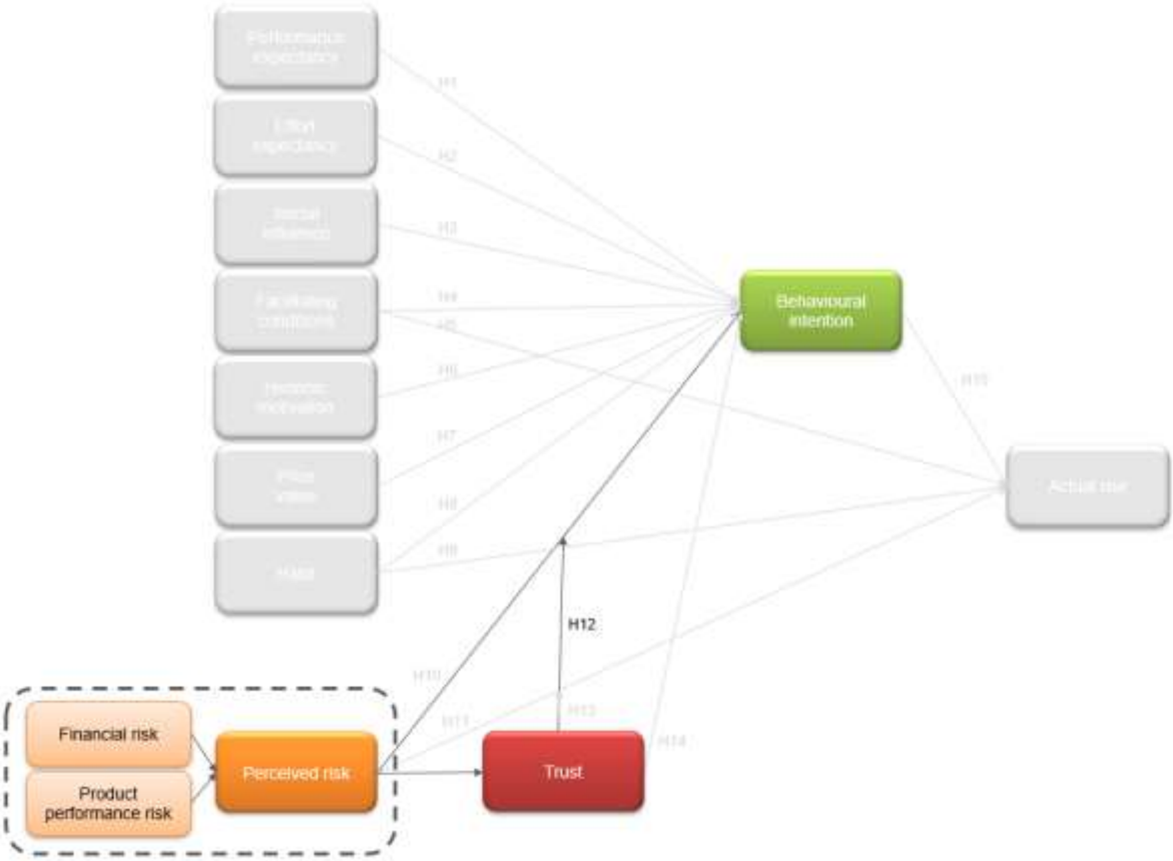


Figure 5.5: The relationship between perceived risk and behavioural intention, mediated by trust

***Source**: Researcher's own construct*

As discussed in Chapter 4, section 4.3 and section 5.4.3, perceived risk refers to the type and level of risk perceived by a consumer during the planning stages of a purchase decision (Chen, 2013:316; Forsythe & Shi, 2003:869). As discussed in Chapter 4, section 4.4, trust is described as one party's willingness to be exposed to the actions of another in the hope that the other party will deliver a specific action without exerting any control over them (Ter Huurne *et al.*, 2017:486). There is a relationship between these two constructs, i.e. perceived risk and trust, according to Amoroso and Hunsinger (2009:25) and Farivar *et al.* (2017:592). Hong and Cha (2013:929) confirm that the relationship is so close, that it is virtually inseparable. Suh *et al.*'s (2015:138) research found trust to be a key antecedent to perceived risk. As trust decreases, perceived risk increases, which reduces behavioural intention (Lim, 2003:218). This is an interesting phenomenon; this study seeks to understand the mediating influence of trust on the relationship between perceived risk and behavioural intention, specifically in relation to South Africans' acceptance and use of mCommerce apps to purchase athleisure apparel.

Farivar *et al.* (2017:592) contend that trust not only has a direct influence on consumers' behavioural intention to conduct transactions online, but also has an indirect influence by reducing consumers' perceived risk. Kesharwani and Bisht (2012:315-316) report similar findings. The state that trust has a statistically significant influence on perceived risk, which suggests that enhancing trust could reduce perceived risk. Gao and Bai (2014:217) concur, stating that one of the most effective methods of diminishing risk and uncertainty is trust. These studies affirm that trust has a mediating influence on the relationship between perceived risk and behavioural intention.

The following hypothesis is therefore proposed:

H_{12}: Trust mediates the negative influence of perceived risk on the behavioural intention of consumers to use mCommerce apps to purchase athleisure apparel.

As demonstrated in the aforementioned studies, hypothesis 12 is validated. The following section validates hypothesis 13.

5.4.6 The relationship between perceived risk and actual use, mediated by trust (H_{13})

This section discusses the relationship between perceived risk and actual use (or adoption), mediated by trust. This relationship is depicted in Figure 5.6.

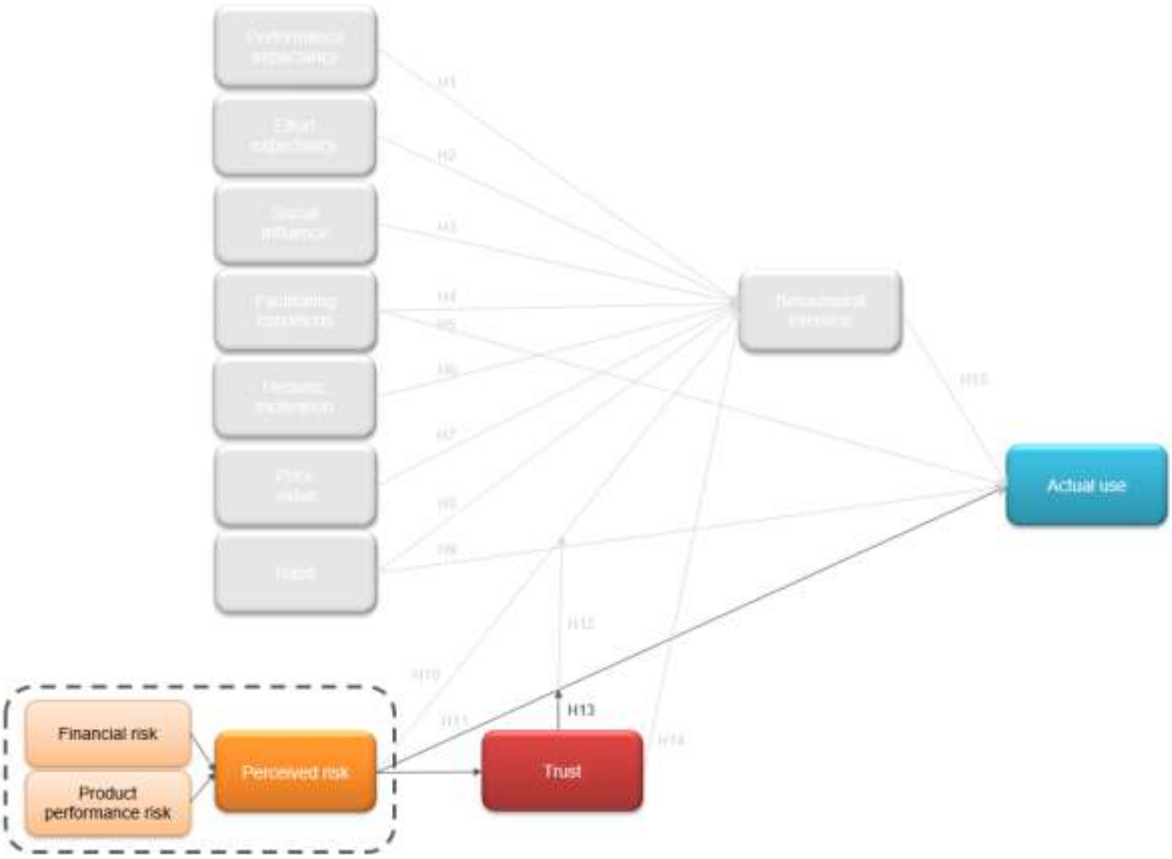


Figure 5.6: The relationship between perceived risk and actual use, mediated by trust
***Source**: Researcher's own construct*

Trust has been regarded as a facilitator of transactional relationships across a number of different industries including marketing, communication and information systems, to name but a few (Huo *et al.*, 2018:131). As discussed in section 5.4.5, trust has been proven to reduce perceived risk (Farivar *et al.*, 2017:592; Gao & Bai, 2014:217; Kesharwani & Bisht, 2012:315-316). Some researchers observe that trust leads to risk-taking as the presence of trust in a relationship boosts confidence, certainty and predictability which, in turn, leads to a greater willingness to take a risk (Huo *et al.*, 2018:131). Suh *et al.* (2015:138) report that studies on digital transactions have found trust to be key in the ultimate success of digital retailing businesses. Trust therefore has an important role to play in this study as it reduces risk and facilitates the acceptance and use of a new technology, such as mCommerce.

A meta-analysis of the effect of trust and perceived risk on use behaviour revealed that as trust increases, perceived risk decreases and users will therefore be more inclined to use an innovation or new technology, such as mCommerce (Wang *et al.*, 2016:39). This points to trust having a mediating influence on the perceived risk associated with the use of a new technology.

The following hypothesis is therefore proposed:

H_{13}: Trust mediates the negative influence of perceived risk on consumers' actual use of mCommerce apps to purchase athleisure apparel.

As demonstrated in the aforementioned studies, hypothesis 13 is validated. The following section validates hypothesis 14.

5.4.7 The relationship between trust and behavioural intention (H_{14})

This section provides an overview of the relationship between trust and behavioural intention (or acceptance), as depicted in Figure 5.7.

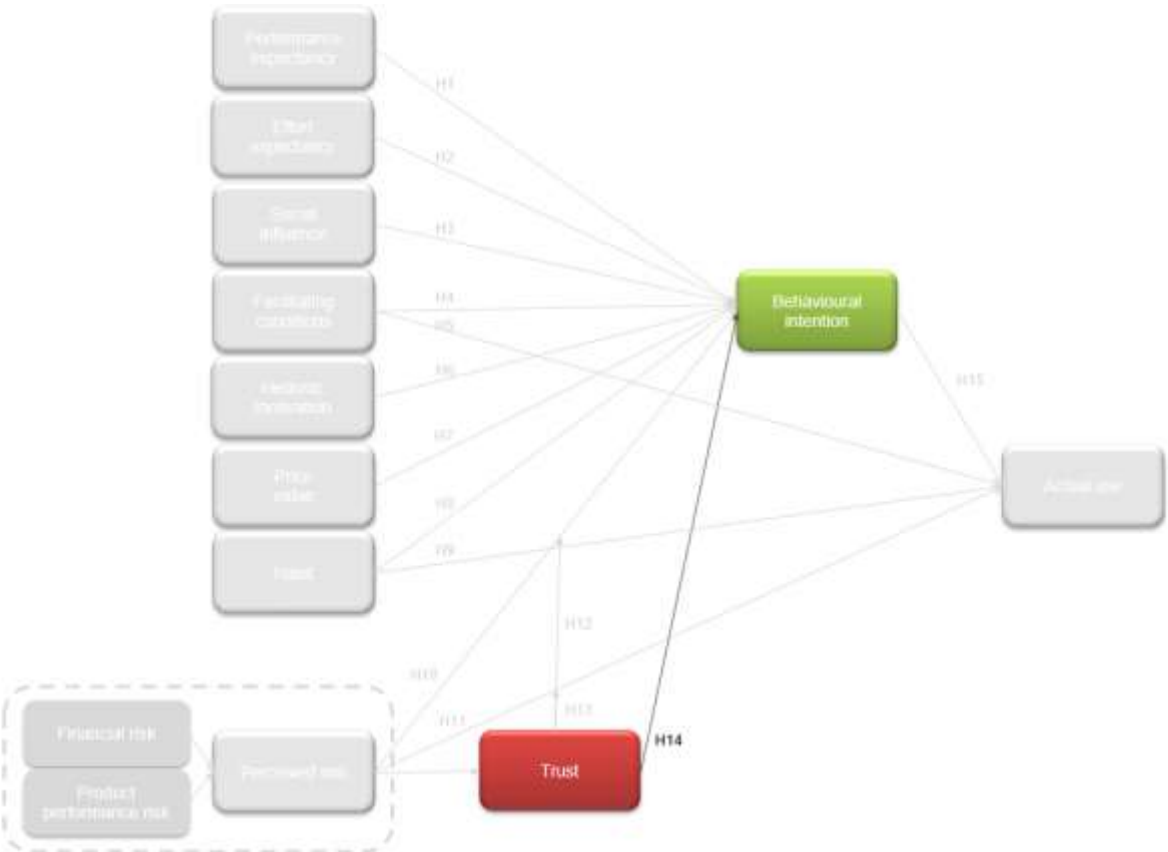


Figure 5.7: The relationship between trust and behavioural intention

***Source**: Researcher's own construct*

As discussed in Chapter 4, section 4.4 and section 5.4.5, Ter Huurne *et al.* (2017:486) describe trust as one party's willingness to be open to the actions of another party, built on the belief that the other party will perform a specific action that is of importance to the first party, regardless of whether or not the other party can be controlled or monitored. In the context of online or mobile shopping, trust denotes an individual's expectations of a website, mobile site or app. More specifically, it denotes expectations linked to the believability of the information on the website, mobile site or app, whether it will deliver on expectations and whether it elicits confidence. Once a positive impression of the website, mobile site or app is formed in the consumer's mind, only then is trust established (Rogers, 2010:26-27). Daud and Hassan (2011:169) state that greater the consumer's trust in the seller, the greater the likelihood of behavioural intention to purchase. The relationship between these two constructs, i.e. trust and behavioural intention, has been researched by a number of different researchers including Gupta *et al.* (2018), Farivar *et al.* (2017), Chaouali *et al.* (2016), Suh *et al.* (2015), Gao *et al.* (2014), Vasileiadis (2014), Chong (2013) and Joubert and van Belle (2013), which are elaborated on below.

The construct of trust and its influence on behavioural intention has been tested in studies on online and mobile shopping (Farivar *et al.*, 2017; Suh *et al.*, 2015; Vasileiadis, 2014; Chong, 2013; Joubert & van Belle, 2013). Trust has been proven to increase consumers' behavioural intention to transact in a digital retailing environment (Farivar *et al.*, 2017:591). These researchers tested the importance of trust and risk in consumers' acceptance of social commerce. The findings revealed that trust in the website positively influenced consumers' behavioural intention to use it (Farivar *et al.*, 2017:597). In South Africa specifically, trust has been cited as the most common reason for low online shopping rates (IT News Africa, 2016). Joubert and van Belle's (2013:33) research on mCommerce acceptance in South Africa found that trust significantly influences usage intention. Suh *et al.* (2015:138) affirm that the effects of have a significant influence on consumers' purchase intention of online tickets. Similarly, Vasileiadis (2014:187-188) found trust to have a direct positive influence on consumers' intention to use mCommerce. This researcher advises that online or mobile retailers can safeguard trust by ensuring a good reputation, good security, transparency regarding data usage and certain guarantees in case of dispute, for example, a policy for the return of damaged goods. By ensuring these elements are in place, online or mobile retailers can boost consumer trust in their platforms. Chong (2013:1245) echoes these findings in a study on mCommerce acceptance in China. The results revealed that trust was the strongest predictor of consumers' behavioural intention to adopt mCommerce. The aforementioned studies in online and mobile shopping indicate that trust has a significant influence on behavioural intention.

The construct of trust and its influence on behavioural intention has also been tested in research on the acceptance and use of Internet banking and mobile apps (Gupta *et al.*, 2018; Chaouali *et al.*, 2016; Gao *et al.*, 2014). Gupta *et al.* (2018:145) found perceived trust to significantly influence tourists' behavioural intention to adopt mobile apps. Similarly, Gao *et al.* (2014:162) found that trust had a significant positive influence on consumers' intention to use mobile information services. Chaouali *et al.* (2016:211) also reported that consumers' trust in Internet banking had a statistically significant positive influence on their intention to use Internet banking. The aforementioned studies on Internet banking and mobile app acceptance and use indicates that social influence is a strong predictor of behavioural intention.

The following hypothesis is therefore proposed:

H_{14}: Trust has a positive influence on the behavioural intention of consumers to use mCommerce apps to purchase athleisure apparel.

As demonstrated in the aforementioned studies, hypothesis 14 is validated. The following section validates the final hypothesis, hypothesis 15.

5.4.8 The relationship between behavioural intention and actual use (H_{15})

This section provides an overview of the relationship between behavioural intention (or acceptance) and actual use (or adoption), as depicted in Figure 5.8.

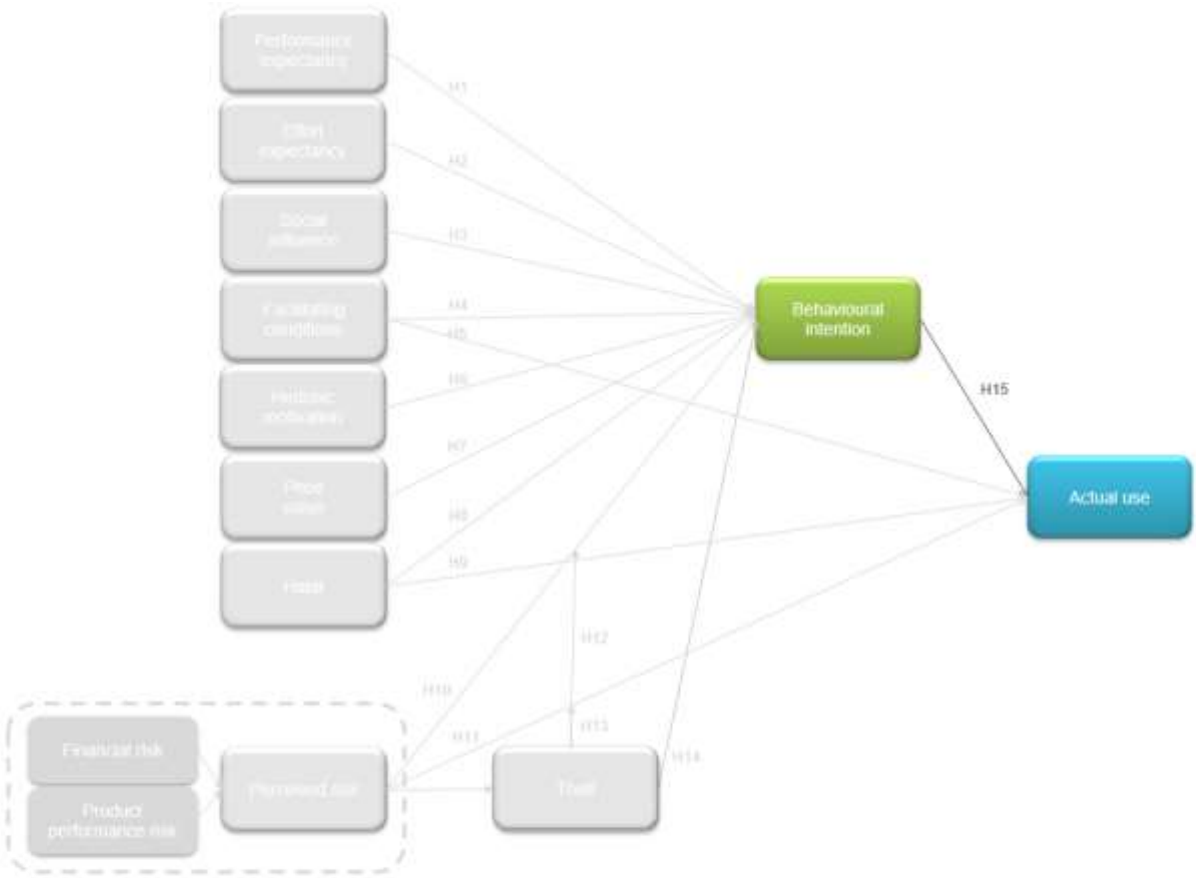


Figure 5.8: The relationship between behavioural intention and actual use

***Source**: Researcher's own construct*

As discussed in Chapter 4, section 4.2.8, Persson and Berndtsson (2015:10) and Davis (1986:16) describe behavioural intention as a measurement of the strength of an individual's intent to perform a specific behaviour. It aims to anticipate an individual's voluntary act. Put differently, behavioural intention means that a user is willing to accept a new technology or innovation and thus the terms 'behavioural intention' and 'acceptance' are often used interchangeably. Kaldi *et al.* (2008:38) and Renaud and van Biljon (2008:2) describe the construct of acceptance as a change in an individual's perceptions, attitudes and actions which results in a willingness to try new activities or innovations. The intention of an individual to use a specific technology is a strong predictor and determining factor of the user actually using or adopting the technology (Miladinovic & Xiang, 2016:12; Persson & Berndtsson, 2015:28; Venkatesh *et al.*, 2012:157).

Actual use is the dependent variable of interest in this study. It refers to an individual's actual use or adoption of a particular technology, for example, a mobile shopping app (Davis, 1986:25). Adoption is described, according to Kaldi et al. (2008:38) and Renaud and van Biljon (2008:1-2), as the phase where an individual selects a technology for use. It is therefore synonymous with actual use. The influence of behavioural intention on actual use has been widely researched in technology acceptance literature and has been cited as the most powerful determinant of actual use (Alalwan *et al.*, 2018:129). Williams *et al.* (2015:460), for example, explored the relationship between the behavioural intention and actual use constructs of the UTAUT2. They discovered that, of 102 studies, behavioural intention had a predictive weighting of 0.82 on actual use (a score of 1 being indicative of the relationship between constructs being significant) (Williams *et al.*, 2015:456). Venkatesh *et al.* (2012:159; 2003:451) report that this construct also significantly influences actual use. Further studies by Alalwan *et al.* (2018), Gupta *et al.* (2018), Lee *et al.* (2018), Tarhini *et al.* (2016), Persson and Berndtsson (2015), Vasileiadis (2014) and Wu and Wang (2005), which focused on new technologies or innovations, and which supported this view, are discussed below.

Behavioural intention and its influence on actual use has been tested in research on the Internet and mobile banking as well as mobile apps (Alalwan *et al.*, 2018; Gupta *et al.*, 2018; Tarhini *et al.*, 2016). Alalwan *et al.*'s (2018:134) Jordanian study on Internet banking acceptance and use found behavioural intention to have a significant influence on actual use. Similarly, Tarhini *et al.* (2016:842) found a significant relationship between behavioural intention and Lebanese consumers' actual use of Internet banking. In the mobile apps industry, Lee *et al.* (2018:34) examined app purchasing by tablet users. The results revealed a significant positive relationship between behavioural intention and tablet users' actual purchase of mobile apps. Likewise, Gupta *et al.* (2018:145) affirm this finding, indicating a strong influence of behavioural intention on tourists' actual use of mobile apps. The aforementioned studies on Internet and mobile banking as well as mobile apps, affirm that behavioural intention has a significant influence on actual use.

Behavioural intention and its influence on actual use has also been tested in research on mobile shopping (Persson & Berndtsson, 2015; Vasileiadis, 2014; Wu & Wang, 2005). Persson and Berndtsson's (2015:61) Swedish study on smartphone shopping acceptance and use found a statistically significant relationship between behavioural intention and Swedish consumers' actual use. According to the qualitative results of this study, shoppers with a more positive view of shopping via their smartphones were more willing to engage and make use of a mobile shopping functionality. Vasileiadis (2014:187) investigated the impact of security concerns and trust on mCommerce acceptance and use. The study also found a statistically significant relationship between behavioural intention and actual use, indicating that behavioural intention is a strong predictor of actual use. Further support for this dates back to 2005. Wu and Wang (2005:740) examined the drivers of mCommerce and found that behavioural intention is an accurate predictor of actual use. Behavioural intent on the part of the consumer is therefore an important determinant of actual usage. The aforementioned studies in mobile shopping affirm that behavioural intention is a strong predictor of actual use.

The following hypothesis is therefore proposed:

H_{15}: Behavioural intention has a positive influence on consumers' actual use of mCommerce apps to purchase athleisure apparel.

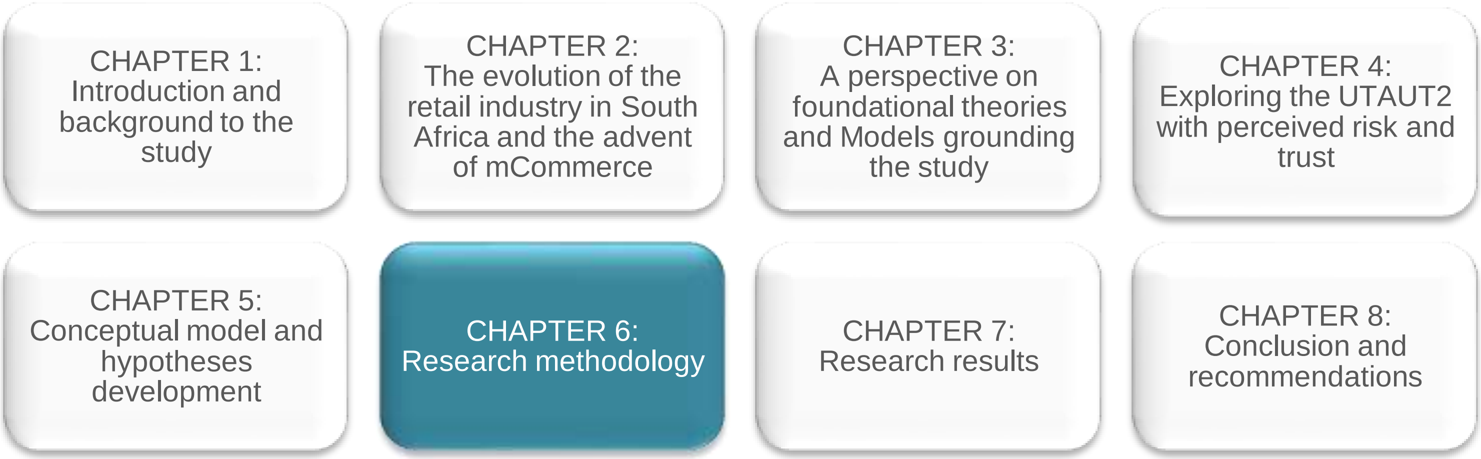
As demonstrated in the aforementioned studies, hypothesis 15 is validated.

5.5 Conclusion

Chapter 5 commenced with an overview of each of the foundational theories and models grounding the study, including the SET, TCT, IDT, TRA, SCT, TAM, TPB and the UTAUT and UTAUT2. It then examined the relationships between the seven independent variables of the UTAUT2 (performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value and habit) and behavioural intention. Thereafter, the relationships between the independent variables of facilitating conditions and habit and actual use were discussed. A view of the relationship between the independent variable of perceived risk and behavioural intention as well as actual use, was then presented. This was followed by the relationship between perceived risk and behavioural intention as well as actual use, mediated by trust. Thereafter, the relationship between the independent variable of trust and behavioural intention was presented. The chapter concluded with a view of the relationship between behavioural intention and actual use. It is imperative to establish a theoretical connection between all the proposed relationships and to determine, by examining prior studies, whether these proposed relationships are likely to be accepted or rejected. Chapter 6 which follows describes the research methodology used in the study.

CHAPTER 6

RESEARCH METHODOLOGY



6.1 Introduction

Chapters 3, 4 and 5 laid the theoretical foundation of this study. This chapter details the research methodology, following the structure of the 'research onion' of Saunders *et al*. (2016:124) (refer to Chapter 1, Figure 1.10). The chapter commences with an overview of the history of research and research philosophies. It then discusses the research philosophy of this study in detail, followed by the approach to theory development. The process of research design is then described, outlining the research problem, the primary and secondary objectives of the research as well as the research hypotheses. The methodological choice, research strategies and time horizon are then presented. This is followed by a description of data collection, data analysis as well as the questionnaire and its different scales. The chapter concludes with a discussion of ethical issues that may be encountered during the research process.

6.2 Research philosophy

Research is a systematic process with the intent of discovering things to ultimately increase knowledge. Researchers organise the new knowledge into a coherent set of related ideas to explain events that have already occurred or to predict events that have yet to occur (Saunders *et al*., 2016:5; van Zyl, 2014:3). Research is conducted across many industries and disciplines. This specific study, for example, is rooted in business research and more specifically, marketing research. This implies applying a scientific research method to obtain insights into specific business phenomena (Quinlan, Babin, Carr, Griffin & Zikmund, 2015:4). Marketing research pairs an organisation to its market through the systematic collection of information (Hair *et al*., 2013:5). Malhotra (2007:7) states that marketing research links consumers to marketers in organisations through information. This information is gathered to identify marketing opportunities and potential problems, to produce, assess and improve marketing actions, to observe and evaluate marketing performance and to enhance the marketer's understanding of the process of marketing. Burns and Bush (2006:7) state that marketing research signifies a method of designing, gathering, analysing and reporting information that can be used to solve a specific research problem. To solve a research problem, it is necessary to select an appropriate research methodology. A methodology provides a systematic approach to solving the problem (Ragab & Arisha, 2018:2). Saunders *et al*.'s (2016:124) 'research onion' (refer to Chapter 1, Figure 1.10) provides a logical framework within which to conduct marketing research.

The first layer of the onion, according to Saunders et al. (2016:124), is the research philosophy. The philosophy or philosophical stance of the research is determined using a research paradigm (Ragab & Arisha, 2018:2). A research paradigm is described by Aliyu, Singhry, Adamu and Abubakar (2015:2) as a structure for the building of theories; these theories profoundly impact the way in which the researcher sees the world, they govern the researcher's perspective and mould the researcher's understanding of the connections between different things. Benzo *et al*. (2018:98) agree, stating that a research paradigm refers to a collection of values, beliefs, attitudes, techniques and procedures that form a structure of understanding. Within this structure, theoretical explanations about things can be created. Saunders *et al*. (2016:124) and Aliyu *et al*. (2015:3) state that basic beliefs define a research paradigm. These beliefs can be summarised into three central assumptions, namely:

i. Ontological assumptions: assumptions concerned with realities faced during the research process;
ii. Epistemological assumptions: assumptions surrounding human knowledge; and

iii. Axiological assumptions: the degree to which the researcher's value set influences the research process.

These assumptions shape the researcher's understanding of the research questions, the methods employed across the various stages of the research process and the final interpretation of the findings (Saunders *et al*., 2016:124).

There are five main research philosophies, namely, positivism, critical realism, interpretivism, postmodernism and pragmatism. Each of the three central assumptions mentioned above (ontology, epistemology and axiology) differs depending on the research philosophy. The two philosophies most often used in marketing research are positivism and interpretivism (Saunders *et al*., 2016:124; Malhotra, Birks & Wills, 2012:194). Each of these is elaborated on below, with reference to the aforementioned three assumptions.

The positivist research philosophy has a preference for the collection of quantitative data through observable reality and searching for relationships and regularities in the collected data to create generalisations (Benzo *et al*., 2018:96-97; Ragab & Arisha, 2018:3; Saunders *et al*., 2016:135-136). A positivist researcher typically uses existing theory to develop and either confirm or refute hypotheses (Saunders *et al*., 2016:137). From an ontological perspective, positivist researchers believe that reality is tangible, external and independent of their interest in it. They further believe that reality can be separated into different constructs. From an epistemological perspective, positivist researchers consider knowledge to be a series of objective statements that can be tested through empirical research which then leads to these statements being confirmed or denied. These statements can then be generalised to the broader population. Finally, from an axiological point of view, positivist researchers believe in objectivity and complete neutrality during the research process through the use of scientific methods to gather data. This ensures that the research remains objective and "value-free" (Ragab & Arisha, 2018:4; Chilisa & Kawulich, 2012:8-9).

Interpretivism accentuates the difference between humans and physical phenomena through the ability of humans to create meaning. This research philosophy is predominantly concerned with creating a more meaningful understanding of different social contexts and worlds (Ragab & Arisha, 2018:3; Saunders *et al*., 2016:140;

Bryman & Bell, 2011:14). From an ontological perspective, interpretivist researchers believe that reality is intangible and constructed by people. Some of it can be shared amongst a group, but some realities are very personal. This directly contradicts the ontological beliefs of the positivist researcher. From an epistemological point of view, knowledge is seen as subjective and unique to each person's experience. Research findings therefore cannot be generalised to the entire population. Finally, from an axiological perspective, seeing that knowledge is considered as subjective, interpretivist researchers believe that social inquiry is completely bound by values (Ragab & Arisha, 2018:4; Chilisa & Kawulich, 2012:10).

This study is rooted in the positivist research philosophy as it aims to produce accurate knowledge that is free from ambiguity surrounding the constructs that influence consumers' acceptance and use of mCommerce apps to purchase fashion apparel in South Africa, with specific focus on athleisure apparel. A summary of this can be found in Annexure 2.

This concludes the discussion on the first layer of the research onion, namely, the research philosophy. The second layer of the onion is the approach to theory development, as discussed below.

6.3 Approach to theory development

The nature and link between theory and research can be defined by clearly understanding deductive and inductive reasoning (Bryman & Bell, 2011:9). Deductive theory is founded on the researcher deducing a hypothesis based on what is known about a specific domain from a theoretical or practical point of view (Ragab & Arisha, 2018:5; Benzo *et al*., 2018:182; Saunders *et al*., 2016:51; Bryman & Bell, 2011:9-11). This approach "involves the development of a theory that is subjected to a rigorous test through a series of propositions" (Saunders *et al*., 2016:146). Given this, deductive theory is the principal approach to theory development in natural sciences research. From a theory, a hypothesis is developed and data is then collected. Next, the findings are analysed and interpreted, the hypothesis is accepted or rejected and the theory is revised. The process then repeats itself, as shown in Figure 6.1 below.

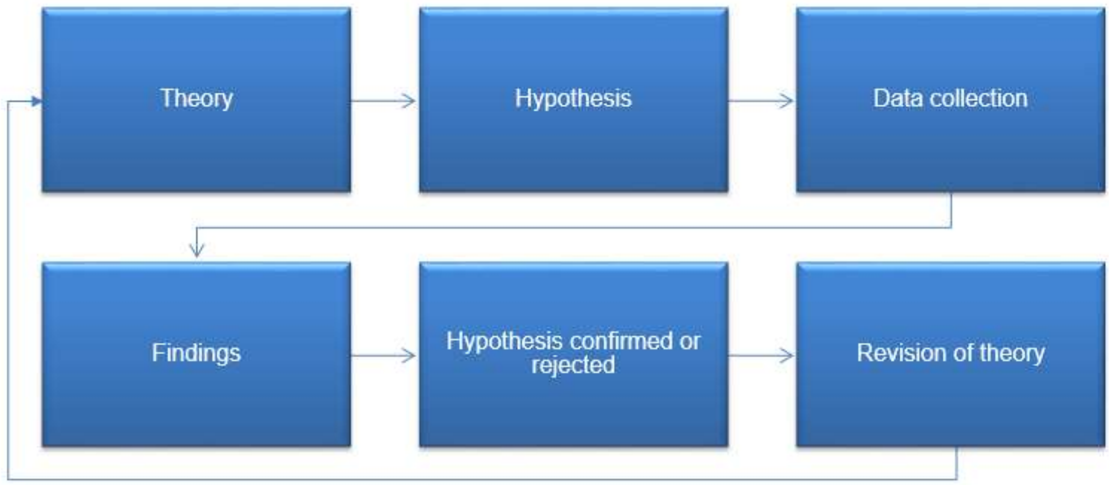


Figure 6.1: Deductive theory
***Source**: Bryman and Bell (2011:9)*

Inductive theory, on the other hand, draws inferences from observations (Benzo *et al*., 2018:182; Ragab & Arisha, 2018:5; Saunders *et al*., 2016:51; Bryman & Bell, 2011:9-11). The present study is grounded in deductive theory, as mCommerce and the purchase of athleisure apparel have been researched to formulate a new testing model. This model was used to determine the constructs influencing consumers' acceptance and use of mCommerce apps to purchase fashion apparel in South Africa, with a specific focus on athleisure apparel. Fifteen hypotheses were developed for testing (refer to Chapter 1, Figure 1.9 for the research model).

This concludes the discussion of the second layer of the research onion, the approach to theory development. Layers 3 to 5 – methodological choice, research strategies and time horizon – can be combined and referred to as the 'research design' (Saunders *et al*., 2016:162-163). This is discussed below.

6.4 Research design

A research design refers to an outline or plan describing how the researcher will attempt to answer the research problem (Saunders *et al*., 2016:163; Hair *et al*., 2013:36). This section commences with a description of the research problem and the primary and secondary objectives of the research, which are derived from the research problem. This is followed by a summary of the 15 proposed hypotheses for this study. Information on the secondary research conducted for this study is then presented, after which the primary research methodology is detailed. The methodological choice – including the purpose of the research and whether the research design will be quantitative, qualitative or mixed method-based – follows. The various data collection sources are then listed. Finally, the section concludes with a description of data collection and analysis (Saunders *et al*., 2016:163-164).

6.4.1 Identification and formulation of the research problem

The research problem was previously formulated and stated in Chapter 1, section 1.3.

6.4.2 Development of the research objectives

After defining the problem or opportunity, researchers should state their research objectives. These describe exactly what the research is setting out to achieve (University of London, 2019; Abdulai & Owusu-Ansah, 2014:6).

6.4.2.1 Primary and secondary objectives of the research

The research objectives were previously formulated in Chapter 1, section 1.5.

6.4.3 Research hypotheses

Following the identification of the research objectives, the research hypotheses can be formulated. The research hypotheses were previously formulated and stated in Chapter 1, section 1.7.4.

6.4.4 Methodological choice

The methodological choice of the research design involves identifying the purpose of the research at hand – exploratory, descriptive, or causal (also known as explanatory) – and selecting the most appropriate research design. This could be either quantitative, qualitative or mixed methods (Saunders *et al*., 2016:164).

6.4.4.1 Purpose of the research design

In order to select the most suitable research design, it is imperative to first consider the purpose of the research. There are three distinct purposes to research design in marketing research, namely, exploratory, descriptive and causal (Ragab & Arisha, 2018:6; Hair *et al*., 2013:36). An exploratory design sheds light onto consumer attitudes or behaviours (Benzo *et al*., 2018:106; Hair *et al*., 2013:36-37) and allows the researcher to ask open-ended questions on a particular area of interest (Saunders *et al*., 2016:174). In a descriptive design, the collection of quantitative data is used to answer a specific research problem or set of research questions. It provides a more accurate summary of a situation, event or group of individuals (Benzo *et al*., 2018:106; Saunders *et al*., 2016:175; Hair *et al*., 2013:36-37). Finally, a causal design allows the researcher to determine cause-and-effect relationships between variables by means of data collection.

The purpose of this research is descriptive as the research problem has been clearly stated, the research objectives have been set and the hypotheses have been formulated. The following section discusses the research design that was used in this study.

6.4.4.2 Research design

There are three distinct research designs, according to Saunders et al. (2016:165), namely, quantitative, qualitative and mixed methods. A quantitative research design is commonly associated with studies rooted in the positivist research philosophy (Benzo *et al*., 2018:96-97; Saunders *et al*., 2016:135-136). It is used to quantify data through statistical analysis (Malhotra, 2007:143). It is also most commonly associated with the deductive approach to theory development as it uses data to test theory. This type of research typically examines relationships between variables in a numerical fashion (Benzo *et al*., 2018:302; Ragab & Arisha, 2018:7; Saunders *et al*., 2016:166; Aliyu *et al*., 2015:17).

A qualitative research design, on the other hand, is most often applied to research grounded in the interpretivist research philosophy (Saunders *et al*., 2016:168). A qualitative design is usually applied to smaller samples; it probes more deeply into the experiences and views of the participants and seeks to truly understand these as opposed to quantifying data through the application of statistical analyses (Ragab & Arisha, 2018:7; Malhotra, 2007:143). It is thus most commonly associated with the inductive approach to theory development as it uses data to develop theory (Saunders *et al*., 2016:168).

Finally, a mixed methods research design combines quantitative and qualitative techniques in data collection and analytical procedures. This design is typically used if a study is grounded in either the critical realist or pragmatist philosophy. This type of research design can use both a deductive and an inductive approach to theory development (Saunders *et al*., 2016:169; 170).

The purpose of this research has been defined as descriptive as it seeks to answer a specific research question, i.e. determining the constructs that influence consumers' acceptance and use of mCommerce apps to purchase fashion apparel in South Africa, with a specific focus on athleisure apparel (Benzo *et al*., 2018:106; Saunders *et al*., 2016:175; Hair *et al*., 2013:36-37). Based on the above discussion, it is evident that a quantitative research design is best-suited to this study as it is positivist in nature and examines relationships between variables in a numerical fashion (Ragab & Arisha, 2018:7; Saunders *et al*., 2016:166; Aliyu *et al*., 2015:17).

A quantitative research design can use either a single method of data collection (e.g. a questionnaire) or multiple methods of data collection (e.g. a questionnaire and a structured interview) (Saunders *et al*., 2016:166). When a single method is used, the research design is referred to as mono-method quantitative. This is the proposed methodological choice for this study as the required research is gathered by means of questionnaire only.

6.4.5 Conducting secondary research

Hair *et al*. (2013:26) describe secondary research as "information previously collected for some other problem or issue". This type of information is readily available and can be collected rapidly and affordably. By first examining secondary research, it is possible to better define the research problem, decide on the best possible approach to address the research problem, formulate a suitable research design and interpret the primary research with greater insight (Hair *et al*., 2013:50; Bryman & Bell, 2011:268; Malhotra, 2007:106-107).

It should be noted that the collection and use of secondary research is considered a "general rule" prior to proceeding with primary research collection (Malhotra, 2007:107). Secondary research lends itself well to descriptive and causal research; as this study is descriptive in nature, it has assisted the researcher to better understanding the research problem at hand (Saunders *et al*., 2016:318). The theoretical chapters of this study (i.e. Chapters 3, 4 and 5) as well as the industry research chapter (i.e. Chapter 2) were compiled using relevant information obtained from secondary research. This was done to assist the researcher in obtaining a more thorough understanding of the research problem. The sources used to obtain the secondary research include the Emerald, Science Direct and SA ePublications databases as well as various accredited websites and academic textbooks.

The theoretical chapters of this study provide a solid foundation upon which the study could be built. During the compilation of these chapters, a gap in the literature was identified (see Chapter 1, section 1.3), which called for further research. This study seeks to determine the constructs that influence consumers' acceptance and use of mCommerce apps to purchase athleisure apparel in South Africa. Primary research was therefore required to investigate the research problem further.

6.4.6 Selection of a primary research method

Hair *et al*. (2013:26) and Malhotra (2007:106) describe primary research as the collection of information with the aim of answering a current research problem. It is the process of generating and analysing new information or data, that is still unpublished

(Benzo *et al*., 2018:49). As the nature of this study required a descriptive and quantitative research design, it was necessary to collect primary data. Relationships between different variables were examined with the intent of determining the constructs that influence consumers' acceptance and use of mCommerce apps to purchase athleisure apparel in South Africa. According to the positivist research philosophy, the collection of quantitative data is favoured as relationships in the collected data can be discovered and generalised to the broader population (Saunders *et al*., 2016:135-136). The proposed research design therefore aligns well with the positivist research philosophy.

This section concludes the discussion on the third layer of the research onion, i.e. the methodological choice. The following section provides insights into the fourth layer – the research strategy.

6.4.7 Research strategy

A research strategy refers to the plan used to answer the research questions (Saunders *et al*., 2016:177). In order to ensure coherence in the research methodology, the research strategy must be aligned with the research design and the methodological choice. Two research strategies are exclusively quantitative in nature, namely – experimental and survey. An experimental strategy is concerned with studying the probability of an independent variable having an effect on a dependent variable (Saunders *et al*., 2016:178; Quinlan *et al*., 2015:159; Hair *et al*., 2013:122; Malhotra, 2007:224). A survey strategy, on the other hand, favours data collection by means of questionnaires. It allows for the collection of standardised data from a large population and can be used to suggest reasons for relationships between variables (Saunders *et al*., 2016:181; Aliyu *et al*., 2015:18; Hair *et al*., 2013:109; Malhotra, 2007:121). This strategy is well-suited to descriptive research and was therefore chosen for this study (Saunders *et al*., 2016:181-182).

This concludes the discussion on the fourth layer of the research onion, i.e. the research strategy. The following section provides insights into the fifth layer – the time horizon.

6.4.8 Time horizon

There are two types of time horizon for descriptive studies, namely, cross-sectional and longitudinal (Benzo *et al*., 2018:125; Saunders *et al*., 2016:200; Quinlan *et al*. 2015:282; Malhotra *et al*., 2012:91, 94). A cross-sectional study collects data from a specific population at only one point in time. A longitudinal study, on the other hand, measures a fixed sample of a population repeatedly. The present study was therefore cross-sectional in nature as data was only collected once from respondents.

However, the study can be further classified as being a multiple-cross sectional study, as information was drawn from two samples of participants at one time. As detailed in Chapter 1, section 1.8.4 and section 6.4.10.1, the target population consisted of South African consumers who used an mCommerce app over the last 12 months. Consumers who simply browsed using an mCommerce app were included in the study along with those consumers who did make a purchase. The former served to measure behavioural intention to use (as part of phase 1, testing Model A) while the latter served to measure actual use (as part of phase 2, testing Model B) (see Chapter 1, Figure 1.9 for Models A and B).

This concludes the discussion on the fifth layer of the research onion, i.e. the time horizon. The following section discusses the sixth and final layer – data collection techniques and procedures.

6.4.9 Data collection method

As discussed above, the study is descriptive in nature and follows a mono-method quantitative research design. In this type of design, one of two approaches is typically used – asking questions and/or observation. These approaches are used to elicit what participants are thinking, feeling or doing and are well-aligned with the survey strategy selected for this study. This is because they allow for the collection of quantitative data from a large population through a process of question and answer (Hair *et al*., 2013:109; Malhotra *et al*., 2012:327).

Given that this study seeks to determine the constructs that influence consumers' acceptance and use of mCommerce apps to purchase athleisure apparel in South Africa, data had to be collected from a large population to identify possible relationships between variables (Saunders *et al*., 2016:181-182). Asking questions through a questionnaire was therefore deemed to be the most suitable data collection method for this study as relationships in the collected data can be identified and generalised to a greater population (Saunders *et al*., 2016:135-136).

A questionnaire is a term used to describe the collection of primary data from respondents using a set of predetermined questions (Ragab & Arisha, 2018:14; Saunders *et al*., 2016:437; Hair *et al*., 2013:188). It is one of the most frequently used data collection methods in research. To ensure a sufficient number of respondents a hybrid method was used through self-completed and interviewer-administered questionnaires. Self-completed questionnaires can be distributed via the Internet and are completed by respondents themselves (Benzo *et al*., 2018:318; Saunders *et al*., 2016:440). Email was used to position the questionnaire towards consumers in South Africa. Respondents accessed the questionnaire by clicking on a link provided in an email. In addition, interviewer-administered questionnaires were leveraged to improve the response rate. Interviewer-administered questionnaires are done in-person either in the respondent's home, at their place of work, or via mall-intercept which refers to the respondent being approached whilst shopping in a mall (Malhotra, 2007:187-188). Field workers from Osmoz Consulting were contracted to assist with this.

In order to achieve the study objectives and capture rich data, a well-designed questionnaire needs to be formulated (Saunders *et al*., 2016:439). The following section outlines the design of the questionnaire.

6.4.9.1 The questionnaire

Designing a questionnaire is done by following a systematic process. This ensures that the data collected through it is accurate (Hair *et al*., 2013:188). There are three essential components in the design of a questionnaire, each of which is discussed in this section. These include the cover letter, the design of the questionnaire itself, as well as alignment between the secondary objectives of the research and the items in the questionnaire.

- ***The cover letter***

A cover letter conveys important information about the questionnaire and the actions required of the respondent. The letter often influences the respondent's decision whether or not to continue with the questionnaire. Therefore it should be written in such a way that it increases the likelihood of participation (Saunders *et al*., 2016:468; Lavrakas, 2008). For the purposes of this study, the cover letter (see Annexure 3) introduced the study and its purpose. It stressed the importance of completing the questionnaire, advised the estimated time that would be required to complete it and explained how to submit the questionnaire following completion. The letter also contextualised the notion of athleisure and included some pictured examples of it. Lastly, and most importantly, the anonymity of the respondents was assured.

- **The questionnaire design**

Three types of variables need to be catered for when designing an effective questionnaire, namely, (i) opinion variables – what do the respondents think? (ii) behaviour variables – what do the respondents do? and (iii) attribute (demographic) variables – who are the respondents? (Ragab & Arisha, 2018:14). With this in mind, the questionnaire was broken down as follows:

Screening questions**:** The screening questions sought to determine whether or not the respondent had used an mCommerce app to purchase athleisure apparel. Based on the answers to these questions, respondents were channelled through to the appropriate sections of the questionnaire built using Model A or Model B.

Section A**:** This section elicited the demographic information of respondents through questions on age, gender, ethnicity, level of education, home language and employment status.

Section B: This section sought to determine the constructs influencing consumers' behavioural intention to use mCommerce apps to purchase athleisure apparel. It included all constructs from the UTAUT2, including performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value and habit. It further included the additional constructs of perceived risk and trust and their influence on behavioural intention. It also examined whether trust mediated the influence of perceived risk on behavioural intention.

Section C: In this section, the construct of actual use was positioned.

Scales used to measure each of the constructs in Section B were adapted from a number of different studies (see Annexure 4), all of which were published in journals contained in the Association of Business Schools' Academic Journal Guide. Venkatesh *et al.* (2003; 2012) are the two main studies referenced for the UTAUT2 construct scales, i.e. performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, habit and behavioural intention.

Scales for the perceived risk construct were sourced from: Alalwan *et al*. (2018:135-136) who analysed the intention to adopt and the actual adoption of Internet banking, Marriott and Williams (2018:143-144) who examined the influence of perceived risk and trust on mobile shopping, Yang *et al*. (2015:268) who looked at perceived risk in mobile payment acceptance, Dai *et al*. (2014:19) who investigated the impact online shopping experience on risk perception and purchase intention, Martins *et al*. (2014:11) who researched Internet banking adoption, Forsythe *et al*. (2006:61) who developed a scale to measure perceived benefits and risks of online shopping, Featherman and Pavlou (2003:470-471) who studied the adoption of e-services and McKnight, Choudhury and Kacmar (2002:319) who explored consumer intention to transact on a website.

The trust construct was built using items from the same studies referenced to build the perceived risk construct, namely, Alalwan *et al*. (2018:135-136), Marriott and Williams (2018:143-144), Martins *et al*. (2014:11) and Forsythe *et al*. (2006:61).

The final construct – actual use – was compiled by combining five items from different studies. Other studies referenced in the compilation of the various scales used only one item to measure actual use (Martins *et al*., 2014:11; Venkatesh *et al.*, 2012:178;

Venkatesh *et al.*, 2003:460), however, after consulting the study supervisors and the University of Johannesburg's (UJ's) Statistical Consultation Service (Statkon), it was decided to extend the construct to include five items as opposed to one. This was intended to extract richer insights from consumers who had used mCommerce apps to purchase athleisure apparel. The construct was built using items from Chopdar *et al*. (2018:123-124) who examined the adoption of mobile shopping apps and Klopping and McKinney (2004:48) who extended the technology acceptance model (TAM) to eCommerce.

The scales consisted of 4 to 13 items, depending on the construct, and totalled 56 statements. Previously validated five-point Likert scales ranging from 1 = strongly disagree to 5 = strongly agree were used to measure each of the statements for Section B with Section C using multiple choice, nominal scales. Annexure 4 summarises the sections of the questionnaire with the previously validated items and scales used, including the studies referenced.

- **Aligning the secondary objectives to the items in the questionnaire**

In designing the questionnaire, it was necessary to ensure that each of the secondary objectives of the research was represented in the questionnaire. Annexure 5 indicates each secondary objective and the section in the questionnaire that represents it.

6.4.9.2 Compiling the scales

As mentioned in the previous section, the questionnaire employs previously validated five-point Likert scales ranging from 1 = strongly disagree to 5 = strongly agree. A Likert scale requires respondents to indicate their level of agreement or disagreement with particular statements ranging from least to most. Rankings usually range from five to seven levels (Saunders *et al*., 2016:457; Allen & Seaman, 2007; Malhotra, 2007:274). A Likert scale is well-suited to collecting opinion data and was therefore appropriate for the purposes of this study (Saunders *et al*., 2016:457; Malhotra, 2007:274). Respondents find Likert scales easy to understand, making them well-suited to questionnaires (Malhotra, 2007:275).

As detailed in Annexure 4, the scales used to measure each construct were adapted from various different studies. The journals within which each of these studies were published all feature in the Association of Business Schools' Academic Journal Guide. Annexure 6 details the scales for this study as well as the sources used to develop them.

6.4.9.3 Pilot test of the questionnaire

In order to identify any potential challenges in the questionnaire before formally administering it, a pilot test was conducted (see Annexure 7). The pilot test was conducted on a small sample of respondents in June 2019. These respondents were not included in the final results. The pilot test provided an opportunity to assess the validity of the questionnaire as well as the expected reliability of the data (Saunders *et al*., 2016:473; Malhotra *et al*., 2012:476).

Osmoz Consulting focused its pilot testing efforts on students from UJ's Auckland Park campus whilst the researcher approached friends and family. In total, 357 respondents were approached and asked the screening questions. Consequently, 317 students approached by fieldworkers from Osmoz Consulting did not have mCommerce apps on their smartphones. However, 33 students did have these apps, along with the 7 respondents approached by the researcher, totalling 40 respondents for the pilot test. Amongst the 40 respondents who took part in the pilot test, 22 had used an mCommerce app to browse and buy athleisure apparel while 18 had only used it to browse and not to purchase.

During pilot-testing of a questionnaire, it is imperative to determine the questionnaire's validity and reliability.

- **Validity**

Validity assesses whether the questionnaire measures what it is intended to measure (Ragab & Arisha, 2018:15; Taherdoost, 2016:28; Quinlan *et al*., 2015:24; Bryman & Bell, 2011:38). There are a number of different types of validity, however, for the purposes of the pilot test, only content or face validity was assessed. Content or face validity refers to a subjective judgement that considers the extent to which a specific measure seems to have a relation to a specific construct. It is the subjective assessment surrounding the presentation of, in this instance, the questionnaire, from a relevance, consistency and clarity point of view (Taherdoost, 2016:29; Malhotra *et al*., 2012:436). Content or face validity is assessed prior to data being collected to ensure the questionnaire covers all areas of the intended research (Hair *et al*., 2013:167).

The questionnaire used in this study (Annexure 7) was informed by the extensive literature review in Chapters 3, 4 and 5. Scales to measure each of the constructs were adapted from journals contained in the Association of Business Schools' Academic Journal Guide. This ensured content or face validity. In addition, statisticians from both Osmoz Consulting and Statkon were consulted to ensure that the proposed scales were valid and would provide accurate answers to the research objectives. The questionnaire was approved by these parties prior to the commencement of data collection for the pilot test as well as the full data collection. Further validity assessments for the full data collection are presented in Chapter 7, section 7.7.1.3. In addition to validity, an assessment of reliability is also required.

- **Reliability**

Reliability can be assessed by determining the extent to which there is an association between the individual items of particular constructs, referred to as internal consistency (Hair *et al*., 2013:166; Bryman & Bell, 2011:38; Malhotra, 2007:285). Internal consistency is tested through Cronbach's alpha. This value ranges from 0 to 1, with 0 indicating no correlation between items and therefore no consistency and 1 indicating perfect correlation and complete consistency. A result of 0.8 or below is considered unsatisfactory (Bryman & Bell, 2011:38). The results of the pilot test (Annexure 8) showed all Cronbach alpha's for standardised items to be greater than 0.8, except for the construct of price value. This was due to one specific item, PV4 (Annexure 9), which stated that "athleisure apparel available via mobile shopping apps is expensive". As it was negatively worded, it skewed the results for the full data collection procedure. This was amended to a positively worded statement, namely, "athleisure apparel available via mobile shopping apps is affordable".

6.4.10 Sampling design process

The concept of sampling is described as the study of a smaller group of individuals which is representative of a larger population. Sampling is applied extensively as a number of constraints – including financial and time resources – often make it impractical for a researcher to study and collect data from an entire population (Ragab & Arisha, 2018:10; Malhotra, 2007:335). The sampling design process comprises a number of different steps, each of which is discussed in greater detail below. These steps include defining the target population, determining the sampling method and establishing the sampling frame and sampling units (Ragab & Arisha, 2018:111).

6.4.10.1 Defining the target population

A population can be described as a group of units which shares specific attributes and from which a sample can be drawn. The population comprises individuals who are likely to have the answers to the questions the researcher seeks to address (Ragab & Arisha, 2018:11; Malhotra *et al*., 2012:494; Malhotra, 2007:335).

The target population of this study consisted of South African consumers who used an mCommerce app over the last 12 months. Consumers who only browsed using an mCommerce app as well as those who actually made a purchase were both included in the study. The former were used to measure behavioural intention to use (as part of phase 1, testing Model A) while the latter were used to measure actual use (as part of phase 2, testing Model B).

66% of consumers, according to Effective Measure (2017a:2), purchase either online or via their mobile phones at most once every three months. IT News Africa (2017) reports that 67% of South African shoppers who shop online or via mobile phone, purchase less than ten products a year. Twelve months was therefore selected as an optimal period of time in order for a sufficient sample to be drawn as the frequency of mCommerce purchases are low in South Africa.

6.4.10.2 Sampling method

Hair *et al*. (2013:140) and Zikmund and Babin (2010:423) describe non-probability sampling as a sampling design where the likelihood of each unit's selection for inclusion in the study is unknown. For this particular study, the selected method of non-probability sampling is a combination of two-part quota and convenience sampling.

With quota sampling, the sample is representative of the population being investigated. This is because the variability in the sample for various quota variables is designed to reflect the variability of the actual population (Saunders *et al*., 2016:299; Bryman & Bell, 2011:180; Zikmund & Babin, 2010:425). As the target population comprises South African consumers who use or have used an mCommerce app to purchase athleisure apparel over the last 12 months, as well as consumers who have purely used it for browsing purposes, the quotas were created to ensure that the data collected was representative of the population of South Africa (see Chapter 1, Table 1.1).

In convenience sampling, the sample can be drawn at the researcher's convenience and permits a large number of respondents to be interviewed within a shorter period of time (Hair *et al*., 2013:145; Zikmund & Babin, 2010:424). As this study sought to collect 500 questionnaire responses (see Chapter 1, Tables 1.1 and 1.2), convenience sampling was deemed to be well-suited.

6.4.10.3 Defining the sampling frame and sampling units

Malhotra *et al*. (2012:497) and Malhotra (2007:337) define a sampling frame as a "representation of the elements of the target population". In order to ensure that the sample for this study was representative of the South African population, the current demographic breakdown of the country had to be established. Statistics South Africa reports that the population of South Africa is estimated to be 56.52 million (Stats SA, 2017:1). This total amount can be broken down as follows: 80.8% (45.6 million) are Black, 8.8% (4.9 million) are Coloured, 8.0% (4.4 million) are White and 2.5% (1.4 million) are Indian/Asian (Stats SA, 2017:1). Gender is split relatively evenly with approximately 51% of the population being female (28.82 million) and 49% being male (27.69 million). Approximately 25.3% (14.3 million) of the population resides in Gauteng, followed by KwaZulu Natal with 19.6% (11.1 million) (Stats SA, 2017:1). Considering that the majority of the population resides in Gauteng, the sample was drawn from this province. Effective Measure (2017a:5) confirms that Gauteng is home to the largest percentage of online shoppers in South Africa, with a total of 43%.

Now that an understanding of the source of the sample has been established, it is important to describe the size of the sample. To have a 95% confidence level in the data obtained, according to Survey Monkey (2020), a population of 1,000,000+ requires a sample size of at least 384. This is depicted in Table 6.1 below.

Table 6.1: Sample size

Population	**Margin of Error**			**Confidence Level**		
	10%	**5%**	**1%**	**90%**	**95%**	**99%**
100	50	80	99	74	80	88
500	81	218	476	716	218	286
1,000	88	278	906	215	278	400
10,000	96	370	4,900	264	370	623
100,000	96	383	8,763	270	383	660
1,000,000+	97	384	9,513	271	384	664

Source*: Survey Monkey (2019)*

The proposed quotas for this study, as depicted in Chapter 1, Table 1.1, were compiled based on the aforementioned ethnic and gender demographics of South Africa as well as the sample size data provided by Survey Monkey. Given that this study seeks to test two models, Model A and Model B, a sample size of 500 was proposed. This is supported by the studies referenced in the compilation of the scales for the study. Alalwan *et al*. (2018:129) included a sample of 500, of which 70% responded; Chopdar *et al*. (2018:118-119) included a sample of 366 respondents, Hew *et al*. (2015:1274) included a sample of 288 respondents while Shaw and Sergueeva’s (2019:49) questionnaire was completed by 526 respondents. In addition to this, to ensure successful factor analysis, at least 300 respondents should be included in a study (Chan & Idris, 2017:403; Pallant, 2016:184).

6.4.10.4 Response rates

In order to achieve the desired sample size of 500, according to Malhotra *et al*. (2012:499), a larger group of respondents will have to be contacted as incidence and completion rates are usually less than 100%. An incidence rate refers to the percentage of respondents eligible to take part in the study, whereas the completion rate specifically considers to the percentage of qualified respondents who completed the questionnaire. As discussed in section 6.4.9, this study used a hybrid method of both self-completed and interviewer-administered questionnaires to ensure the desired number of completed questionnaires was reached. Malhotra *et al*. (2012:543) estimate a response rate of 66.7%, therefore 750 respondents were targeted in order to collect the desired 500 completed questionnaires.

6.4.11 Collecting the data

After formalisation of the sampling design process, collection of the data can commence. The data was collected via email distribution and through the use of fieldworkers from Osmoz Consulting, who handed out questionnaires for completion. The self-completed questionnaires were emailed to respondents while interviewer-administered questionnaires were completed by fieldworkers from Osmoz Consulting. The email questionnaires had to be completed in full before respondents were allowed to submit them. Fieldworkers approached respondents requesting their participation in the research. Respondents were given a hard copy of the questionnaire including the covering letter (see Annexure 7). Upon successful completion of each questionnaire, the fieldworker checked that all questions were answered. The questionnaire was then returned to the fieldworker.

6.4.12 Data preparation

Following the collection of the data, the first step was to prepare the data for analysis. Malhotra (2007:429) identifies several steps in this process, as illustrated in Figure 6.2 below.

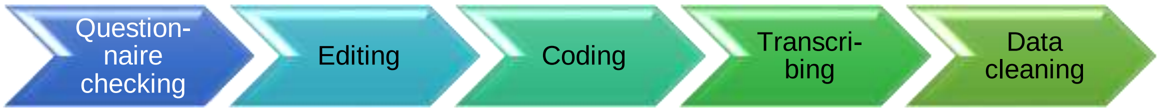


Figure 6.2: Data preparation process
Source*: Malhotra (2007:429)*

Firstly, after collecting all physical and electronic questionnaires, Osmoz Consulting checked each one for completeness. In addition, the researcher also performed independent checks on the questionnaires.

The second step in the process – editing – involved a review of the collected questionnaires to improve accuracy (Aaker, Kumar, Leone & Day, 2013:346; Zikmund & Babin, 2010:493; Malhotra, 2007:429). In this step, raw data was checked for mistakes made by respondents (Hair *et al*., 2013:245). Osmoz Consulting edited questionnaires that were submitted with illegible or inconsistent answers by excluding these from the final sample.

In the third step – coding – different values were assigned to group responses from the questionnaires. Thus, numerical values (0-9) were assigned to every response to every question in the questionnaire (Hair *et al*., 2013:249; Zikmund & Babin, 2010:498; Malhotra, 2007:431). All questions were closed-ended and thus were assigned codes prior to data collection.

The fourth step involved transcription, commonly referred to as data entry. In this step, the coded data was entered into a specific software package on a computer, in this instance, IBM's Statistical Package for the Social Sciences (SPSS), version 24 (Hair *et al*., 2013:252; Malhotra, 2007:435). Osmoz Consulting transcribed all physically-collected questionnaires into SPSS and added the electronically-collected questionnaires as well. A second resource at Osmoz Consulting verified all manually-captured physically-collected questionnaires.

The fifth step involved data cleaning – a process where the data was checked for consistency and where any missing responses were treated (Malhotra, 2007:436).

Consistency checks looked for data with extreme values, out of range when compared to the rest of the data set. Such data was excluded and required correction. Osmoz Consulting evaluated captured data and the SPSS software assisted by identifying extreme values. Variables were checked systematically against edited and coded questionnaires to ensure accurate data capturing (Malhotra, 2007:436). Missing responses denote values of variables that were unknown because of one of two reasons – respondents either did not correctly record their answer or the answer recorded was abstruse. Osmoz Consulting evaluated the data for missing responses and substituted all missing responses with a mean response to each variable, thus applying a neutral value that would not impact the greater data set (Malhotra, 2007:437). Following the successful completion of data processing, Osmoz Consulting handed the captured data over to Statkon for analysis.

6.4.13 Data analysis strategy

Hair *et al*. (2013:267) state that data analysis enables the unearthing of interesting patterns that can be difficult to identify but have the potential to create new knowledge about specific topics or improve decision-making capability. Statkon carried out the data analysis for this research. As indicated in Chapter 1, section 1.7.4, this study included 15 hypotheses for testing. Hypothesis testing can be done by applying one of three possible statistical analysis techniques, namely, univariate, bivariate or multivariate statistical analysis. Univariate statistical analysis tests hypotheses that only involve a single variable while bivariate statistical analysis tests hypotheses that involve two variables. Multivariate statistical analysis tests models that involve multiple hypotheses and variables (Zikmund & Babin, 2010:538). As this study included 15 hypotheses, multivariate analysis was deemed to be best-suited.

Before data analysis can commence, it is necessary to test whether the statistical assumptions that underpin most multivariate techniques are met (Hair, Black, Babin, Anderson & Tatham, 2006:79). These include assumptions of normality, outliers, linearity and missing data. Details concerning these assumptions are presented in the following section. Thereafter, several statistical procedures can be applied to the data to assist in better understanding and learning from the collected data, including descriptive and inferential statistics, validity and reliability, exploratory factor analysis (EFA), structural equation modelling (SEM) and confirmatory factor analysis (CFA).

6.4.13.1 Statistical assumptions

To ensure multivariate statistical techniques can be applied to the collected data, certain statistical assumptions needed to be met, including assumptions of normality, outliers, linearity, and missing data. Details concerning these assumptions are presented in the following sections.

- **Assumption of normality**

Normality describes the shape of the distribution of the data for a specific variable and how it corresponds to a normal data distribution. Statistical tests conducted using the data set will be rendered invalid if there is significant disparity between the shape of the data distribution compared to a normal data distribution. Normality in the data is a pre-requisite in order to apply F and t statistics (Hair *et al*., 2006:79).

An assessment of normality can be done by testing for skewness and kurtosis. Skewness describes the balance of the distribution of data, i.e. whether it is shifted to the right or the left side or whether it is balanced and centered (Hair *et al*., 2006:80). A positive skew indicates that the majority of the scores sits below the mean whereas a negative skew indicates majority of the data sits above the mean (Kline, 2011:60). Kurtosis is used to describe the height of the distribution, i.e. how flat or peaked the distribution of data is, in comparison to a normal distribution. The closer both these values are to 0, the more normal the data distribution (Hair *et al*., 2006:80).

Statistical tests can also be conducted to assess normality, including the Shapiro-Wilk and Kolmogorov-Smirnov tests (Hair *et al*., 2006:82). The Shapiro-Wilk test detects withdrawals from normality due to skewness or kurtosis or both whereas the Kolmogorov-Smirnov test specifically looks at kurtosis by considering the largest vertical difference between the hypothesised and observed distributions (Razali & Wah, 2011:23; 25). Details surrounding these tests and the assumption of normality are discussed in Chapter 7, section 7.5.2.1, however, it should be noted that normality was expected given the sample size (n=500). Due to the size, any effects of non-normality in the data should have been cancelled out.

- **Assumption of outliers**

The second assumption is in relation to outliers, also referred to as homoscedasticity. This is described as the assumption that a dependent variable will exhibit the same level of variance across a range of independent variables (Hair *et al*., 2006:83). In essence, it involves highlighting unusual data points that are far removed from the main mass of data (Information Technology Laboratory, National Institute of Standards and Technology, 2019).

In order to assess homoscedasticity, histograms as well as box and whisker plots can be used. The histogram allows the researcher to compare a set of data using a simple statistical measure such as the mean (Spitzer, Wildenhain, Rappsilber & Tyers, 2014:121). Box and whisker plots are more advanced and display the distribution of a set of data to assist in the identification of outliers (Galarnyk, 2018). They visualise the minimum, maximum, median, lower and upper quartile of the data set (Spitzer *et al.,* 2014:121). Details of these tests are discussed in Chapter 7, section 7.5.2.2.

- **Assumption of linearity**

Correlations embody only linear associations between variables; therefore, linearity is an implied assumption. Linearity can be examined graphically by assessing scatterplots of the variables to identify non-linear data patterns. A straight line, indicative of a linear relationship, should be visible (Hair *et al*., 2006:85). Details of linearity are discussed in Chapter 7, section 7.5.2.3.

- **Assumption of missing data**

In self-administered questionnaires, missing data is a regular occurrence. This occurs when participants fail to complete the questionnaire in full, either due to the question being too sensitive or due to the participant being in a hurry (Hair *et al*., 2013:253). An assessment was conducted to screen for missing values; however, none were found. Therefore, the assumption of missing data was met. Details are provided in Chapter 7, section 7.5.2.4.

Once each of the aforementioned statistical assumptions has been met, data analysis can proceed. A number of different statistical procedures was applied to the data, including descriptive and inferential statistics, validity and reliability, EFA, SEM and CFA. These are elaborated on in the following sections.

6.4.13.2 Descriptive and inferential statistics

As shown in Figure 6.3 below, descriptive statistics are primarily concerned with describing the data gathered from the sample whereas inferential statistics go beyond the gathered data. With this statistical procedure, the researcher aims to infer what an entire population might do, based on the insights gleaned from the sample (Quinlan *et al*., 2015:359-361; Zikmund & Babin, 2010:440).

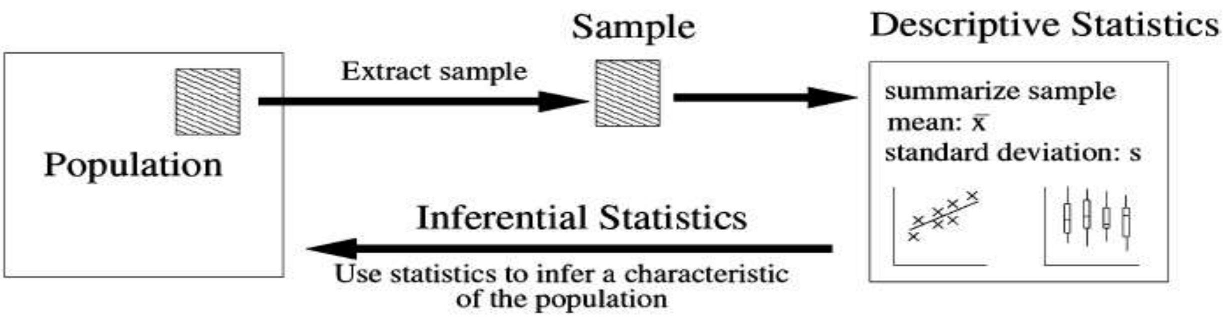


Figure 6.3: The relationship between descriptive and inferential statistics
Source*: King and Eckersley (2019:2)*

- **Descriptive statistics**

Descriptive statistics allow the researcher to draw comparisons and create descriptions for different variables numerically (Saunders *et al*., 2016:527; Zikmund & Babin, 2010:516). As described above, these statistics are concerned with describing data gathered from a sample, for example, describing the age, gender, level of education, etc. (Quinlan *et al*., 2015:359). Descriptive statistics used to compare and describe variables include measures of central tendency, measures of dispersion and measures of variability (Saunders *et al*., 2016:527; Aaker *et al*., 2013:351). Measures of central tendency, according to Hair *et al.* (2013:170), Bryman and Bell, (2011:319) and Malhotra (2007:460), refer to basic summary statistics including the mean, median and mode. These statistics assist in locating the centre of a distribution of responses.

Saunders *et al*. (2016:528) elaborate on this definition, stating that these statistics can provide a general impression of values in the distribution of responses for quantitative studies that can be regarded as common or average. Measures of dispersion seek to define how the distribution of responses is dispersed around the central tendency (Saunders *et al*., 2016:529; Hair *et al*., 2013:170; Bryman & Bell, 2011:319; Malhotra, 2007:461). This set of measures includes the frequency distribution, range and standard deviation. Finally, measures of variability include skewness and kurtosis as described in section 6.4.13.1, and assessment of normality. Each of these measures is described in Table 6.2 and discussed in Chapter 7, sections 7.5.1 and 7.5.2 for Model A, and section 7.6.1 for Model B.

Table 6.2: Descriptive statistics: Measures and definitions

Descriptive statistical measure	**Definition**
Measures of central tendency	
Mean	The average value between several different elements. The mean is derived by adding all elements together and dividing the amount by the number of elements (Saunders *et al*., 2016:720; Quinlan *et al*., 2015:360; Hair *et al*., 2013:268; Bryman & Bell, 2011:319; Malhotra, 2007:460).
Median	In the distribution of responses, half of the total values fall above this value and half of the total values fall below it (Saunders *et al*., 2016:720; Quinlan *et al*., 2015:360; Hair *et al*., 2013:170; Malhotra, 2007:460).
Mode	The value that arises the most often in the distribution of responses (Saunders *et al*., 2016:720; Quinlan *et al*., 2015:360; Hair *et al*., 2013:170; Bryman & Bell, 2011:319; Malhotra, 2007:460).
Measures of dispersion	
Frequency distribution	A summarisation of the number of times a response to a scale question was captured by the entire sample of respondents (Aaker *et al*., 2013:350; Hair *et al*., 2013:170; Zikmund & Babin, 2010:441).
Range	This represents the difference between the smallest response and the largest response in the frequency distribution (Saunders *et al*., 2016:720; Quinlan *et al*., 2015:360; Hair *et al*., 2013:273; Bryman & Bell, 2011:319; Zikmund & Babin, 2010:445).
Standard deviation	The average distance of the values in the distribution from the mean (Hair *et al*., 2013:273).
Measures of variability	
Skewness	Describes the balance of the distribution of data, i.e. if is it shifted to the right or left side or if it is balanced and centred (Hair *et al*., 2006:80).
Kurtosis	Describes the height of the distribution, i.e. how flat or peaked the distribution of data is, in comparison to a normal distribution (Hair *et al*., 2006:80).

- **Inferential statistics**

Inferential statistics are used to infer what an entire population might do, based on the insights gleaned from the sample (Quinlan *et al*., 2015:361; Zikmund & Babin, 2010:440). Inferential statistics allow for the testing of hypotheses and to generalise the findings of those tests to the greater population (Center for Innovation in Research and Teaching, 2019). Each of the inferential statistics used in this study is defined in Table 6.3 and discussed in Chapter 7, section 7.5.4 for Model A and section 7.6.4 for Model B.

Table 6.3: Inferential statistics: Measures and definitions

Inferential statistical measure	**Definition**
T-test	A t-test determines whether the means from two groups are statistically different from each other (Quinlan *et al*., 2015:362).
Correlation test	This statistic describes the extent to which an independent variable predicts a dependent variable (Quinlan *et al*., 2015:362).
Simple linear regression	Similar to the correlation test, simple linear regression describes the extent to which an independent variable predicts a dependent variable, including how well the line fits the data (Quinlan *et al*., 2015:362).
Multiple linear regression	This statistic describes how well several independent variables predict a dependent variable (Quinlan *et al*., 2015:362; Hair *et al*., 2006:18).

Following descriptive and inferential statistics, assessments of validity and reliability are conducted.

6.4.13.3 Validity and reliability

As detailed in earlier sections, an assessment of validity and reliability is key to evaluate the research instrument's success. Validity helps in assessing whether the questionnaire measures what it is intended to measure (Ragab & Arisha, 2018:15; Taherdoost, 2016:28; Quinlan *et al*., 2015:24; Bryman & Bell, 2011:38), and reliability considers the extent to which there is an association between the individual items of particular constructs within the questionnaire (Hair *et al*., 2013:166; Bryman & Bell, 2011:38; Malhotra, 2007:285). Details surrounding each of these assessments is provided below.

- **Validity**

Validity assesses whether the research instrument, in this instance, the questionnaire, measures what it is intended to measure (Ragab & Arisha, 2018:15; Taherdoost, 2016:28; Quinlan *et al*., 2015:24; Bryman & Bell, 2011:38). There are a number of different types of validity relevant to this study, as illustrated in Figure 6.4.

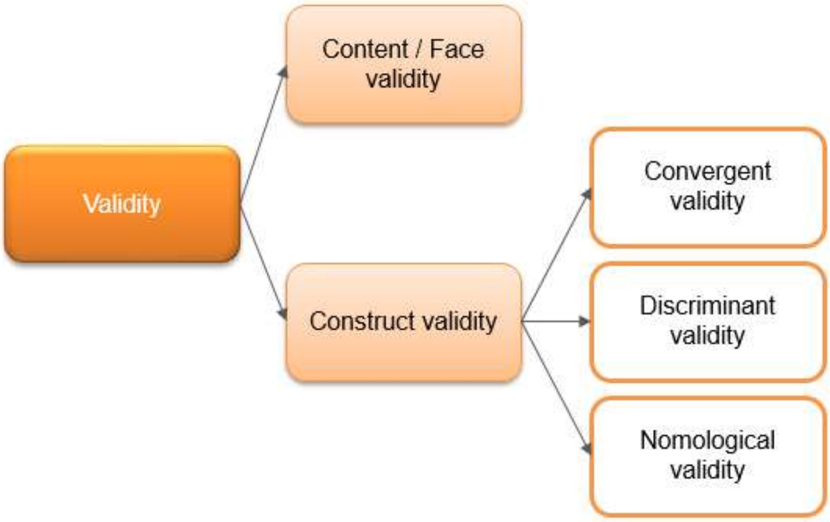


Figure 6.4: Types of validity relevant to this study

***Source**: Adapted from Taherdoost (2016:29)*

Content or face validity was assessed as part of the pilot test of the questionnaire.

Construct validity is concerned with how well a particular concept, behaviour or idea (a construct) was transformed into an operating reality. Construct validity comprises three components, namely, convergent, discriminant and nomological validity (Taherdoost, 2016:31; Malhotra *et al*., 2012:436-437; Malhotra, 2007:287). Each of these are elaborated on below.

Convergent validity refers to "the correlation between two different scales used to measure the same construct" (Saunders *et al*., 2016:713). Malhotra *et al*. (2012:436) and Malhotra (2007:287) support this definition. To ensure convergent validity, the various factor loadings of scale items must be more than 0.50. The average variance extracted (AVE) for each construct should also exceed 0.50 (Sun, Lee & Law, 2019:94; Nam, Lee & Lee, 2018:5; Hair *et al*., 2013:167). Refer to Chapter 7, section 7.5.4.1.3 for a view of convergent validity for this study. Upon assessing convergent validity, discriminant validity should follow.

Discriminant validity is described as the extent to which measures that are intended to be different, are actually different and do not correlate with each other (Saunders *et al*., 2016:451; Taherdoost, 2016:31; Quinlan *et al*., 2015:116; Malhotra *et al*., 2012:437; Bryman & Bell, 2011:39; Malhotra, 2007:287). Discriminant validity, according to Quinlan *et al*. (2015:116), can be determined by assessing whether two scales correlate above 0.75. If this occurs, discriminant validity between these two scales should be re-evaluated as the correlation is too similar. In order for discriminant validity to be met, all maximum shared variances (MSVs) should be less than the AVEs (Alumran, Hou, Sun, Yousef & Hurst, 2014:4). Sun *et al*. (2019:94) and Nam *et al*. (2018:5) add that in order to confirm discriminant validity, it is also important to ensure the square root of the AVE is greater than the correlations between the constructs. Chapter 7, section 7.5.4.1.3 elaborates on discriminant validity for this study. Upon assessing discriminant validity, nomological validity should follow.

Nomological validity is concerned with finding key correlations between various constructs as predicted by theory (Busser & Shulga, 2018:75; Malhotra *et al*., 2012:437; Malhotra, 2007:287). In the context of this study, the independent variables presented in the model should have a statistical correlation with one another. Refer to Chapter 7, section 7.5.4.1.3 for a view of nomological validity for this study. Once validity assessments are completed, an assessment of reliability is needed.

- **Reliability**

Reliability is essential when producing quality research (Saunders *et al*., 2016:202). A reliable questionnaire should produce consistent or repeated findings whenever it is administered (Ragab & Arisha, 2018:15; Hair *et al*., 2013:165; Malhotra, 2007:284). To determine the reliability of a questionnaire, internal consistency should be examined. Internal consistency is described as the extent to which there is correlation between the individual items or questions of a particular construct (Hair *et al*., 2013:166; Bryman & Bell, 2011:38; Malhotra, 2007:285). Internal consistency can be tested through the coefficient alpha, also commonly referred to as Cronbach's alpha, a calculation that determines "the average of all possible split-half measures that result from different ways of dividing the scale questions" (Hair *et al*., 2013:166). The value ranges from 0 to 1 with 0 indicating no correlation between items and therefore no consistency and 1 indicating perfect correlation and complete consistency (Bryman & Bell, 2011:38). A result of 0.8 or below, according to Bryman and Bell (2011:38), is considered low and not acceptable. Hair *et al*. (2013:166) state that any value below 0.7 indicates low and unsatisfactory internal consistency, whereas Malhotra *et al*.

(2012:434) and Malhotra (2007:285) advise that a value of 0.6 or less is considered unsatisfactory. The reliability examination for the final questionnaire for this study is presented in Chapter 7, section 7.5.3 for Model A and 7.6.3 for Model B.

In addition to the different types of validity and reliability assessments discussed thus far, it is also imperative to conduct factor analysis, using the exploratory technique (Mazzocchi, 2008:221).

6.4.13.4 Exploratory factor analysis (EFA)

Malhotra *et al*. (2012:774) describe factor analysis as various procedures that are used by researchers to reduce and summarise data. EFA commences with the observed data, identifying underlying variables likely to exist that are unobservable and unknown to the researcher (Bryman & Bell, 2011:328; Mazzocchi, 2008:221; Suhr, 2006:1). In EFA, researchers can analyse data without any prejudiced ideas as to each of the factors and their possible relation to one another. The procedure determines the number of variables, as the approach is exploratory in nature. This means that relationships between variables need not be defined upfront; they are created as the procedure unfolds (Mooi & Sarstedt, 2011:218).

Pallant (2016:183-186) describes three distinct steps in conducting factor analysis, namely, (i) assessing the appropriateness of the data for factor analysis, (ii) factor extraction and (iii) factor rotation and interpretation. Each of these are elaborated on below.

- **Step 1: Assessing the appropriateness of the data for factor analysis**

Factor analysis was deemed suitable for this study given the sample size requirements. As per Chapter 1, Table 1.1, 500 questionnaires were to be fielded, exceeding Pallant's (2016:184) recommended requirement of 300. There are, however, two statistical techniques that can assist in determining factorability, namely, Bartlett's test of sphericity and the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy. Bartlett's test examines whether variables are uncorrelated in the sampled population (Malhotra *et al*., 2012:776). This test result should be significant, i.e. $p<0.05$, for factor analysis to be considered suitable (Fávero & Belfiore, 2019:389;

Pallant, 2016:184). The KMO measure is an index used to determine the level of appropriateness of factor analysis. The higher the values, e.g. between 0.5 and 1.0, the more appropriate the factor analysis. The lower the values, e.g. 0.5 and below, the factor analysis is deemed inappropriate (Fávero & Belfiore, 2019:387; Pallant, 2016:184; Malhotra *et al*., 2012:777). Details on these tests are contained in Chapter 7, section 7.6.2.1.

- **Step 2: Factor extraction**

In this step, the smallest number of factors which together, represent interrelationships among variables, are determined (Pallant, 2016:184). This is done through the Principal Axis Factor method which is used to extract factors in a successive fashion until there is a significant enough variance accounted for in the correlation matrix (Yong & Pearce, 2013:84). Details can be found in Chapter 7, section 7.6.2.2.

Following this analysis, deciding whether to retain factors or not can be determined through Kaiser's criterion and a Scree plot. Kaiser's criterion, commonly referred to as the Eigenvalue rule, is a statistic that is representative of the total variance explained by a particular factor. The rule states that only factors with a value of 1.0 or more should be retained by the researcher for further investigation. Along with Kaiser's criterion, it is necessary to evaluate the Scree plot. This is also known as the Catell Scree test, which plots all the Eigenvalues. All factors that sit above the elbow of the plot should be retained (Pallant, 2016:185; Suhr, 2006:3). Details are contained in Chapter 7, section 7.6.2.2.

- **Step 3: Factor rotation and interpretation**

Once steps 1 and 2 are completed, the factors have been determined. The third and final step of EFA is to interpret these factors. There are two main routes to rotation and interpretation, which will result in either uncorrelated or correlated factor solutions, often referred to as orthogonal or oblique factor solutions. For the purposes of this study, orthogonal rotation was sufficient. The Varimax approach with Kaiser normalisation was employed, a technique that "minimises the number of variables that have high loadings on each factor" (Fávero & Belfiore, 2019:397; Pallant, 2016:185-

186). Details are contained in Chapter 7, section 7.6.2.3. In addition to EFA, SEM and CFA are also conducted, both of which are elaborated on in the following section.

6.4.13.5 Structural equation modelling (SEM)

SEM is a confirmatory statistical procedure that judges a model formulated by theory, against the data collected against it (Jak, 2015:v; 4; Hair *et al*., 2006:711). It simultaneously tests all hypothesised relationships between variables in a single model. Fit indices are then used to evaluate the model's overall fit. SEM provides a general and convenient framework for statistical analysis that encompasses several multivariate statistical techniques including CFA and multiple regression analysis (Hox & Bechger, 1999:354).

In order to conduct SEM, the proposed model needed to be broken up into two views – the measurement model and the structural model. The former depicts how different variables come together to denote constructs whereas the latter depicts each construct's association with the other (Hair *et al*., 2006:714). A path diagram assists in depicting these different components of the model in specific ways, enabling SEM (Jak, 2015:v; 4).

- **Path diagram**

Path analysis was first introduced by Sewall Wright in 1921, forming the basis of SEM (Hox & Bechger, 1999:355). A path diagram comprises different boxes and circles, connected to each other by arrows. Independent variables are denoted through boxes while dependent variables are denoted through circles. The paths between these variables are denoted using arrows with the variable at the tail-end of the arrow being the cause of the variable at the point-end of the arrow. From a statistical point of view, a single-headed arrow is representative of a regression coefficient whereas a double-headed arrow indicates a covariance. The path diagrams for this study are presented in Chapter 7, section 7.5.4.

- **Confirmatory factor analysis (CFA)**

CFA is often referred to as a statistic of SEM. It is a powerful, statistical technique used to estimate multiple and concurrent relationships between several dependent variables (Mazzocchi, 2008:316-317). CFA is used to verify the underlying factor structure of a set of observed variables. It allows the researcher to test whether relationships exist between observed variables and their underlying latent constructs (Bryman & Bell, 2011:328; Suhr, 2006:1). Contrary to EFA, with CFA, a relationship between variables needs to first be specified by the researcher based on pre-existing theory (Mazzocchi, 2008:317). It therefore allows for confirmation of relationships between variables (Mooi & Sarstedt, 2011:218). Table 6.4 summarises the various CFA statistical tests, mostly goodness-of-fit (GOF) indices that were conducted for this study.

Table 6.4: Statistical tests used in CFA

Statistical test	Description	Recommended cut off points
Model Chi-square Test (x^2)	Indicates the amount of variance between expected and observed covariance matrices (Hooper, Coughlan & Mullen, 2008:53; Suhr, 2006:1).	Value of ≤3 (Awang, 2012:56).
Root Mean Square Error of Approximation (RMSEA)	An index indicating “the difference between the observed covariance matrix per degree of freedom and the hypothesised covariance matrix which denotes the model”. Values range from 0 to 1 (Cangur & Ercan, 2015:157; Suhr, 2006:2).	Value of ≤0.05-0.06 indicates an acceptable fit (Newsom, 2018:3; Hooper *et al*., 2008:54; Suhr, 2006:2; Sun, 2005:249; Hu & Bentler, 1999:4).
Comparative Fit Index (CFI)	The CFI is an incremental fit index, defined as “equal to the discrepancy function adjusted for sample size”. Values range from 0 to 1 (Cangur & Ercan, 2015:158; Suhr, 2006:2).	Value of ≥0.90 indicates a good fit (Newsom, 2018:2; Cangur & Ercan, 2015:159; Hooper *et al*., 2008:55; Suhr, 2006:2).
Tucker-Lewis Index (TLI)	An incremental fit index (Cangur & Ercan, 2015:158).	Value ≥0.90 indicates an acceptable fit (Newsom, 2018:2); value of ≥0.95 indicates a good fit (Sun, 2005:249).

Goodness-of-fit is used to show how well the model in question replicates the covariance matrix among the different indicator items (Zikmund & Babin, 2010:553; Hair *et al*., 2006:745). If a theory compilation was done perfectly, the estimated covariance matrix and the actual observed covariance matrix should be aligned. This comparison therefore provides an estimated model fit – the closer these two matrices are to each other, the better the model fit.

Absolute fit and incremental fit can be tested. An absolute fit index determines the model fit by showing how well the theory, compiled by the researcher, fits the sample data (Hair, Black, Babin & Anderson, 2010:666). The Model Chi-square test and Root Mean Square Error of Approximation (RMSEA), as depicted in Table 6.4, were applied to assess absolute fit. The results of these tests for the measurement model are presented in Chapter 7, section 7.5.4.1.1 and for the structural model in Chapter 7, section 7.5.4.2.1.

An incremental fit index assesses how well the research model fits an alternative model, at a relative basis (Hair *et al*., 2010:668). The Comparative Fit Index (CFI) and Tucker-Lewis Index (TLI), as depicted in Table 6.4, were applied to assess incremental fit. The results of these tests for the measurement model are presented in Chapter 7, section 7.7.1.1 and for the structural model in Chapter 7, section 7.7.2.1. Further SEM statistical techniques that will be applied to this study include correlation- and multiple regression analysis, each of which are elaborated on below.

- **Correlation analysis**

Examining relationships in quantitative data analysis can be done using correlation and regression analysis. For correlation analysis, the Pearson correlation coefficient "measures the degree of linear association between two variables" (Hair *et al*., 2013:316; Malhotra, 2007:536). The statistic's value ranges between -1.00 and 1.00, with 0.00 representing no association between variables. The larger the value, the stronger the relationship. The statistic can be either positive or negative, depending upon the direction of the relationship between the variables (Hair *et al.,* 2013:316). The result of this test is provided in Chapter 7, section 7.5.4.1.2.

- **Multiple regression analysis**

Malhotra (2007:552) defines multiple regression analysis as "a statistical technique that simultaneously develops a mathematical relationship between two or more independent variables and an interval-scaled dependent variable". Table 6.5 summarises the various multiple regression analysis statistical techniques that were conducted in this study. The results are provided in Chapter 7, section 7.5.4 for Model A and section 7.6.4 for Model B.

Table 6.5: Multiple regression analysis statistical techniques

Statistical test	Description
Coefficient of multiple determination (r^2)	Measures the strength of association (Malhotra, 2007:553).
Adjusted r^2	To account for diminishing returns, the R^2 can be adjusted for a number of independent variables (Malhotra, 2007:553).
F-test	Tests the null hypothesis that $R^2 = 0$ (Malhotra, 2007:553).
Partial regression coefficient (b_1)	"Denotes the change in the predicted value, per unit change, when other independent variables are held constant" (Malhotra, 2007:554).

Following the above, each research hypothesis of the study is discussed independently in Chapter 7, section 7.5.4.2.2 for Model A and section 7.6.4 for Model B.

6.4.14 Reporting on the research findings

The last step in the research design was to report on the findings, as presented in Chapters 7 and 8. Chapter 7 provides a detailed account of the data analysis while Chapter 8 contains conclusions, key recommendations and strategies which would be of use to South African fashion retailers selling athleisure apparel.

6.5 Ethical considerations

Ethical considerations are of the utmost importance when conducting research involving human participants (Malhotra, 2007:421). This study was approved by UJ's College of Business and Economics Research Ethics Committee. The full application process was followed, and data collection commenced once approval was received from the committee on 12 June 2019.

Informed consent was sought from all participants through the cover letter (Annexure 3). The letter, which introduced the study, stressed the importance of completing the questionnaire, estimated the time required to complete it and described the process of submitting the questionnaire once completed. The letter also emphasised the anonymity of the respondents.

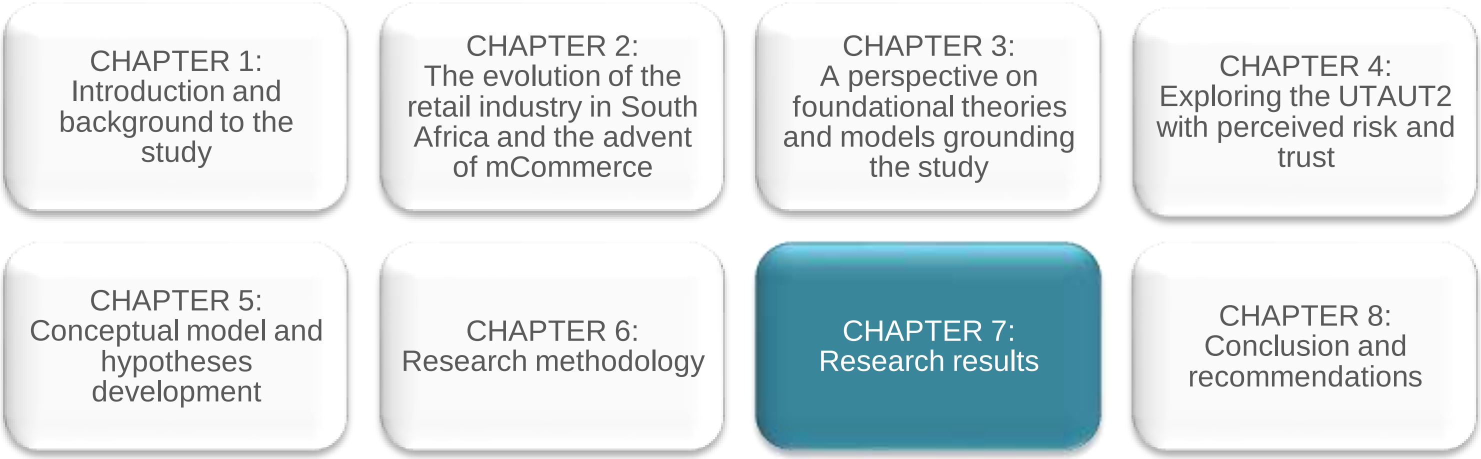
Fieldworkers from Osmoz Consulting assisted with gathering the data and capturing it onto SPSS. All physical questionnaires (paper-based records) were kept in a steel safe during this period with access limited to Osmoz Consulting. All electronically-completed questionnaires were retained in a secure cloud drive with access limited to the researcher, research supervisors and Osmoz Consulting by means of a unique username and password. Once the data was captured, it was stored in an access-controlled and password-protected cloud drive with access limited to the researcher, research supervisors and Osmoz Consulting. After 12 months, all paper-based records will be destroyed using a paper shredder and computer-based records will be permanently deleted from the cloud drive.

6.6 Conclusion

Chapter 6 provided a detailed description of the research methodology used in this study based on Saunders *et al*.'s (2016:124) 'research onion' approach. The chapter described the research philosophy, approach to theory development and process of research design. The methodological choice, research strategy and time horizon were then presented, followed by the data collection techniques and procedures. The chapter concluded with ethical considerations. The next chapter, Chapter 7, provides a detailed account of the data analysis process.

CHAPTER 7

RESEARCH RESULTS



7.1 Introduction

Chapter 6 provided a detailed account of the research methodology based on the 'research onion' (refer to Chapter 1, Figure 1.10) of Saunders *et al.* (2016:124). The current chapter presents and interprets the empirical results of the study. The chapter commences with an overview of the research objectives and hypotheses. The realisation rate is then discussed, followed by statistical analysis of the results. It is important to note that the model has been split for more accurate reporting of the results.

As detailed in Chapter 1, section 1.8.4, this study was conducted in two phases. Phase 1 (using Model A in Chapter 1, Figure 1.9) tested the influence of specific constructs on behavioural intention to determine consumers' acceptance of mCommerce apps to purchase athleisure apparel. Phase 2 (using Model B in Chapter 1, Figure 1.9) tested the influence of specific constructs on actual use to determine consumers' use of mCommerce apps to purchase athleisure apparel.

For Model A, the outcome variable (behavioural intention) was measured as a latent construct made up of multiple items, using structural equation modelling (SEM). For Model B, the outcome variable (actual use) was represented as five unique binary categorical outcomes. This model was therefore not analysed using SEM but a T-test analysis was used instead to establish the significance of the proposed relationships (as justified in sections 7.7.3 and 7.7.4).

The results are discussed in section 7.5, and are structured as follows. The analysis of Model A includes an overview of the factor analysis, normality, outliers, linearity and missing data as well as reliability analysis. SEM was conducted on the data, including confirmatory factor analysis (CFA) and goodness-of-fit (GoF) assessments on both the measurement and structural models for Model A specifically. The section closes with a summary of the hypotheses for Model A. The analysis of Model B includes factor analysis, with a view on factor extraction, factor rotation and interpretation. Exploratory factor analysis (EFA) was then conducted on the data. The section closes with a summary of the research hypotheses for Model B. The chapter concludes with a view of the final model including only the accepted hypotheses.

Figure 7.1 illustrates the flow of the entire chapter, guiding the reader as to the different sections that are covered.

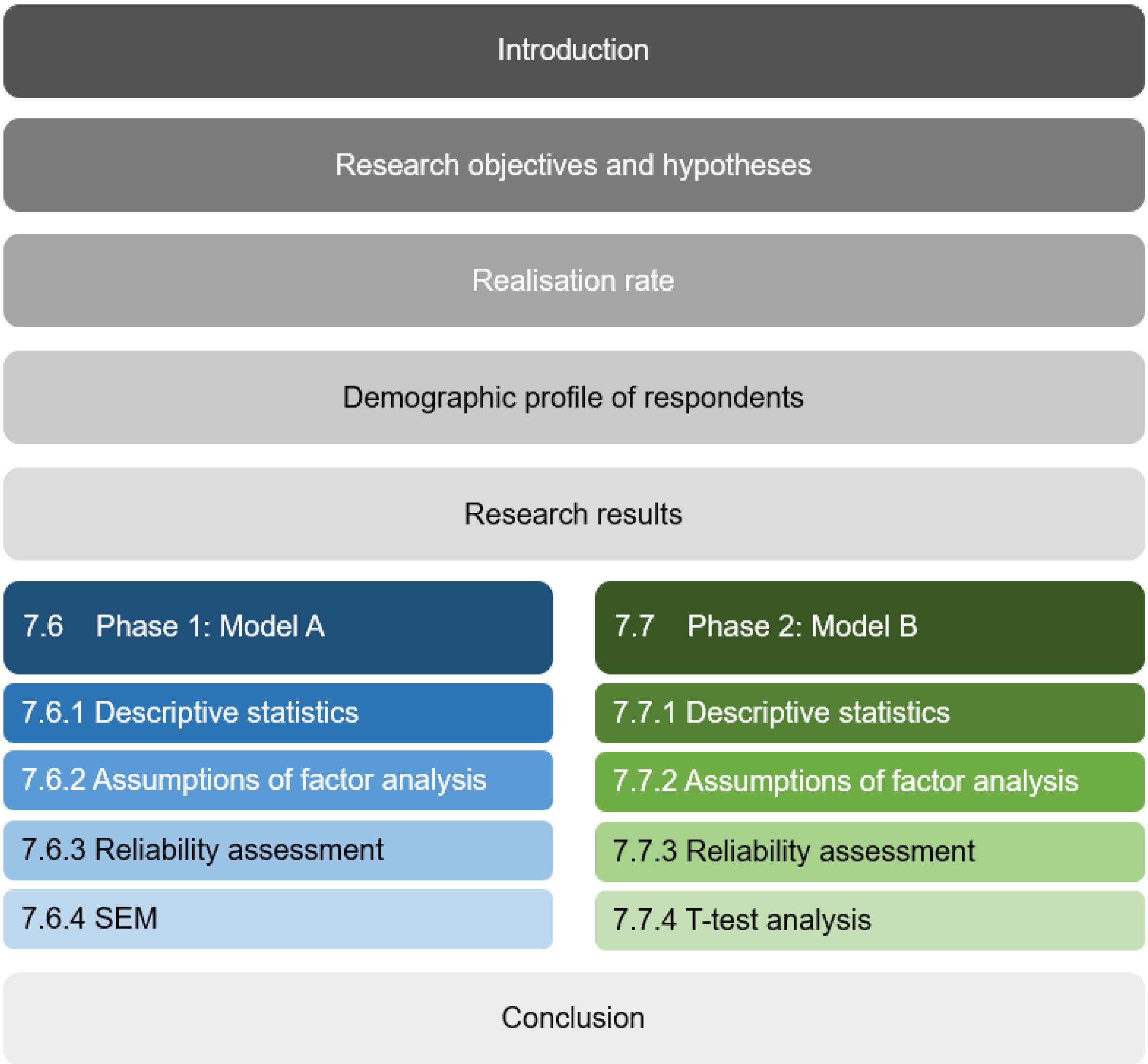


Figure 7.1: Structure of Chapter 7

7.2 Summary of research problem, research objectives and research hypotheses

7.2.1 Research problem

Refer to Chapter 1, section 1.3 for the research problem.

7.2.2 Research objectives

As established in Chapter 1, section 1.5, the primary research objective of this study is to determine the constructs that influence consumers' acceptance and use of mCommerce apps to purchase athleisure apparel in South Africa. The secondary research objectives are also stated in Chapter 1, section 1.5.

7.2.3 Research hypotheses

Following the identification of the research objectives, the research hypotheses were formulated, as stated in Chapter 1, section 1.7.4. This study aimed to confirm or reject the aforementioned hypotheses. The following sections outline the results of these tests.

7.3 Realisation rate

As stated in Chapter 1, section 1.8.4, and Chapter 6, section 6.4.10.2, a combination of two-part quota- and convenience sampling was used to gather the data for the study. The quotas, as broken down in Chapter 1, Table 1.1, were compiled based on the ethnic and gender demographics of South Africa (StatsSA, 2017b:1). A sample of 500 was required to ensure a 95% confidence level in the data (Survey Monkey, 2020) and to permit successful factor analysis (Pallant, 2016:184). The required sample of 500 was reached. The breakdown of the ethnicity quota requirements are detailed in Table 7.1. All ethnicity quotas were reached barring the Coloured quota, with 8.8% of the sample being required, but only 3.6% being met.

Table 7.1: Ethnicity quotas required versus quotas reached

Ethnicity	Number of respondents required	Percentage of South African population	Number of respondents in actual sample	Percentage of actual sample
Black	404	80.8%	404	80.8%
Coloured	44	8.8%	18	3.6%
Indian/Asian	12	2.5%	13	2.6%
White	40	8.0%	63	12.6%
Other	-	-	2	0.4%
Total	**500**	**100%**	**500**	**100%**

The breakdown of the gender quota requirements is detailed in Table 7.2. Gender quotas were reached.

Table 7.2: Gender quotas required versus quotas reached

Gender	Number of respondents required	Percentage of South African population	Number of respondents in actual sample	Percentage of actual sample
Male	250	50%	249	49.8%
Female	250	50%	251	50.2%
Total	**500**	**100%**	**500**	**100%**

7.4 Demographic description of respondents

The demographic description of the respondents is presented in Table 7.3. As indicated in the table, 500 respondents were targeted with the questionnaire and completed it, aligned to the original sample requirement (see as detailed in Chapter 1, section 1.8.4 and Chapter 6, section 6.4.10. Of these respondents, 250 made use of an mCommerce app to simply browse (i.e. they did not make a purchase) while 250 had previously made a purchase (i.e. they had bought an athleisure apparel item using the app). The full sample of 500 is included in this demographic description. The gender distribution was almost equal, as intended, i.e. female (n=251, 50.2%) compared to male (n=249, 49.8%). This is aligned to the demographic profile of South Africa (see Chapter 1, section 1.8.4 and Chapter 6, section 6.4.10) (StatsSA, 2017b:1). All respondents (n=500, 100%) owned a smartphone. Most had used an app to browse and/or buy products from their smartphones within the last week (n=197, 39.4%) or the last month (n=176, 35.2%). The majority of the respondents were Black (n=404, 80.8%), aligned with the set quotas. This reflects the demographic profile of South Africa (see Chapter 1, section 1.8.4 and Chapter 6, section 6.4.10) (StatsSA, 2017b:1). The highest education level for the majority of the respondents was a university degree (n=150, 30%), closely followed by Matric (Grade 12) (n=147, 29.4%). As expected, more than half of the sample was aged between 18-24 years old (n=284, 56.8%). A very small portion of the sample (n=27, 5.4%) was aged over 40. The predominant languages spoken were Zulu (n=101, 20.2%) and English (n=95, 19%). More than half of the respondents were full-time students (n=281, 56.2%) while 22.4% (n=112) were employed on a full-time basis. Approximately a third of the respondents (33.6%, n=168) purchased all their athleisure apparel in-store, with only 4.2% (n=21) purchasing all their athleisure apparel online.

Table 7.3: Demographic description of respondents

1. DO YOU HAVE A SMARTPHONE?			
		Frequency	Valid %
	Yes	500	100%
2. HAVE YOU USED AN APP ON YOUR SMARTPHONE TO BROWSE AND/OR BUY ATHLEISURE APPAREL (I.E. CLOTHING FOR EXERCISE AND GENERAL WEARING AS DEPICTED IN THE PICTURES ABOVE)? EXAMPLES OF APPS INCLUDE ZANDO, SUPERBALIST OR TAKEALOT.COM			
		Frequency	Valid %
	Browse	250	50%
	Buy	66	13.2%
	Browse and buy	184	36.8%
	Total	500	100%
3. WHEN WAS THE LAST TIME YOU USED AN APP TO BROWSE AND/OR BUY PRODUCTS FROM YOUR SMARTPHONE?			
		Frequency	Valid %
	Within the last week	197	39.4%
	Within the last month	176	35.2%
	Within the last year	83	16.6%
	More than 12 months ago	44	8.8%
	Total	500	100%
A1. GENDER:			
		Frequency	Valid %
	Male	249	49.8%
	Female	251	50.2%
	Total	500	100%
A2: ETHNICITY:			
		Frequency	Valid %
	Black	404	80.8%
	White	63	12.6%
	Coloured	18	3.6%
	Asian/Indian	13	2.6%
	Other (specify)	2	0.4%
	Total	500	100%
A3. EDUCATION: your highest level			
		Frequency	Valid %
	Matric/Grade 12	147	29.4%
	National Diploma/Certificate	66	13.2%
	University degree	150	30%
	Post-graduate degree	137	27.4%
	Total	500	100%
A4. HOW OLD ARE YOU?			
		Frequency	Valid %
	18 – 24 years old	284	56.8%
	25 – 29 years old	99	19.8%
	30 – 35 years old	67	13.4%
	35 – 40 years	23	4.6%
	Older than 40 (Please write down your age)	27	5.4%
	Total	500	100%
A5. HOME LANGUAGE:			

		Frequency	Valid %
	Afrikaans	29	5.8%
	English	95	19%
	Ndebele	8	1.6%
	Northern Sotho	46	9.2%
	Sotho	34	6.8%
	Swazi	21	4.2%
	Tsonga	43	8.6%
	Tswana	45	9%
	Venda	12	2.4%
	Xhosa	35	7%
	Zulu	101	20.2%
	Other (specify)	31	6.2%
	Total	500	100%
A6. EMPLOYMENT STATUS:			
		Frequency	Valid %
	Self-employed	25	5%
	Full-time employed by organisation	112	22.4%
	Part-time employed by organisation	28	5.6%
	Full-time student	281	56.2%
	Part-time student	22	4.4%
	Home executive	2	0.4%
	Unemployed	30	6%
	Total	500	100%
A7: OF THE ATHLEISURE APPAREL YOU PURCHASE, WHAT PROPORTION IS PURCHASED ONLINE AND IN-STORE?			
		Frequency	Valid %
	All online	21	4.2%
	Most online	82	16.4%
	About half online and half in-store	95	19%
	Most in-store	134	26.8%
	All in-store	168	33.6%
	Total	500	100%

Main findings 1, 2 and 3 can be deduced from the aforementioned demographics.

Main finding 1:
The typical respondent who participated in this study is a young (76.6% are below the age of 30), Black (80.8%) student (60.0%) who speaks Zulu (20.2%) and English (19%). It can be assumed that these respondents are more affluent than the average South African as they all own smartphones (100%).

Main finding 2:
A total of 50% of respondents use an mCommerce app to only browse athleisure apparel and 50% of respondents use an mCommerce app to browse and buy athleisure apparel.

Main finding 3:
Although 50% of respondents indicated that they used mCommerce apps to browse and buy athleisure apparel, the majority of the respondents (60.4%) preferred purchasing in-store.

As discussed in the introduction of this chapter, given the fact that two separate models were tested, the following section outlines the structure of the results discussion.

7.5 Structure of the results discussion

As discussed in section 7.1, Model A (see Chapter 1, Figure 1.9) tested the influence of specific constructs on behavioural intention to determine consumers' acceptance of mCommerce apps to purchase athleisure apparel. Model B (see Chapter 1, Figure 1.9) tested the influence of specific constructs on actual use to determine consumers' use of mCommerce apps to purchase athleisure apparel.

Figure 7.2 illustrates the structure of the research results discussion for each model. Section 7.6 discusses the results for Model A, followed by section 7.7, which discusses the results for Model B.

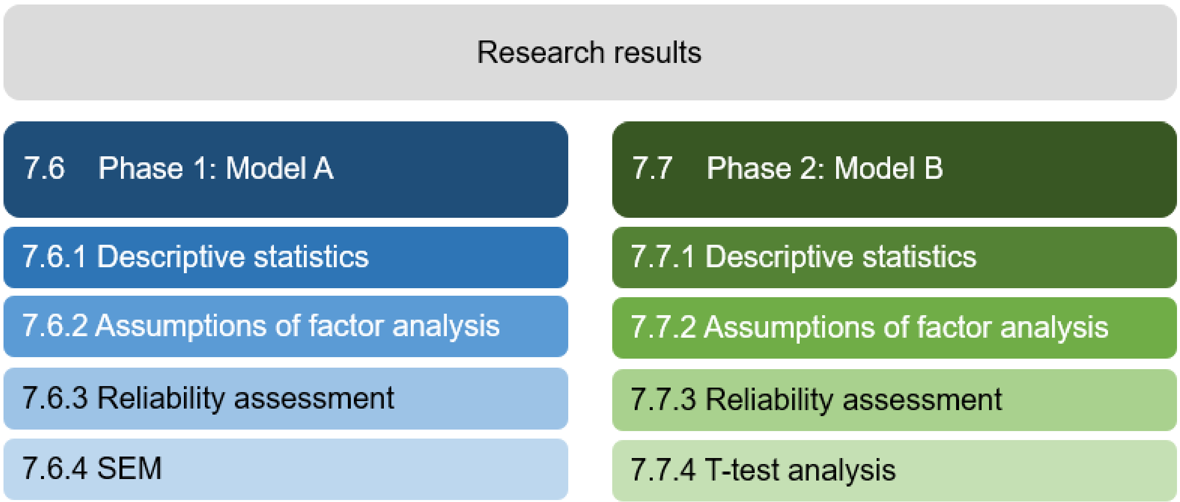


Figure 7.2: Structure of the results discussion

The following section provides a detailed account of the results for

PHASE 1: MODEL A

(Model A reflects behavioural intention as the dependent variable)

7.6 Phase 1: Model A – Results discussion

7.6.1 Descriptive statistics

This section explores and discusses the descriptive statistics for the sample data set for Model A. It commences with an overview of the mean and standard deviation for each of the constructs, leading into a detailed discussion of the results to provide empirical feedback on the hypotheses under investigation.

7.6.1.1 Mean and standard deviation scores

Section 7.6.1.1 and its sub-sections discuss the mean and standard deviation results for each of the constructs for Model A, detailed in Table 7.4. As defined in Chapter 6, Table 6.2, the mean is the average value between several different elements (Saunders *et al.*, 2016:720; Quinlan *et al.*, 2015:360; Hair *et al.*, 2013:268; Bryman & Bell, 2011:319; Malhotra, 2007:460). The standard deviation refers to the average distance of the values in their distribution from the mean (Hair *et al.*, 2013:273).

Table 7.4: Mean and standard deviation scores for Model A constructs

Construct/Item	Item mean	Item std dev	Overall mean	Overall std dev
Performance expectancy (PE)			**3.53**	**1.111**
PE1. I find mobile shopping useful in my daily life when browsing and/or purchasing athleisure apparel.	3.58	1.109		
PE2. Using mobile shopping apps helps me to do my shopping for athleisure apparel more quickly.	3.62	1.109		
PE3. Using mobile shopping apps increases my chances of achieving tasks that are important to me, such as browsing and/or purchasing athleisure apparel.	3.52	1.073		
PE4. Using mobile shopping apps for browsing and/or purchasing athleisure apparel increases my productivity.	3.40	1.152		
Effort expectancy (EE)			**4.09**	**0.931**
EE1. Learning how to use mobile shopping apps to browse and/or purchase athleisure apparel is easy for me.	4.16	0.952		
EE2. My interaction with mobile shopping apps when browsing and/or purchasing athleisure apparel is clear and understandable.	4.09	0.907		
EE3. I find mobile shopping apps easy to use when browsing and/or purchasing athleisure apparel.	4.05	0.914		
EE4. It is easy for me to become skilful at using mobile shopping apps to browse and/or purchase athleisure apparel.	4.04	0.953		
Social influence (SI)			**2.96**	**1.146**
SI1. People who are important to me think that I should use mobile shopping apps to browse and/or purchase athleisure apparel.	2.89	1.169		
SI2. People who influence my behaviour think that I should use mobile shopping apps to browse and/or purchase athleisure apparel.	2.94	1.147		
SI3. People whose opinions I value prefer that I use mobile shopping apps to browse and/or purchase athleisure apparel.	2.89	1.165		
SI4. People around me consider it appropriate to use mobile shopping apps to browse and/or purchase athleisure apparel.	3.14	1.102		
Facilitating conditions (FC)			**4.03**	**0.954**
FC1. I have the resources necessary to use mobile shopping apps to browse and/or purchase athleisure apparel.	4.09	0.932		
FC2. I have the knowledge necessary to use mobile shopping apps to browse and/or purchase athleisure apparel.	4.17	0.861		
FC3. Mobile shopping apps are compatible with other technologies I use when browsing and/or purchasing athleisure apparel.	4.03	0.948		
FC4. I can get help from others when I have difficulties using mobile shopping apps to browse and/or purchase athleisure apparel.	3.85	1.077		
Hedonic motivation (HM)			**3.56**	**1.095**
HM1. Using mobile shopping apps to browse and/or purchase athleisure apparel is fun.	3.66	1.097		
HM2. Using mobile shopping apps to browse and/or purchase athleisure apparel is enjoyable.	3.64	1.058		
HM3. Using mobile shopping apps to browse and/or purchase athleisure apparel is very entertaining.	3.45	1.105		
HM4. Using mobile shopping apps to browse and/or purchase athleisure apparel is very pleasurable.	3.48	1.121		
Price value (PV)			**3.52**	**0.990**
PV1. Athleisure apparel available via mobile shopping apps is reasonably priced.	3.50	1.020		

PV2. Athleisure apparel on mobile shopping apps offers good value for money.	3.51	1.002		
PV3. At current prices, mobile shopping apps provide good value for athleisure apparel.	3.52	0.951		
PV4. Athleisure apparel available via mobile shopping apps is affordable.	3.54	0.987		
Habit (HT)			**2.61**	**1.213**
HT1. The use of mobile shopping apps to browse and/or purchase athleisure apparel has become a habit for me.	2.75	1.202		
HT2. I am addicted to using mobile shopping apps to browse and/or purchase athleisure apparel.	2.33	1.187		
HT3. I must use mobile shopping apps to browse and/or purchase athleisure apparel.	2.56	1.225		
HT4. Using mobile shopping apps to browse and/or purchase athleisure apparel has become natural to me.	2.81	1.238		
Perceived risk (PR)			**3.45**	**1.175**
FR1. The chance of me losing money is high when using mobile shopping apps to purchase athleisure apparel.	3.12	1.271		
FR2. My credit card number may not be secure when using mobile shopping apps to purchase athleisure apparel.	3.33	1.238		
FR3. The use of mobile shopping apps to purchase athleisure apparel is a financial risk.	3.29	1.175		
PPR1. The probability of receiving the wrong item is high when using mobile shopping apps to purchase athleisure apparel.	3.47	1.128		
PPR2. Using a mobile shopping app to purchase athleisure apparel is risky because I can't examine the product before making payment.	3.75	1.129		
PPR3. The athleisure apparel product purchased may not be suitable in size, style or colour.	3.73	1.107		
Trust (TR)			**3.39**	**1.050**
TR1. I trust that my mobile device will be reliable when I shop for athleisure apparel via mobile apps.	3.61	1.079		
TR2. I trust the shopping systems available on mobile apps to browse and/or purchase athleisure apparel.	3.41	1.010		
TR3. Mobile app retailers selling athleisure apparel are trustworthy.	3.28	1.034		
TR4. Mobile app retailers selling athleisure apparel have high integrity.	3.26	1.024		
TR5. Mobile app retailers selling athleisure apparel have my best interests in mind.	3.21	1.036		
TR6. When shopping online for athleisure apparel, I feel that my mobile device is just as reliable as my computer.	3.54	1.117		
Behavioural intention (BI)			**3.71**	**1.024**
BI1. I intend to use mobile shopping apps to purchase athleisure apparel in the future.	3.74	1.019		
BI2. I will use mobile shopping apps to purchase athleisure apparel where feasible.	3.82	0.929		
BI3. I plan to use mobile shopping apps to purchase athleisure apparel in future.	3.78	0.994		
BI4. I predict I will use mobile shopping apps to purchase athleisure apparel in future.	3.83	0.989		
BI5. I will use mobile shopping apps to purchase athleisure apparel in my daily life.	3.39	1.191		

7.6.1.1.1 Performance expectancy (PE)

Table 7.4 details the mean and standard deviation scores for each of the four items used to measure performance expectancy as well as the overall scores. The overall mean score was 3.53 (1=strongly disagree and 5=strongly agree), over the midpoint of 3 (3=neutral). This indicates that the majority of the respondents agreed with the statements regarding performance expectancy. The highest level of agreement was with item PE2, i.e. "Using mobile shopping apps helps me to do my shopping for athleisure apparel more quickly". The mean score for this item was 3.62. The lowest level of agreement was for item PE4, i.e. "Using mobile shopping apps for browsing and/or purchasing athleisure apparel increases my productivity", with a mean score of 3.40. The item with the highest level of variance was PE4, i.e. "Using mobile shopping apps for browsing and/or purchasing athleisure apparel increases my productivity", with a variance of 1.152. Main finding 4, therefore is as follows:

Main finding 4:
The majority of the respondents agreed that the use of mCommerce apps was beneficial to them when purchasing athleisure apparel. It can therefore be assumed that consumers will use mCommerce apps if they feel that the app will provide them with utility or a benefit in return.

7.6.1.1.2 Effort expectancy (EE)

The mean and standard deviation scores for each of the four items used to measure effort expectancy as well as the overall score for the construct are depicted in Table 7.4. The overall mean score was 4.09 (1=strongly disagree and 5=strongly agree), over the midpoint of 3 (3=neutral). This indicates that the majority of the respondents strongly agreed with the statements regarding effort expectancy. The highest level of agreement was with item EE1, i.e. "Learning how to use mobile shopping apps to browse and/or purchase athleisure apparel is easy for me". The mean score for this item was 4.16. The standard deviation scores for this construct ranged from 0.907 to 0.953, indicating minimal variability between the responses for each of the statements on effort expectancy. The item with the highest level of variance was EE4, i.e. "It is easy for me to become skilful at using mobile shopping apps to browse and/or purchase athleisure apparel", with a variance of 0.953. Main finding 5, therefore is as follows:

Main finding 5:
The largest number of respondents who participated in this study strongly agreed that it would be easy for them to use mCommerce apps. It can be inferred that this was indeed the case as all respondents owned a smartphone (100%) and the majority of the sample (56.8%) were between the ages of 18 and 24 years. Therefore, they could be considered technologically savvy and *au fait* with using apps.

7.6.1.1.3 Social influence (SI)

The mean and standard deviation scores for social influence are captured in Table 7.4. The overall mean score was 2.96 (1=strongly disagree and 5=strongly agree), just under the midpoint of 3 (3=neutral). This indicates that the majority of the respondents neither agreed nor disagreed with the statements for this specific construct. The highest level of agreement was with item SI4, i.e. "People around me consider it appropriate to use mobile shopping apps to browse and/or purchase athleisure apparel". The mean score for this item was 3.14. All other items' mean scores fell below the midpoint of 3. The item with the highest level of variance was SI1, i.e. "People who are important to me think that I should use mobile shopping apps to browse and/or purchase athleisure apparel", with a variance of 1.169. Main finding 6, therefore is as follows:

Main finding 6:
The majority of the respondents felt impartial as to the influence of their friends and family on their usage of mCommerce apps.

7.6.1.1.4 Facilitating conditions (FC)

Table 7.4 details the mean and standard deviation scores for each of the four items used to measure facilitating conditions as well as the overall scores. The overall mean score was 4.03 (1=strongly disagree and 5=strongly agree), over the midpoint of 3 (3=neutral). This indicates that the majority of the respondents strongly agreed with the statements regarding facilitating conditions. The highest level of agreement was with item FC2, i.e. “I have the knowledge necessary to use mobile shopping apps to browse and/or purchase athleisure apparel”. The mean score for this item was 4.17. The lowest level of agreement was for item FC4, i.e. “I can get help from others when I have difficulties using mobile shopping apps to browse and/or purchase athleisure apparel”, with a mean score of 3.85. The standard deviation scores for this construct ranged from 0.861 to 1.077, indicating a degree of variance between the responses. The item with the highest level of variance was FC4, i.e. “I can get help from others when I have difficulties using mobile shopping apps to browse and/or purchase athleisure apparel”, with a variance of 1.077. Further analysis was done in this chapter (section 7.6.3), however, item FC4’s low mean score (3.85) and high standard deviation (1.077), compared to other items, warranted it being removed from the model. Main finding 7, therefore is as follows:

Main finding 7:
The majority of the respondents felt strongly that they were well-equipped and had the necessary resources to use mCommerce apps. It can be inferred that this was indeed the case as all the respondents owned a smartphone (100%) and therefore had access to the Internet.

7.6.1.1.5 Hedonic motivation (HM)

The mean and standard deviation scores for each of the four items used to measure hedonic motivation as well as the overall score for the construct are depicted in Table 7.4. The overall mean score was 3.56 (1=strongly disagree and 5=strongly agree), over the midpoint of 3 (3=neutral). This indicates that the majority of the respondents agreed with the statements on hedonic motivation. The highest level of agreement was with item HM1, i.e. “Using mobile shopping apps to browse and/or purchase athleisure apparel is fun”. The mean score for this item was 3.66. The item with the highest level of variance was HM4, i.e. “Using mobile shopping apps to browse and/or purchase athleisure apparel is very pleasurable”, with a variance of 1.121. Main finding 8, therefore is as follows:

Main finding 8:
The majority of the respondents felt that using mCommerce apps brought them a measure of joy and entertainment.

7.6.1.1.6 Price value (PV)

The mean and standard deviation scores for price value are captured in Table 7.4. The overall mean score was 3.52 (1=strongly disagree and 5=strongly agree), over the midpoint of 3 (3=neutral). This indicates that the majority of the respondents agreed with the statements for this specific construct. The highest level of agreement was with item PV4, i.e. “Athleisure apparel available via mobile shopping apps is affordable”. The mean score for this item was 3.54. The standard deviation scores for this construct ranged from 0.951 to 1.020, indicating minimal variability between the responses for each of the statements. The item with the highest level of variance was PV1, i.e. “Athleisure apparel available via mobile shopping apps is reasonably priced”, with a variance of 1.020. Main finding 9, therefore is as follows:

Main finding 9:
The majority of the respondents agreed that mCommerce apps offered athleisure apparel at good prices.

7.6.1.1.7 Habit (HT)

Table 7.4 details the mean and standard deviation scores for each of the four items used to measure habit as well as the overall scores. The overall mean score was 2.61 (1=strongly disagree and 5=strongly agree), below the midpoint of 3 (3=neutral). This indicates that the majority of the respondents disagreed with the statements regarding habit. The highest level of agreement was with item HT4, i.e. “Using mobile shopping apps to browse and/or purchase athleisure apparel has become natural to me”. The mean score for this item was 2.81. This same item displayed the highest level of variance at 1.238. Main finding 10, therefore is as follows:

Main finding 10:
The majority of the respondents did not feel that purchasing via mCommerce apps had become a habit or natural to them.

7.6.1.1.8 Perceived risk (PR)

The mean and standard deviation scores for each of the six items used to measure perceived risk as well as the overall score for the construct are depicted in Table 7.4. The first three items measured financial risk while the last three measured product performance risk. The overall mean score was 3.45 (1=strongly disagree and 5=strongly agree), over the midpoint of 3 (3=neutral). This indicates that the majority of the respondents agreed with the statements on perceived risk. The highest level of agreement was with item PR5 (product performance risk), i.e. “Using a mobile shopping app to purchase athleisure apparel is risky because I can’t examine the product before making the payment”. The mean score for this item was 3.75. PR6 (product performance risk), i.e. “The athleisure apparel product purchased may not be suitable in size, style or colour” featured the second highest mean score of 3.73. The lowest level of agreement was with item PR1 (financial risk), i.e. “The chance of me losing money is high when using mobile shopping apps to purchase athleisure apparel”, with a mean score of 3.12. The standard deviation scores for this construct ranged from 1.107 to 1.271, indicating a degree of variance between the responses for each of the statements on perceived risk. Along with displaying the lowest level of agreement (mean=3.12), PR1 (financial risk) also displayed the highest level of variance, 1.271. Main finding 11, therefore is as follows:

Main finding 11:
The majority of the respondents agreed that they felt exposed to risks, including financial and product performance risk, when transacting via mCommerce apps. Interestingly, the highest level of agreement was with the statement regarding consumers’ ability to examine products before purchasing.

7.6.1.1.9 Trust (TR)

The mean and standard deviation scores for trust are captured in Table 7.4. The overall mean score was 3.39 (1=strongly disagree and 5=strongly agree), over the midpoint of 3 (3=neutral). This indicates that the majority of the respondents agreed with the statements for this specific construct. The highest level of agreement was with item TR1, i.e. "I trust that my mobile device will be reliable when I shop for athleisure apparel via mobile apps". The mean score for this item was 3.61. TR6, i.e. "When shopping online for athleisure apparel, I feel that my mobile device is just as reliable as my computer" featured the second highest mean score of 3.54. The lowest level of agreement was with item TR5, i.e. "Mobile app retailers selling athleisure apparel have my best interests in mind", with a mean score of 3.21. The item with the highest level of variance was TR6, i.e. "When shopping online for athleisure apparel, I feel that my mobile device is just as reliable as my computer", with a variance of 1.117. Main finding 12, therefore is as follows:

Main finding 12:
The majority of the respondents agreed that they could trust retailers, systems and payment processes when shopping via mCommerce apps. Their trust in retailers, systems and processes was therefore strong, despite feeling exposed to certain risks.

7.6.1.1.10 Behavioural intention (BI)

Table 7.4 details the mean and standard deviation scores for each of the five items used to measure behavioural intention as well as the overall scores. The overall mean score was 3.71 (1=strongly disagree and 5=strongly agree), above the midpoint of 3 (3=neutral). This indicates that the majority of the respondents agreed with the statements on behavioural intention. The highest level of agreement was with item BI4, i.e. "I predict I will use mobile shopping apps to purchase athleisure apparel in future". BI2 featured a mean score of 3.82, very close to BI4. This item stated: "I will use mobile shopping apps to purchase athleisure apparel where feasible". The lowest level of agreement was with item BI5, i.e. "I will use mobile shopping apps to purchase athleisure apparel in my daily life”, with a mean score of 3.39. The standard deviation scores for this construct ranged from 0.929 to 1.191, indicating a degree of variance between the responses for each of the statements surrounding behavioural intention. Item BI5 not only displayed the lowest level of agreement (mean=3.39) but also the highest level of variance, 1.191. Main finding 13, therefore is as follows:

Main finding 13:
The majority of the respondents agreed that they would either start using or continue using mCommerce apps in the future.

In order to determine relationships between the various constructs, it was necessary to conduct factor analysis, however, before this could be completed, certain statistical assumptions had to be met first.

7.6.2 Assumptions of factor analysis

As outlined in section 6.4.13, the assumptions of factor analysis include those of normality, outliers, linearity and missing data. This was required to ensure multivariate statistical techniques could be applied to the data (Hair *et al.*, 2006:79). For Model A, details on these assumptions are presented in the following sections.

7.6.2.1 Normality

As described in Chapter 6, section 6.4.13.1, normality refers to the shape of the distribution of the data for a specific variable as well as how it relates to a normal data distribution. An assessment of normality can be done by means of skewness and kurtosis tests.

Hair *et al.* (2006:80) explain that skewness is a measure that indicates the balance of the distribution of data (if is it shifted to the right or left side or if is it balanced). A positive skew indicates that most scores sit below the mean. A negative skew shows most scores sitting above the mean (Kline, 2011:60). Kurtosis is a measure used to indicate the height of the distribution (how flat or peaked the distribution is, compared to a normal distribution). The closer both the skewness and kurtosis values are to 0, the more normal the data distribution (Hair *et al.*, 2006:80). It should be noted that, as detailed in Chapter 6, section 6.4.13.1, the normality of this data set was expected, given the sample size (n=500).

Table 7.5 summarises the skewness and kurtosis for each of the constructs in the study. It can be concluded that the data set was normally distributed from a skewness perspective, as all skewness values were between 1 and -1. From a kurtosis perspective, however, the effort expectancy and facilitating conditions constructs delivered kurtosis scores of 1.162 and 1.182. Further analysis using Kolmogorov-Smirnov and Shapiro-Wilk tests can assist in validating normality.

Table 7.5: Skewness and kurtosis

Construct	Skewness	Kurtosis
Performance expectancy (PE)	-0.474	0.012
Effort expectancy (EE)	-0.930	1.162
Social influence (SI)	-0.020	-0.357
Facilitating conditions (FC)	-0.840	1.182
Hedonic motivation (HM)	-0.465	-0.174
Price value (PV)	-0.388	0.142
Habit (HT)	0.185	-0.799
Perceived risk: Financial risk (FR)	-0.145	-0.162
Perceived risk: Product performance risk (PPR)	-0.396	-0.318
Trust (TR)	-0.450	0.278
Behavioural intention (BI)	-0.546	0.186

As detailed in Chapter 6, section 6.4.13.1, the Kolmogorov-Smirnov and Shapiro-Wilk tests were used for the validation of normality. Both these tests confirmed the assumption of normality at a 5% level of significance ($p<0.05$) (Kundu, Mishra & Khare, 2002:12). Table 7.6 summarises the p-values of the Kolmogorov-Smirnov and Shapiro-Wilk tests for the constructs in order to determine whether they fulfilled the requirements for normality.

Table 7.6: Kolmogorov-Smirnov and Shapiro-Wilk test results

Construct	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	Df	Sig.	Statistic	Df	Sig.
Performance expectancy (PE)	0.098	500	0.000	0.966	500	0.000
Effort expectancy (EE)	0.133	500	0.000	0.906	500	0.000
Social influence (SI)	0.097	500	0.000	0.979	500	0.000
Facilitating conditions (FC)	0.132	500	0.000	0.930	500	0.000
Hedonic motivation (HM)	0.104	500	0.000	0.950	500	0.000
Price value (PV)	0.093	500	0.000	0.969	500	0.000
Habit (HT)	0.084	500	0.000	0.966	500	0.000
Perceived risk: Financial risk (FR)	0.076	500	0.000	0.969	500	0.000
Perceived risk: Product performance risk (PPR)	0.090	500	0.000	0.953	500	0.000
Trust (TR)	0.088	500	0.000	0.974	500	0.000
Behavioural intention (BI)	0.115	500	0.000	0.956	500	0.000

As detailed in Table 7.6, both the Kolmogorov-Smirnov and the Shapiro-Wilk p-values ($p=0.000$) confirm that the data for the sample achieved normality ($p<0.05$). This affirms the normal distribution of the sample. In addition to this, Kundu *et al.* (2002:14) state that for a larger sample size, Kolmogorov-Smirnov should be in the 0.062 region and Shapiro-Wilk in the 0.975 region. When referring to Table 7.6, the only values that fell far outside the aforementioned cut-off values were again, effort expectancy and facilitating conditions, but not to such a degree that this would warrant the removal of these constructs. It is worth noting that Kim (2013:52; 53) states that these two tests (i.e. Kolmogorov-Smirnov and Shapiro-Wilk) work well for small to medium-sized samples, such as $n \leq 300$, but that they are not as reliable for larger samples, such as this study, at $n=500$. Absolute skew values of larger than 2 or absolute kurtosis values larger than 7 would be considered non-normal. As is evident from Table 7.5, none of the constructs for this particular study achieved such values. Main finding 14, therefore is as follows:

Main finding 14:
The assessment of normality indicated satisfactory skewness and kurtosis values; therefore, the assumption of normality was met.

It was therefore considered appropriate to proceed with SEM. The following section provides detail on the assessment of outliers.

7.6.2.2 Outliers

As described in Chapter 6, section 6.4.13.1, outliers (homoscedasticity) refer to the assumption that one dependent variable exhibits the same level of variance across a range of independent variables. To assess homoscedasticity, histograms were evaluated as well as box and whisker plots.

Annexure 10 features histograms for each of the constructs in this study. Outliers were identified in performance expectancy, effort expectancy, facilitating conditions, hedonic motivation, price value, perceived risk: product performance risk and trust. The remaining constructs, i.e. social influence, habit, perceived risk: financial risk and behavioural intention displayed fairly even distributions. The data for these constructs could therefore be considered to have normality.

Box and whisker plots were used to better understand the outliers for performance expectancy, effort expectancy, facilitating conditions, hedonic motivation, price value, perceived risk: product performance risk and trust. These are featured in Annexure 11. As is evident from Annexure 11, the box and whisker plots appear uneven, containing outliers for performance expectancy, effort expectancy, facilitating conditions, hedonic motivation, price value, perceived risk: product performance risk and trust. These outliers were, however, not removed as they did not pose any significant threats to the study. It was therefore considered appropriate to proceed with SEM. The following section provides detail surrounding the assessment of linearity.

7.6.2.3 Linearity

As explained in Chapter 6, section 6.4.13.1, linearity can be graphically assessed by examining scatterplots of each of the various constructs to identify nonlinear patterns in the data. Annexure 12 shows the scatterplots for each of the different constructs. Straight lines should be visible, indicative of linear relationships (Hair *et al.*, 2006:85). When evaluating the various scatterplots in Annexure 12, linear relationships can be seen, meaning that the basic assumptions of linearity were met. It was therefore considered appropriate to proceed with SEM. The following section provides detail surrounding the assessment of missing data.

7.6.2.4 Missing data

As mentioned in Chapter 6, section 6.4.13.1, all questionnaires were evaluated for missing data and as discussed in section 7.3, no missing values were identified. It was therefore considered appropriate to proceed with SEM.

Based on the aforementioned information, the statistical assumptions of normality, outliers, linearity and missing data were met and multivariate statistical techniques could be applied to the data for Model A, as presented in section 7.6.4 (Hair *et al.*, 2006:79).

That concludes the factor analysis assumptions prior to conducting SEM for Model A. The following section unpacks the reliability of the research instrument.

7.6.3 Reliability assessment

As per the discussion in Chapter 6, section 6.4.13.3, an assessment of reliability establishes the success of the research instrument. The assessment considers the extent to which there is an association between the individual items of particular constructs within the questionnaire (Hair *et al.*, 2013:166; Bryman & Bell, 2011:38; Malhotra, 2007:285). To assess questionnaire reliability, internal consistency can be examined. Hair *et al.* (2013:166), Bryman and Bell (2011:38) and Malhotra (2007:285) describe internal consistency as the extent to which there is correlation between the individual items or questions of a particular construct. The test can be completed by assessing Cronbach's alpha, a calculation that determines "the average of all possible split-half measures that result from different ways of dividing the scale questions" (Hair *et al.*, 2013:166).

Table 7.7 summarises the Cronbach alpha values for each of the constructs in Model A. Hair *et al.* (2013:166) state that any value lower than 0.7 indicates low and unsatisfactory internal consistency. As is evident, all Cronbach alpha values were above 0.7. The two lowest ones were associated with facilitating conditions (α=0.764) and perceived risk: product performance risk (α=0.796), with the former posing more of a problem than the latter. A further analysis on the construct of facilitating conditions revealed that item FC4, i.e. “I can get help from others when I have difficulties using mobile shopping apps to browse and/or purchase athleisure apparel” was the main cause of the low Cronbach alpha value for this construct. As per Table 7.4, this item had the lowest mean (3.85) and highest standard deviation (1.077). If this item were to be removed, the Cronbach alpha value for facilitating conditions would change from 0.764 to 0.787. As explained in section 7.6.1.2.4, the results for this item warranted its removal from this study.

The constructs displaying the highest Cronbach alpha values included hedonic motivation (α=0.937), trust (α=0.905) and price value (α=0.883). With the exception of item FC4, overall, all other constructs and associated items were deemed reliable and were therefore retained for further analysis.

Table 7.7: Cronbach’s alpha for each Model A construct

Construct	**Scale items**	**Cronbach’s alpha**
Performance expectancy (PE)	PE1, PE2, PE3, PE4	0.824
Effort expectancy (EE)	EE1, EE2, EE3, EE4	0.866
Social influence (SI)	SI1, SI2, SI3, SI4	0.865
Facilitating conditions (FC)		
Incl. FC4	FC1, FC2, FC3, FC4	0.764
Excl. FC4	FC1, FC2, FC3	0.787
Hedonic motivation (HM)	HM1, HM2, HM3, HM4	0.937
Price value (PV)	PV1, PV2, PV3, PV4	0.883
Habit (HT)	HT1, HT2, HT3, HT4	0.868
Perceived risk: Financial risk (FR)	FR1, FR2, FR3	0.816
Perceived risk: Product performance risk (PPR)	PPR1, PPR2, PPR3	0.796
Trust (TR)	TR1, TR2, TR3, TR4, TR5, TR6	0.905

Main finding 15, therefore is as follows:

Main finding 15:
The results of the reliability test indicate that all scale items used to measure the various constructs presented good internal consistency with the exception of item FC4 which was removed. All items were therefore deemed reliable and retained for further analysis.

As the reliability of the constructs for Model A was deemed satisfactory (α>0.7), (Hair *et al.*, 2013:166), SEM could continue. These results are presented in the following section.

7.6.4 Structural equation modelling (SEM)

As discussed in Chapter 6, section 6.4.13.5, SEM provides a general framework for statistical analysis that encompasses several multivariate statistical techniques such as CFA and multiple regression analysis (Hox & Bechger, 1999:354). As this study tests models that involve multiple hypotheses and variables, multivariate analysis was deemed to be best suited (Zikmund & Babin, 2010:538). SEM is used to judge a model formulated by theory against the data collected against it (Jak, 2015:v; 4; Hair *et al.*, 2006:711). SEM requires the proposed research model (refer to Chapter 1, Figure 1.9) to be broken up into a measurement model and a structural model. The measurement model depicts how different variables come together to denote constructs while the structural model depicts each construct's association with the other (Hair *et al.*, 2006:714). The following sections contain the CFA and hypothesis testing results on the measurement and structural models of Model A specifically. EFA was not conducted on Model A as the fit statistics using CFA were considered sufficient (see sections 7.5.4.1.1 and 7.5.4.2.1).

7.6.4.1 Measurement model: CFA

As explained in Chapter 6, section 6.4.13.5, CFA is often regarded as a statistic of SEM. Mazzocchi (2008:316-317) points out that CFA allows researchers to estimate multiple and concurrent relationships amongst several dependent variables. It is applied in an effort to verify the underlying factor structure of a set of observed variables and allows the researcher to test whether relationships exist between observed variables and their underlying latent constructs (Bryman & Bell, 2011:328; Suhr, 2006:1). Before CFA can proceed, it requires a relationship between variables to first be specified based on pre-existing theory (Mazzocchi, 2008:317). This subsequently allows the confirmation of relationships between variables (Mooi & Sarstedt, 2011:218). A number of CFA statistical tests, mostly GoF indices (see

Chapter 6, Table 6.4), were conducted for this study. The following sections elaborate on the results of these tests.

7.6.4.1.1 Goodness-of-fit (GoF) assessment

Firstly, absolute fit and incremental fit were tested. The absolute fit index is assessed through the Model Chi-square test and Root Mean Square Error of Approximation (RMSEA). The Model Chi-square test highlights the level of variance between expected and observed covariance matrices (Hooper *et al.*, 2008:53; Suhr, 2006:1). Awang (2012:56) states that the level of acceptance for Model Chi-square degrees of freedom is ≤3. The RMSEA, as explained in Chapter 6, section 6.4.13.5, highlights "the difference between the observed covariance matrix per degree of freedom and the hypothesised covariance matrix which denotes the model" (Cangur & Ercan, 2015:157; Suhr, 2006:2). An RMSEA value of ≤0.05 is regarded as an acceptable fit (Hu & Bentler, 1999:4). Newsom (2018:3), Hooper *et al.* (2008:54), Suhr (2006:2) and Sun (2005:249) state that an RMSEA of ≤0.06 is suitable. Table 7.8 summarises the Model Chi-square and RMSEA values for absolute fit assessment of the measurement model.

As is evident from the results, the Model Chi-square test achieved a fit of 1.670 for Model A and 1.695 for the re-specified Model A, with the FC4 item removed. Both were below the requirement of 3, indicating an acceptable fit (Awang, 2012:56). That being said, the Model Chi-square is not always the best fit statistic to use as it is heavily influenced by sample size and model complexity, hence the use of multiple fit statistics (Newsom, 2018:1; Koubaa, Tabbane & Jallouli, 2013:329; Hooper *et al.,* 2008:54; 56; Sun, 2005:245).

RMSEA achieved a fit of 0.037 for Model A and retained the same score for the re-specified Model A, both below the requirement of ≤0.06, which indicated an acceptable fit (Newsom, 2018:3; Hooper *et al.,* 2008:54; Suhr, 2006:2; Sun, 2005:249). Similar to the Model Chi-square, the RMSEA is not the best fit statistic as it is heavily influenced by the Model Chi-square and therefore sample size and model complexity impact the result (Hooper *et al.,* 2008:54). Incremental fit indices are elaborated on next.

The incremental fit index determines how well the research model fits an alternative model, at a relative basis (Hair *et al.*, 2010:668). The Comparative Fit Index (CFI) and the Tucker-Lewis Index (TLI) determine incremental fit. The CFI requires a value of ≥0.90 which indicates a good fit (Newsom, 2018:2; Cangur & Ercan, 2015:159; Hooper *et al.*, 2008:55; Suhr, 2006:2; Hu & Bentler, 1999:4). The TLI also requires a value ≥0.90 which indicates an acceptable fit (Newsom, 2018:2), with 0.95 indicating a good fit (Sun, 2005:249). Table 7.8 summarises the CFI and TLI values for incremental fit assessment.

As is evident from the results, the CFI test achieved a fit of 0.946, which is above the requirement of ≥0.90, indicating an acceptable fit (Newsom, 2018:2; Cangur & Ercan, 2015:159; Hooper *et al.,* 2008:55; Suhr, 2006:2). The TLI test achieved a fit of 0.939 which is also above the requirement of ≥0.90, indicating an acceptable fit and very close to 0.95, indicating a good fit (Newsom, 2018:2; Sun, 2005:249). On adjusting the model and removing item FC4, the CFI remained consistent, however the TLI changed slightly to 0.940, still indicating a good fit.

Table 7.8: Measurement model: GoF assessment

Goodness-of-fit category	**Selected indices (statistical tests)**	**Acceptable fit**	**Initial Model A-fit outcomes**	**Re-specified Model A fit-outcomes (removing FC4)**
Absolute fit index	Model Chi-square test (X^2)	Value of ≤3 (Awang, 2012:56).	1.670	1.695
	RMSEA	Value of ≤0.05-0.06 indicates an acceptable fit (Newsom, 2018:3; Hooper *et al*., 2008:54; Suhr, 2006:2; Sun, 2005:249; Hu & Bentler, 1999:4).	0.037	0.037
Incremental fit index	CFI	Value of ≥0.90 indicates a good fit (Newsom, 2018:2; Cangur & Ercan, 2015:159; Hooper *et al*., 2008:55; Suhr, 2006:2).	0.946	0.946
	TLI	Value ≥0.90 indicates an acceptable fit (Newsom, 2018:2); value of ≥0.95 indicates a good fit (Sun, 2005:249).	0.939	0.940

Based on the information provided in Table 7.8, the model was considered to have satisfactory goodness-of-fit and no re-specification was required. Main finding 16, therefore is as follows:

Main finding 16:
The goodness-of-fit assessment for the proposed measurement model was satisfactory, indicating a good model fit.

In an effort to improve the goodness-of-fit of the final structural model, correlations were determined between the various constructs, as presented below.

7.6.4.1.2 Multicollinearity

To determine whether multicollinearity was present in the data set, correlations between the various latent constructs were examined using Pearson's correlation coefficient. This statistical measure (r) measures the strength of association or the strength of a linear relationship between two constructs. It can vary from -1.00 to 1.00, with the value of 0 representing absolutely no association (Hair *et al.*, 2013:316; Malhotra, 2007:536). Multicollinearity is defined as "a situation in which several independent variables are highly correlated with each other", for example, when variables are correlated at 0.50 or higher (Hair *et al.*, 2013:332).

Table 7.9 depicts the correlation matrix between the various constructs. The cells containing an asterisked value (*) indicate a strong correlation (r>0.50). The square root of AVEs (√AVE) is indicated on the diagonal.

Table 7.9: Correlation matrix

	PE	***EE***	***SI***	***FC***	***HM***	***PV***	***HT***	***FR***	***PPR***	***TR***	***BI***
PE	**0.739**										
EE	0.452	**0.789**									
SI	0.375	0.070	**0.789**								
FC	0.331	0.691*	0.121	**0.743**							
HM	0.360	0.363	0.231	0.412	**0.889**						
PV	0.409	0.239	0.285	0.266	0.161	**0.810**					
HT	0.393	0.115	0.405	0.106	0.327	0.311	**0.791**				
FR	0.148	0.084	0.113	0.172	0.052	0.001	0.008	**0.773**			
PPR	0.170	0.046	0.116	0.025	0.078	0.152	0.196	0.020	**0.758**		
TR	0.404	0.246	0.288	0.338	0.228	0.364	0.331	0.320	0.279	**0.786**	
BI	0.474	0.388	0.254	0.400	0.334	0.333	0.396	0.144	0.172	0.592*	0.820

As is evident, there is no multicollinearity in the data set. It is interesting to note, however, that there is a significant correlation between effort expectancy and facilitating conditions (r=0.691) and trust and behavioural intention (r=0.592). Even though these exceeded 0.50, they were still well below 0.85. Awang (2012:55) states that a correlation value of above 0.85 indicates too strong a linear relationship which contributes to a multicollinearity problem. Main finding 17, therefore is as follows:

Main finding 17:
The correlation matrix measuring the relationship between the various constructs was satisfactory, with no concerns of multicollinearity evident in the data.

When conducting CFA, it is important to conduct an evaluation of the validity of the measurement model, as discussed below.

7.6.4.1.3 Validity assessment

As discussed in Chapter 6, section 6.4.13.3, an assessment of validity is used to determine whether a questionnaire measures what it is intended to measure (Ragab & Arisha, 2018:15; Taherdoost, 2016:28; Quinlan *et al.*, 2015:24; Bryman & Bell, 2011:38). Table 7.10 summarises the average variance extracted (AVE) and R^2 values for this study. To ensure validity, AVE for each construct must be >0.50 (Sun, Lee & Law, 2019:94; Nam, Lee & Lee, 2018:5; Hair *et al.*, 2013:167; Urbach, 2010:19). All constructs' AVE values were greater than this. Urbach (2010:21) states that R^2 values of 0.670 are considered substantial, values of 0.333 are considered average and values of 0.190 are considered weak. When considering the R^2 values in Table 7.10, it can be seen that all were >0.30, barring item FC4, which was removed. Items with low R^2 values (<0.20), according to Hooper *et al*. (2008:56), should be removed as they contain high levels of error. All values scoring >0.30 indicates good predictive capability of the constructs, suggesting that the data fits the model well.

Table 7.10: Measurement model: Validity assessment

Construct	Scale items	AVEs	R^2 values
Performance expectancy (PE)	PE1	0.546	0.459
	PE2		0.543
	PE3		0.656
	PE4		0.526
Effort expectancy (EE)	EE1	0.622	0.606
	EE2		0.708
	EE3		0.662
	EE4		0.513
Social influence (SI)	SI1	0.623	0.629
	SI2		0.732
	SI3		0.704
	SI4		0.425
Facilitating conditions (FC)	FC1	0.552	0.551
	FC2		0.571
	FC3		0.533
	FC4		- (item removed)
Hedonic motivation (HM)	HM1	0.790	0.788
	HM2		0.870
	HM3		0.759
	HM4		0.742
Price value (PV)	PV1	0.656	0.625
	PV2		0.670
	PV3		0.729
	PV4		0.598
Habit (HT)	HT1	0.625	0.605
	HT2		0.698
	HT3		0.575
	HT4		0.620
Perceived risk: Financial risk (FR)	FR1	0.598	0.516
	FR2		0.626
	FR3		0.653
Perceived risk: Product performance risk (PPR)	PPR1	0.575	0.506
	PPR2		0.649
	PPR3		0.570
Trust (TR)	TR1	0.618	0.416
	TR2		0.564
	TR3		0.791
	TR4		0.765
	TR5		0.658
	TR6		0.516
Behavioural intention (BI)	BI1	0.672	0.743
	BI2		0.692
	BI3		0.808
	BI4		0.749
	BI5		0.365

Validity is a multi-faceted process (see Chapter 6, Figure 6.4), requiring assessments of content or face as well as convergent, discriminant and nomological validity (Taherdoost, 2016:31; Malhotra *et al.*, 2012:436-437; Malhotra, 2007:287). Each of these are elaborated on below.

- **Content or face validity**

As discussed in Chapter 6, section 6.4.9, the questionnaire (refer to Annexure 7) was informed by the literature review in Chapters 1, 3, 4 and 5. Scales to measure each of the constructs were adapted from journals contained in the Association of Business Schools' Academic Journal Guide. This ensured content or face validity.

- **Convergent validity**

Convergent validity considers the extent to which two measures of constructs which, according to theory should correlate, actually do correlate (Taherdoost, 2016:31; Quinlan *et al.*, 2015:116; Hair *et al.*, 2013:167; Malhotra *et al.*, 2012:436). As mentioned in Chapter 6, section 6.4.13.3, in order for convergent validity to be met, factor loadings of each scale item should exceed 0.50 and the AVE for each construct should also exceed 0.50 (Sun *et al.*, 2019:94; Nam *et al.*, 2018:5; Hair *et al.*, 2013:167; Urbach, 2010:19). Table 7.11 depicts the factor loadings for each of the scale items. As is evident, all factor loadings were over the 0.50 mark, indicating that convergent validity was met. Table 7.12 presents the AVEs for each of the different constructs in this study. As can be seen, AVEs for all constructs were greater than 0.50. In addition, as explained in section 7.6.3 and Table 7.7, the reliability of the constructs for Model A was deemed satisfactory (α>0.7) (Hair *et al.*, 2013:166).

Table 7.11: Factor loadings for each scale item

Construct/Item	**Factor loading**
PE1. I find mobile shopping useful in my daily life when browsing and/or purchasing athleisure apparel.	0.677
PE2. Using mobile shopping apps helps me to do my shopping for athleisure apparel more quickly.	0.737
PE3. Using mobile shopping apps increases my chances of achieving tasks that are important to me, such as browsing and/or purchasing athleisure apparel.	0.810
PE4. Using mobile shopping apps for browsing and/or purchasing athleisure apparel increases my productivity.	0.725
EE1. Learning how to use mobile shopping apps to browse and/or purchase athleisure apparel is easy for me.	0.778
EE2. My interaction with mobile shopping apps when browsing and/or purchasing athleisure apparel is clear and understandable.	0.841
EE3. I find mobile shopping apps easy to use when browsing and/or purchasing athleisure apparel.	0.814
EE4. It is easy for me to become skilful at using mobile shopping apps to browse and/or purchase athleisure apparel.	0.717
SI1. People who are important to me think that I should use mobile shopping apps to browse and/or purchase athleisure apparel.	0.793
SI2. People who influence my behaviour think that I should use mobile shopping apps to browse and/or purchase athleisure apparel.	0.856

SI3. People whose opinions I value prefer that I use mobile shopping apps to browse and/or purchase athleisure apparel.	0.839
SI4. People around me consider it appropriate to use mobile shopping apps to browse and/or purchase athleisure apparel.	0.652
FC1. I have the resources necessary to use mobile shopping apps to browse and/or purchase athleisure apparel.	0.743
FC2. I have the knowledge necessary to use mobile shopping apps to browse and/or purchase athleisure apparel.	0.756
FC3. Mobile shopping apps are compatible with other technologies I use when browsing and/or purchasing athleisure apparel.	0.730
HM1. Using mobile shopping apps to browse and/or purchase athleisure apparel is fun.	0.888
HM2. Using mobile shopping apps to browse and/or purchase athleisure apparel is enjoyable.	0.933
HM3. Using mobile shopping apps to browse and/or purchase athleisure apparel is very entertaining.	0.872
HM4. Using mobile shopping apps to browse and/or purchase athleisure apparel is very pleasurable.	0.861
PV1. Athleisure apparel available via mobile shopping apps are reasonably priced.	0.791
PV2. Athleisure apparel on mobile shopping apps offer good value for money.	0.818
PV3. At current prices, mobile shopping apps provide good value for athleisure apparel.	0.854
PV4. Athleisure apparel available via mobile shopping apps are affordable.	0.774
HT1. The use of mobile shopping apps to browse and/or purchase athleisure apparel has become a habit for me.	0.778
HT2. I am addicted to using mobile shopping apps to browse and/or purchase athleisure apparel.	0.836
HT3. I must use mobile shopping apps to browse and/or purchase athleisure apparel.	0.758
HT4. Using mobile shopping apps to browse and/or purchase athleisure apparel has become natural to me.	0.787
FR1. The chance of me losing money is high when using mobile shopping apps to purchase athleisure apparel.	0.718
FR2. My credit card number may not be secure when using mobile shopping apps to purchase athleisure apparel.	0.791
FR3. The use of mobile shopping apps to purchase athleisure apparel is a financial risk.	0.808
PPR1. The probability of receiving the wrong item is high when using mobile shopping apps to purchase athleisure apparel.	0.711
PPR2. Using a mobile shopping app to purchase athleisure apparel is risky because I can’t examine the product before making the payment.	0.806
PPR3. The athleisure apparel product purchased may not be suitable in size, style or colour.	0.754
TR1. I trust that my mobile device will be reliable when I shop for athleisure apparel via mobile apps.	0.645
TR2. I trust the shopping systems available on mobile apps to browse and/or purchase athleisure apparel.	0.752
TR3. Mobile app retailers selling athleisure apparel are trustworthy.	0.889
TR4. Mobile app retailers selling athleisure apparel have high integrity.	0.875
TR5. Mobile app retailers selling athleisure apparel have my best interest in mind.	0.811
TR6. When shopping online for athleisure apparel, I feel that my mobile device is just as reliable as my computer.	0.718
BI1. I intend to use mobile shopping apps to purchase athleisure apparel in the future.	0.862
BI2. I will use mobile shopping apps to purchase athleisure apparel where feasible.	0.832
BI3. I plan to use mobile shopping apps to purchase athleisure apparel in future.	0.899
BI4. I predict I will use mobile shopping apps to purchase athleisure apparel in future.	0.866
BI5. I will use mobile shopping apps to purchase athleisure apparel in my daily life.	0.604

Main finding 18, therefore is as follows:

Main finding 18:
As AVEs for all constructs were greater than 0.50 and the reliability of the constructs for Model A was deemed satisfactory (α>0.7), convergent validity of the research instrument was met.

- **Discriminant validity**

Discriminant validity refers to the extent to which measures that are intended to be different, are actually different and do not correlate with one another (Saunders *et al.*, 2016:451; Taherdoost, 2016:31; Quinlan *et al.*, 2015:116; Malhotra *et al.*, 2012:437; Bryman & Bell, 2011:39; Malhotra, 2007:287). In order for discriminant validity to be met, all maximum shared variances (MSVs) should be less than the AVEs (Alumran *et al.*, 2014:4). Table 7.12 presents the MSVs against the AVEs for all constructs. As can be seen, MSVs for all constructs were less than the AVEs.

Table 7.12: Convergent and discriminant validity for each of the model's constructs

Construct	**AVE**	**MSV**
Performance expectancy (PE)	0.546	0.225
Effort expectancy (EE)	0.622	0.477
Social influence (SI)	0.623	0.164
Facilitating conditions (FC)	0.552	0.477
Hedonic motivation (HM)	0.790	0.170
Price value (PV)	0.656	0.167
Habit (HT)	0.625	0.164
Perceived risk: Financial risk (FR)	0.598	0.022
Perceived risk: Product performance risk (PPR)	0.575	0.078
Trust (TR)	0.618	0.350
Behavioural intention (BI)	0.678	0.350

In addition, Sun *et al*. (2019:94) and Nam *et al*. (2018:5) state that it is important to ensure that the √AVE is greater than the correlations between the constructs. As is evident from Table 7.9, all √AVEs were larger than the correlation estimates. Main finding 19, therefore is as follows:

Main finding 19:
As all the constructs' MSVs were less than the AVEs and the √AVEs were greater than the correlations between the constructs, discriminant validity of the research instrument was met.

- **Nomological validity**

Lastly, Busser and Shulga (2018:75), Malhotra *et al.* (2012:437) and Malhotra (2007:287) state that nomological validity searches for noteworthy correlations between constructs, as predicted by theory. To contextualise this to the current study, the various independent constructs presented in the model (see Chapter 1, Figure 1.9) should display a statistical correlation with one another. As can be seen from Table 7.9, all constructs correlated well with one another, with no multicollinearity evident. In addition, when considering the R^2 values in Table 7.10, it is evident that all were >0.30, indicating good predictive capability (Urbach, 2010:21). Nomological validity was therefore also met. Main finding 20, therefore is as follows:

Main finding 20:
As all constructs correlated well with one another with no multicollinearity evident and all R^2 values were >0.30, good predictive capability of the constructs was met. As such, nomological validity of the research instrument was met.

Thus, the measurement model clearly demonstrated the required levels of content or face, convergent, discriminant and nomological validity. Given these results, the next step in the CFA could continue and consequently, the structural model was developed to test the hypotheses. The following section elaborates on this.

7.6.4.2 Structural model: CFA

The structural model was determined based on the measurement model. As described in Chapter 6, section 6.4.13.5 and the introduction of this section, the structural model depicts each construct's association with the other (Hair *et al.*, 2006:714). Each of the hypothesised relationships depicted in the model (see Chapter 1, Figure 1.9), was tested, however, the structural model needed to be evaluated before proceeding with the goodness-of-fit. This is presented in the following section.

7.6.4.2.1 Goodness-of-fit (GoF) assessment

Similar to the GoF assessment conducted for the measurement model in section 7.6.4.1.1, a GoF assessment against absolute and incremental fit was completed for structural Model A. As is evident from Table 7.13, from an absolute fit perspective, the Model Chi-square achieved a fit of 1.958, indicating an acceptable fit as it was below the requirement of ≤3 (Awang, 2012:56). The RMSEA achieved a fit of 0.044, below the requirement of ≤0.06, which is acceptable (Newsom, 2018:3; Hooper *et al.,* 2008:54; Suhr, 2006:2; Sun, 2005:249; Hu & Bentler, 1999:4).

From an incremental fit perspective, the CFI achieved a fit of 0.924, indicating a good fit as it was ≥0.90 (Newsom, 2018:2; Cangur & Ercan, 2015:159; Hooper *et al.,* 2008:55; Suhr, 2006:2). The TLI achieved a fit of 0.917, also indicating an acceptable fit as it was ≥0.90 (Newsom, 2018:2). As is evident from Table 7.9, the values remained fairly consistent, with the GoF assessment done for measurement Model A (re-specified) in Table 7.8.

Table 7.13: Structural model: GoF assessment

Goodness-of-fit category	**Selected indices (statistical tests)**	**Acceptable fit**	**Model A-fit outcomes**
Absolute fit index	Model Chi-square test (X^2)	Value of ≤3 (Awang, 2012:56).	1.958
	RMSEA	Value of ≤0.05-0.06 indicates an acceptable fit (Newsom, 2018:3; Hooper *et al*., 2008:54; Suhr, 2006:2; Sun, 2005:249; Hu & Bentler, 1999:4).	0.044
Incremental fit index	CFI	Value of ≥0.90 indicates a good fit (Newsom, 2018:2; Cangur & Ercan, 2015:159; Hooper *et al*., 2008:55; Suhr, 2006:2).	0.924
	TLI	Value ≥0.90 indicates an acceptable fit (Newsom, 2018:2); value of ≥0.95 indicates a good fit (Sun, 2005:249).	0.917

Based on the information provided in Table 7.13, the model was considered to have satisfactory goodness-of-fit. Main finding 21 can be deduced as follows:

Main finding 21:
The goodness-of-fit assessment for the proposed structural model was satisfactory, indicating a good model fit.

The proposed structural model is illustrated in Figure 7.3.

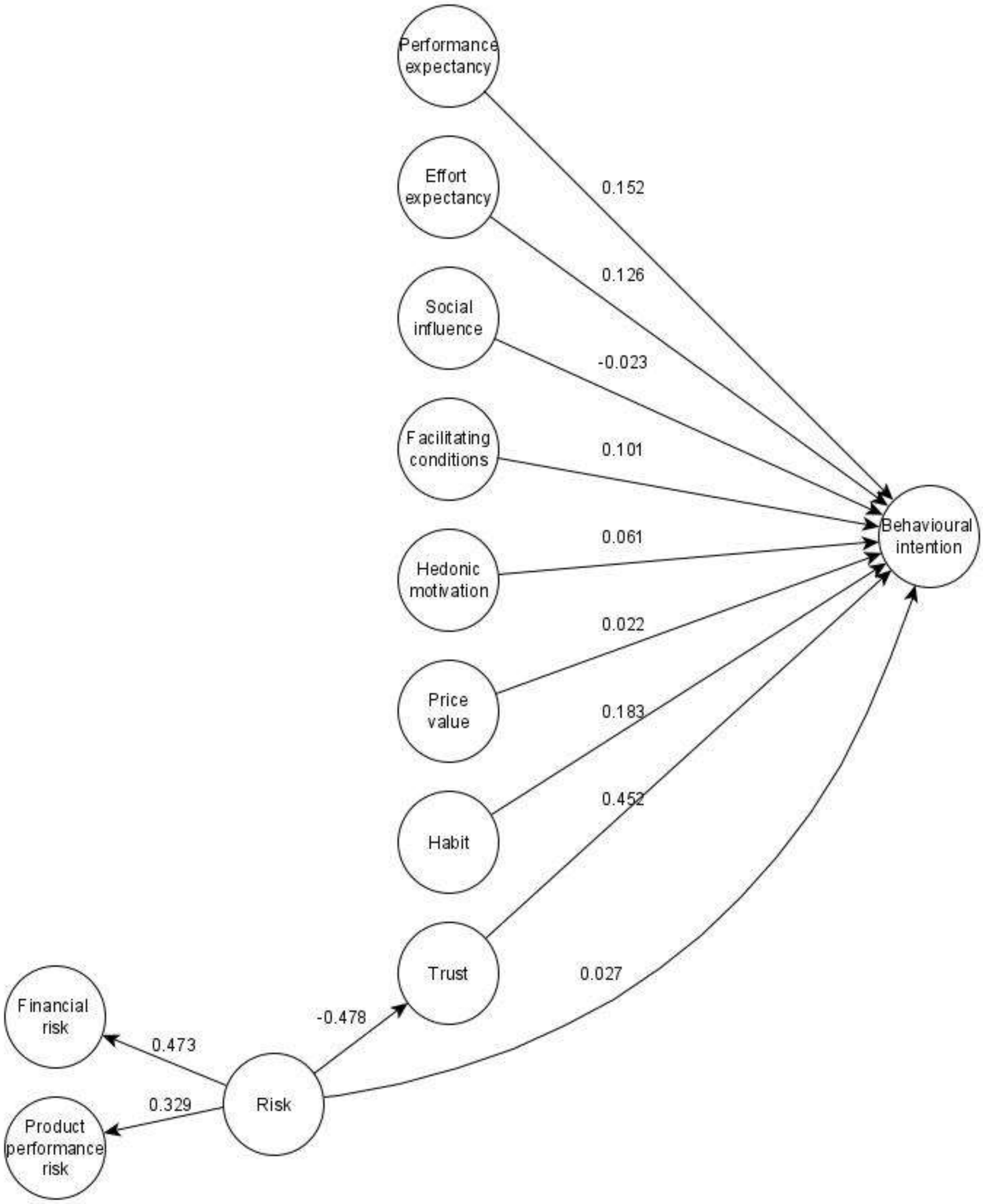


Figure 7.3: The proposed structural model

For the purposes of clarity, the following sections discuss the research hypotheses aligned to the model presented in Chapter 1, Figure 1.9. In order to adequately measure the proposed hypotheses, each one is discussed independently.

7.6.4.2.2 Testing the research hypotheses

Simply conducting GoF assessments on a structural model, according to Hair *et al.* (2010:677), does not verify that the structure is correct and therefore, additional approaches should be considered. It is advisable to examine the individual parameter estimates (β) as well as the t-statistics (t) of each hypothesis and in doing so, ensure validity. The parameter estimates should score ≥0.50 to be regarded as good (Hair *et al.*, 2010:677), whereas the t-statistics values should exceed 1.96 with a probability value of <0.05 (Malhotra, 2010:705).

Table 7.14 summarises the structural model estimates, including the parameter estimates, t-statistics and p-values for each of the hypothesised relationships in Model A. A discussion follows.

Table 7.14: Structural model estimates for Model A

Structural paths	**Parameter estimate (β)**	**T-statistic (t)**	**P-value**
Performance expectancy (PE) → Behavioural intention (BI)	0.169	2.099	Significant at <0.05
Effort expectancy (EE) → Behavioural intention (BI)	0.137	1.491	-
Social influence (SI) → Behavioural intention (BI)	-0.017	-0.321	-
Facilitating conditions (FC) → Behavioural intention (BI)	0.127	1.301	-
Hedonic motivation (HM) → Behavioural intention (BI)	0.051	1.124	-
Price value (PV) → Behavioural intention (BI)	0.027	0.439	-
Habit (HT) → Behavioural intention (BI)	0.163	3.117	Significant at <0.05
Perceived risk (PR) → Behavioural intention (BI)	0.022	0.445	-
(New) Perceived risk (PR) → Trust (TR)	-0.302	-5.736	Significant at <0.05
Trust (TR) → Behavioural intention (BI)	0.532	7.834	Significant at <0.05

When evaluating Table 7.14 featuring hypotheses from Model A, it is evident that all parameter estimates were non-significant (<0.50), barring the construct of trust (H_{14}) which showed a significant positive association with behavioural intention (β=0.532). The t-statistics ranged from -0.321 to 7.834. Three (38%) were above the required threshold of 1.96, i.e. H_1 performance expectancy (β=0.169, t=2.099), H_8 habit (β=0.163, t=3.117) and H_{14} trust (β=0.532, t=7.834). The path estimates between performance expectancy (H_1), habit (H_8) and trust (H_{14}) were also significant at the 5% level (p<0.05). In addition, a new relationship which did not form part of the original hypothesised relationships emerged from the data analysis. The original hypothesis (H_{12}), i.e. "Trust mediates the negative influence of perceived risk on the behavioural intention of consumers to use mCommerce apps to purchase athleisure apparel", was included in the study as research suggested that trust decreases the perceived risk associated with using a product or service (Farivar *et al.*, 2017:597; Joubert & van Belle, 2013:29; Ribbink *et al.*, 2004:446). The data from this study, however, indicates that perceived risk has a significant negative relationship with trust (β=0.022, t=-5.736, p<0.05). Main findings 22, 23, 24 and 25 can therefore be summarised as follows:

Main finding 22:
Performance expectancy has a significant influence on behavioural intention.

Main finding 23:
Habit has a significant influence on behavioural intention.

Main finding 24:
Perceived risk has a significant negative influence on trust.

Main finding 25:
Trust has a significant influence on behavioural intention.

In the following section, each research hypothesis from Model A (behavioural intention) presented in Chapter 1, Figure 1.9 is discussed independently. In prior technology acceptance research, it is clear that different technological and cultural contexts result in different factors that influence the acceptance of a specific technology (Miladinovic & Xiang, 2016:49; Venkatesh *et al.*, 2012:158). It is therefore understandable that not all the hypotheses were accepted in this South African study.

- **Hypothesis 1: Performance expectancy has a positive influence on the behavioural intention of consumers to use mCommerce apps to purchase athleisure apparel.**

Based on the discussion preceding this section, hypothesis 1 was **accepted**. The data indicates that performance expectancy has a positive influence on behavioural intention, supporting the UTAUT2 (Venkatesh *et al.*, 2012). In the context of this study, this construct refers to the value or utility that a mobile shopping app provides to a consumer, including saving time and effort and offering convenience and efficiency (Alalwan *et al.*, 2018:128; Tarhini *et al.*, 2016:834; Hyben *et al.*, 2015:3; eMarketer, 2013; Alkhunaizan & Love, 2012:86). This finding is consistent with research conducted by Alalwan *et al.* (2018), Chopdar *et al.* (2018), Gupta *et al.* (2018), Chaouali *et al.* (2016), Madan and Yadav (2016), Miladinovic and Xiang (2016), Oliveira *et al.* (2016), Tarhini *et al.* (2016), Hew *et al.* (2015), Martins *et al.* (2014), Akbar (2013), Alkhunaizan and Love (2012), Fai (2011) and AbuShanab and Pearson (2007).

- **Hypothesis 2: Effort expectancy has a positive influence on the behavioural intention of consumers to use mCommerce apps to purchase athleisure apparel.**

Based on the discussion preceding this section, hypothesis 2 was **rejected**. In the context of this study, this construct refers to the ease of use of operating a mobile touchscreen with an app as well as efficiency (Parker & Wang, 2016:490; Sky Technology, 2016). The effort expectancy did not have a positive influence on behavioural intention, a contradictory finding to the UTAUT2 (Venkatesh *et al.*, 2012). However, this finding is consistent with other researchers' findings, including Shaw and Sergueeva (2019), Chopdar *et al.* (2018), Gupta *et al.* (2018), Verkijika (2018), Chaouali *et al.* (2016), Madan and Yadav (2016), Miladinovic and Xiang (2016), Oliveira *et al.* (2016) and Tarhini *et al.* (2016). In this particular study, 100% of the respondents were required to own a smartphone and the majority (56.8%) were aged between 18 and 24 years, therefore it can be deduced that these individuals were familiar with technology and more capable of learning quickly how mobile shopping applications work. The respondents were comfortable with using mobile shopping apps and felt that they were easy to use. It can therefore be concluded that effort expectancy has an insignificant influence on behavioural intention. This finding is corroborated by Chopdar *et al.* (2018:121), who found that effort expectancy did not have an influence on behavioural intention in the United States (US) portion of their study as those consumers are more technologically savvy.

- **Hypothesis 3: Social influence has a positive influence on the behavioural intention of consumers to use mCommerce apps to purchase athleisure apparel.**

Based on the discussion preceding this section, hypothesis 3 was **rejected**. Social influence refers to an individual's belief that those close to them, such as family and friends, believe they should understand and use an innovation or new technology (Venkatesh *et al.*, 2012:159). The results did not reveal social influence as having a positive influence on behavioural intention. Although this was in contradiction to the UTAUT2 (Venkatesh *et al.*, 2012), other researchers have reported the same results. These include Shaw and Sergueeva (2019), Alalwan *et al.* (2018), Chopdar *et al.* (2018), Chaouali *et al.* (2016), Miladinovic and Xiang (2016), Hew *et al.* (2015) and Alkhunaizan and Love (2012). This may be due to the fact that purchasing athleisure apparel is a very personal activity and therefore, social influence would have very little effect on the decision-making process. Chopdar *et al.* (2018:121) and Hew *et al.* (2015:1285) concur with such an interpretation. Another alternative is that online reviews have become widely available over the last few years, thus consumers may be inclined to reference reviews as opposed to the opinions of family and friends when making purchasing decisions (Miladinovic & Xiang, 2016:51).

- **Hypothesis 4: Facilitating conditions have a positive influence on the behavioural intention of consumers to use mCommerce apps to purchase athleisure apparel.**

Based on the discussion preceding this section, hypothesis 4 was **rejected**. Venkatesh *et al.* (2012:159) describe facilitating conditions as a consumer's perception of the resources and support that are available when performing a specific behaviour. In the context of this study, this construct refers to a working Internet connection as well as online customer support being available (Miladinovic & Xiang, 2016:22). The data did not reveal facilitating conditions as having a positive influence on behavioural intention. This is a contradictory finding to the UTAUT2 (Venkatesh *et al.*, 2012) but consistent with the results of Shaw and Sergueeva (2019), Gupta *et al*. (2018) and Oliveira *et al.* (2016). A possible reason for this may be the 100% smartphone access. As all respondents had a smartphone, a working Internet connection was a given. Another possible explanation for this may again be the age skew of respondents, with 56.8% being between the ages of 18-24. The younger generation is constantly connected, adaptable to change and open to new technologies. Therefore, should they run into problems, they would be likely to find ways and means of assisting themselves (Savitz, 2012).

- **Hypothesis 6: Hedonic motivation has a positive influence on the behavioural intention of consumers to use mCommerce apps to purchase athleisure apparel.**

Based on the discussion preceding this section, hypothesis 6 was **rejected**. Venkatesh *et al.* (2012:161) describe hedonic motivation as a consumer's enjoyment associated with using a specific technology. The data did not reveal hedonic motivation to have a positive influence on behavioural intention. Once again, this finding is contradictory to the UTAUT2 (Venkatesh *et al.*, 2012) but consistent with Gupta *et al*. (2018) and Oliveira *et al.* (2016). A potential explanation for this may be the fact that online shopping channels have been reported to be more utilitarian (task-oriented) as opposed to hedonic (pleasure-seeking) (Brown, 2016:3; Liu & Forsythe, 2010:88; 98). The environment created by mobile shopping apps is often not as engaging or exciting compared to brick-and-mortar stores (Brown, 2016:3).

- **Hypothesis 7: Price value has a positive influence on the behavioural intention of consumers to use mCommerce apps to purchase athleisure apparel.**

Based on the discussion preceding this section, hypothesis 7 was **rejected**. Price value refers to the cognitive trade-off a consumer makes between the perceived benefit provided by the technology and the monetary cost of using it (Venkatesh *et al.*, 2012:161). The results did not show price value as having a positive influence on behavioural intention. Although this is contradictory to the UTAUT2 (Venkatesh *et al.*, 2012), other researchers have reported the same results, including Verkijika (2018), Miladinovic and Xiang (2016), Oliveira *et al.* (2016) and Hew *et al.* (2015). Verkijika (2018:1672) confirms that studies on this construct has received mixed results, therefore the finding of this study does not come as a surprise. A possible explanation could be that seeing that mostly students participated in the study (with 56.8% being between the ages of 18-24), they may be more cautious in their spending habits. South Africans tend to also be more price conscious, in a general sense, given that spend is continuously placed under pressure (Dicey, 2017). South Africans compare options to find the best price, have decreased their spending in recent years and have started delaying their purchases (Hattingh *et al.*, 2016). This explanation is supported by Hew *et al.* (2015:1284) and Miladinovic and Xiang (2016:51).

- **Hypothesis 8: Habit has a positive influence on the behavioural intention of consumers to use mCommerce apps to purchase athleisure apparel.**

Based on the discussion preceding this section, hypothesis 8 was **accepted**. The data indicates that habit has a significant positive influence on behavioural intention, supporting the UTAUT2 (Venkatesh *et al.*, 2012). In the context of this study, this construct refers to a consumer's automatic execution of a specific behaviour due to prior learning – in other words, the automatic use of mCommerce apps. This result was expected, given the age skew of respondents (56.8% between the ages of 18-24). Savitz (2012) states that these consumers are accepting of new technologies and are always connected, therefore smartphone usage occurs on a very habitual, almost unconscious level (Lipsman, 2015). As smartphones have become part of consumers' lives, consumers have become reliant on mobile apps as well. Further studies in support of this finding include Chopdar *et al.* (2018), Gupta *et al.* (2018), Miladinovic and Xiang (2016) and Hew *et al.* (2015).

- **Hypothesis 10: Perceived risk has a negative influence on the behavioural intention of consumers to use mCommerce apps to purchase athleisure apparel.**

Based on the discussion preceding this section, hypothesis 10 was **rejected**. The construct of perceived risk is described as consumers' perceptions surrounding the possible negative outcomes they could be exposed to as a result of transacting online (Suh *et al.*, 2015:133). This is a multifaceted construct that covers various context-specific risks (Farivar *et al.*, 2017:590). For the purposes of this study, two risks were focused on – financial risk and product performance risk. This is because these risks are frequently referenced in research related to online and mobile commerce (Marriott & Williams, 2018:138; 139; Farivar *et al.*, 2017:591; Yang *et al.*, 2015:261; Ueltschy, 2004:71; Featherman & Pavlou, 2003:460). The data did not reveal perceived risk as having a negative influence on behavioural intention – a contradictory finding to the researchers referenced above – as well as Alalwan *et al*. (2018), Gupta *et al.* (2018), Verkijika (2018), Madan and Yadav (2016) and Martins *et al.* (2014). Interestingly, Chopdar *et al.*'s (2018:121) cross-country research between India and the US on mobile shopping adoption found American consumers to be less risk-averse than their Indian counterparts. The current study has thus far shown synergies with the American portion of Chopdar *et al.*'s research (see hypotheses 2 and 3). Lu (2017:41) examined the effects of trust and risk on online purchase intention in Canada and also found no relationship between perceived risk and behavioural intention. Similar results were reported by Chin *et al.* (2018:54) and Marriott and Williams (2018:139). The majority of the respondents in those two studies were aged 18-24 (93%) and 18-29 (70%). Both these studies revealed an insignificant relationship between perceived risk and behavioural intention. Aligned with the findings of this study, perhaps this is an indication that younger South African consumers are less risk-averse to potential risks associated with shopping for athleisure apparel online or via a mobile phone.

- **Hypothesis 12: Trust mediates the negative influence of perceived risk on the behavioural intention of consumers to use mCommerce apps to purchase athleisure apparel.**

Based on the discussion preceding this section, hypothesis 12 was **rejected**. The concept of trust in the online shopping context is defined as "the degree of trust consumers have in online exchanges" (Ribbink *et al.*, 2004:447). The original hypothesis was included in this study as research suggests that trust decreases the perceived risk associated with using a product or service (Farivar *et al.*, 2017:597; Joubert & van Belle, 2013:29; Ribbink *et al.*, 2004:446). The results for this particular hypothesis revealed that trust did not have a mediating effect on the negative influence of perceived risk on behavioural intention. Interestingly, however, the research uncovered that perceived risk did have a significant negative influence on trust (β=-0.302; t=-5.736).

There has been much confusion about the directionality of the relationship between perceived risk and trust, according to Kim and Koo (2016:1021) and Mayer, Davis and Schoorman (1995:711). Kim and Koo (2016:1024) evaluated whether a unidirectional relationship exists between (i) trust, perceived risk and behavioural intention as well as (ii) perceived risk, trust and behavioural intention; or whether a bidirectional relationship exists. Their study provided strong support for a bidirectional relationship, indicating that these two constructs are equally influential in the decision-making approach of buyers. A number of other studies, however, have found perceived risk to have a marked influence on trust. De Ruyter, Wetzels and Kleijnen (2000:201) found that perceived risk to have a significant influence on trust. Corritore, Kracher and Wiedenbeck (2003:749) conceptualised a causal model of factors affecting online trust. According to the model, consumers' perception of risk influences their level of trust. Lee and Lee (2007:8) evaluated the factors affecting mobile banking adoption in South Korea and found a significant negative relationship between perceived risk and trust. Chang and Chen (2008:831) investigated trust and perceived risk as mediating variables in the online store purchasing process and found a non-recursive relationship between them. The study found perceived risk to negatively influence trust, supporting the finding in the current study, but also found trust to negatively influence perceived risk. This finding supports the original hypothesis 12 of this study, but which was not proven true after data analysis. Finally, D'Allesandro *et al.* (2012:444) also found perceived risk to have a marked negative influence on trust in online purchasing behaviour in the US.

- **Hypothesis 14: Trust has a positive influence on the behavioural intention of consumers to use mCommerce apps to purchase athleisure apparel.**

Based on the discussion preceding this section, hypothesis 14 was **accepted**. The data indicates that trust has a significant positive influence on behavioural intention, supporting the findings of other researchers in the field of online and mobile shopping app acceptance and use. These include Chin *et al.* (2018), Verkijika (2018), Suh *et al.* (2015), Vasileiadis (2014), Chong (2013) and Joubert and van Belle (2013). This finding is also consistent with research on Internet banking and app acceptance and use, corroborating the results reported by Gupta *et al.* (2018), Chaouali *et al.* (2016) and Gao *et al.* (2014). The finding also reinforces those of Marriott and Williams (2018:136), Bojang (2017:5) and Daud and Hassan (2011:169) who all state that trust is vital in the digital retailing domain. It is imperative to remember that in South Africa specifically, trust has been listed as the most common reason for low online shopping rates, therefore it is critical for mCommerce retailers to focus on this aspect (IT News Africa, 2016).

The summary of the research hypotheses for Model A is shown in Table 7.15.

Table 7.15: Model A hypotheses

Hypotheses		**Accepted**
H_1	Performance expectancy has a positive influence on the behavioural intention of consumers to use mCommerce apps to purchase athleisure apparel	Yes
H_2	Effort expectancy has a positive influence on the behavioural intention of consumers to use mCommerce apps to purchase athleisure apparel	No
H_3	Social influence has a positive influence on the behavioural intention of consumers to use mCommerce apps to purchase athleisure apparel	No
H_4	Facilitating conditions has a positive influence on the behavioural intention of consumers to use mCommerce apps to purchase athleisure apparel	No
H_6	Hedonic motivation has a positive influence on the behavioural intention of consumers to use mCommerce apps to purchase athleisure apparel	No
H_7	Price value has a positive influence on the behavioural intention of consumers to use mCommerce apps to purchase athleisure apparel	No
H_8	Habit has a positive influence on the behavioural intention of consumers to use mCommerce apps to purchase athleisure apparel	Yes
H_{10}	Perceived risk has a negative influence on the behavioural intention of consumers to use mCommerce apps to purchase athleisure apparel	No
H_{12}	Trust mediates the negative influence of perceived risk on the behavioural intention of consumers to use mCommerce apps to purchase athleisure apparel	No
H_{14}	Trust has a positive influence on the behavioural intention of consumers to use mCommerce apps to purchase athleisure apparel	Yes

This concludes the discussion of the results for Model A, which included a review of the descriptive statistics, the assumptions of factor analysis, a reliability assessment and SEM. The following section examines the results for Model B (actual use) using a T-test analysis.

The following section provides a detailed account of the results for

PHASE 2: MODEL B

(Model B reflects actual use as the dependent variable)

7.7 Phase 2: Model B – results discussion

7.7.1 Descriptive statistics: Mean and standard deviation scores

This section examines the descriptive statistics for the sample data set, commencing with the mean and standard deviation for the actual use construct. This is followed by a detailed discussion of the empirical results to provide feedback on the various hypotheses under investigation.

For Model B, the overall mean and standard deviation scores for the actual use construct are presented in Table 7.16. The mean and standard deviations were calculated against a sample of 247 (-3, listwise deletion based on all variables in the procedure), the number of respondents who used an mCommerce app to browse and buy athleisure apparel. As can be seen, item AU1 had a mean score of 3.30, which is >3, indicating that the majority of the respondents last purchased athleisure apparel three months or more ago. Item AU2 had a mean score of 1.87, which is <3, indicating that the majority of the respondents purchased between one and three items. Item AU3 had a mean score of 2.51, which is <3, indicating that the majority of the respondents spent 15 minutes or less shopping for athleisure apparel via mobile shopping apps per week. Item AU4 had a mean score of 1.69, which is <3, indicating that the majority of the respondents visited between one and four mobile shopping apps per month. Lastly, item AU5 had a mean score of 3.12, which is >3, indicating that the majority of the respondents spent R500 or more on their most recent athleisure apparel purchase. The standard deviation scores for this construct ranged from 0.773 to 1.445, indicating a degree of variance between the responses for each of the statements on actual use.

Table 7.16: Actual use (AU): Mean and standard deviation

Construct/Scale item	Mean	Std dev
Actual use (AU)		
AU1. When last did you use a mobile shopping app to purchase athleisure apparel? (Choose only one).	3.30	1.445
AU2. How many athleisure apparel items did you purchase during this time? (Choose only one).	1.87	0.809
AU3. In general, how much time do you spend shopping for athleisure apparel via mobile shopping apps per week? (Choose only one).	2.51	0.831
AU4. On average, how many different mobile shopping apps do you visit in a given month? (Choose only one).	1.69	0.773
AU5. What was the approximate Rand value of your most recent purchase of athleisure apparel? (Choose only one).	3.12	1.339

Main findings 26, 27, 28, 29 and 30 can be deduced by analysing the overall mean and standard deviation scores presented in Table 7.16.

Main finding 26:
Based on the mean score of 3.30 for item AU1, the majority of the respondents last purchased athleisure apparel three months or more ago.

Main finding 27:
Based on the mean score of 1.87 for item AU2, the majority of the respondents purchased between one and three items of athleisure apparel during their last purchase.

Main finding 28:
Based on the mean score of 2.51 for item AU3, the majority of the respondents spent 15 minutes or less shopping for athleisure apparel via mobile shopping apps per week.

Main finding 29:
Based on the mean score of 1.69 for item AU4, the majority of the respondents visited between one and four mobile shopping apps per month. As shown in Table 2.2 in Chapter 2, there are only about five mobile shopping apps selling athleisure apparel in South Africa, therefore this finding was expected.

Main finding 30:
Based on the mean score of 3.12 for item AU5, the majority of the respondents spent R500 or more on their most recent athleisure apparel purchase.

In order to determine relationships between the various constructs, it was necessary to conduct factor analysis, however, before this could be done, the data needed to be assessed for appropriateness.

7.7.2 Assumptions of factor analysis

The process for assumptions of factor analysis includes three distinct steps, namely (i) assessing the appropriateness of the data for factor analysis, (ii) factor extraction and (iii) factor rotation and interpretation (Pallant, 2016:183-186).

7.7.2.1 Assessing the appropriateness of the data for factor analysis

As per the discussion in Chapter 6, section 6.4.13.4, factor analysis was deemed suitable for this study given the sample size of 500. This number exceeds the requirement of 300 recommended by Chan and Idris (2017:403) and Pallant (2016:184). Two statistical techniques can further assist in determining factorability, namely, Bartlett's test of sphericity and the KMO measure of sampling adequacy. Bartlett's test of sphericity examines whether variables are uncorrelated in the population. The test must prove to be significant, i.e. $p<0.05$, if it is to be considered suitable (Fávero & Belfiore, 2019:389; Pallant, 2016:184; Malhotra *et al.*, 2012:776). The KMO measure of sampling adequacy is an index employed to determine the level of appropriateness of factor analysis, which requires higher values (e.g. between 0.5 and 1.0) for it to be considered appropriate (Fávero & Belfiore, 2019:387; Pallant, 2016:184; Yong & Pearce, 2013:88; Malhotra *et al.*, 2012:777).

Table 7.17 details the results for these two statistical techniques. As can be seen, Bartlett's test of sphericity scored 0.000, indicating a suitable set of data. Similarly, the KMO measure of sampling adequacy achieved a score of 0.578. Factor analysis of the actual use construct was therefore suitable and it was deemed appropriate to proceed with EFA.

The second step in the process was to conduct factor extraction.

Table 7.17: Bartlett's test of sphericity and the KMO measure of sampling adequacy

Statistical test		Acceptable fit	Score
KMO measure of sampling adequacy		0.5-1.0 (Fávero & Belfiore, 2019:387; Pallant, 2016:184; Malhotra *et al.*, 2012:777).	0.578
Bartlett's test of sphericity	Approx. Chi-square		66.447
	Df		10
	Sig	p<0.05 (Fávero & Belfiore, 2019:389; Pallant, 2016:184; Malhotra *et al.*, 2012:776).	0.000

7.7.2.2 Factor extraction

As outlined in Chapter 6, section 6.4.13.4, in this step, the Principal Axis Factor method was used for the factor extraction. A minimum value of 0.32 is required to assess whether the items fit well with each other (Yong & Pearce, 2013:85). Chan and Idris (2017:404) suggest 0.3. The results are presented in Table 7.18. As can be seen, all communality extraction scores fall below the minimum value of 0.30, except for item AU2, i.e. "How many athleisure apparel items did you purchase during this time?" which achieved a score of 0.567. Further analysis using Kaiser's criterion and a scree plot was then performed.

Table 7.18: Communality extraction scores for Model B

Construct/Scale item	Communalities	
	Initial	Extraction
AU1. When last did you use a mobile shopping app to purchase athleisure apparel? (choose only one).	0.032	0.227
AU2. How many athleisure apparel items did you purchase during this time? (choose only one).	0.180	0.567
AU3. In general, how much time do you spend shopping for athleisure apparel via mobile shopping apps per week? (choose only one).	0.078	0.147
AU4. On average, how many different mobile shopping apps do you visit in a given month? (choose only one).	0.036	0.107
AU5. What was the approximate rand value of your most recent purchase of athleisure apparel? (choose only one).	0.155	0.262

Kaiser's criterion and scree plots are used to determine interrelationships between variables (Pallant, 2016:184). Kaiser's criterion, or the Eigenvalue rule, represents the total variance explained by a particular factor. According to this rule, only factors with a value of 1.0 or more should be retained for further investigation (NCSS Statistical Software, 2019:12; Pallant, 2016:184). The Catell scree test, which plots all the Eigenvalues, was also conducted. This evaluation requires all factors sitting above the elbow of the plot to be retained (Pallant, 2016:185; Suhr, 2006:3).

Table 7.19 summarises the Eigenvalues for Model B. Only extracted and rotated values are highlighted as these are meaningful to interpret (Yong & Pearce, 2013:89). Factors are arranged in descending order. The five factors explain 100% of the variance. Item AU1, i.e. "When last did you use a mobile shopping app to purchase athleisure apparel?" achieved a low communality score of 0.227, however, the Eigenvalue was >1 (1.592). This item explained 31.833% of the variance. Item AU2, i.e. "How many athleisure apparel items did you purchase during this time?" achieved an acceptable communality score of 0.567 (>0.32) and an acceptable Eigenvalue of >1 (1.126). This item explained 22.512% of the variance. Items AU1 and AU2 thus cumulatively explained 54.346% of the variance. The scree plot in Annexure 13 reinforces these findings and depicts the Eigenvalues for these two items (AU1 and AU2) as sitting above the elbow of the plot.

The remaining items showed problematic results. Item AU3, i.e. "In general, how much time do you spend shopping for athleisure apparel via mobile shopping apps per week?" achieved a low communality score of 0.147 and an Eigenvalue of <1 (0.860). This item explained 17.193% of the variance. Item AU4, i.e. "On average, how many different mobile shopping apps do you visit in a given month?" achieved a low communality score of 0.107 and an Eigenvalue of <1 (0.821). This item explained 16.427% of the variance. Item AU5, i.e. "What was the approximate Rand value of your most recent purchase of athleisure apparel?" achieved a low communality score of 0.262 and an Eigenvalue of <1 (0.602). This item explained 12.035% of the variance. Based on this evaluation, there were only two meaningful factors – AU1 and AU2.

Table 7.19: Total variance explained for Model B

Scale item	Initial eigenvalues			Extraction sums of squared loadings			Rotation sums of squared loadings		
	Total	% of Var	Cumu %	Total	% of Var	Cumu %	Total	% of Var	Cumu%
AU1	1.592	31.833	31.833	0.963	19.253	19.253	0.942	18.841	18.841
AU2	1.126	22.512	54.346	0.348	6.955	26.209	0.368	7.368	26.209
AU3	0.860	17.193	71.538						
AU4	0.821	16.427	87.965						
AU5	0.602	12.035	100.000						

The final step in the process was factor rotation and interpretation, as discussed below.

7.7.2.3 Factor rotation and interpretation

As discussed in Chapter 6, section 6.4.13.4, the final step in conducting EFA is factor rotation and interpretation. Thus, each actual use item was recoded into two categories and factor rotation was done. The factor rotation method used was the Varimax approach with Kaiser normalisation, an orthogonal rotation solution. Orthogonal rotation results in uncorrelated factor solutions (Pallant, 2010:186). As can be seen from Table 7.19, after Varimax rotation, item AU1 explained 18.841% of the variance as opposed to 31.833% and item AU2 explained 7.368% of the variance as opposed to 22.512%. Table 7.20 depicts the rotated factor loadings. The majority of the items had factor loadings below the recommended level of 0.4 (Chan & Idris, 2017:403; Kootstra, 2004:7).

Table 7.20: Rotated factor matrix for Model B

Construct/Scale item	**Factor**	
	1	**2**
AU1. When last did you use a mobile shopping app to purchase athleisure apparel? (choose only one).	-0.028	0.476
AU2. How many athleisure apparel items did you purchase during this time? (choose only one).	0.752	-0.031
AU3. In general, how much time do you spend shopping for athleisure apparel via mobile shopping apps per week? (choose only one).	0.324	0.206
AU4. On average, how many different mobile shopping apps do you visit in a given month? (choose only one).	0.125	0.303
AU5. What was the approximate rand value of your most recent purchase of athleisure apparel? (choose only one).	0.505	0.086

The findings prove that it is not possible to work with the actual use construct as a latent construct made up of five items as the various items do not fit well with each other and therefore cannot be combined to measure a single construct. It was thus decided to represent the actual use construct as five unique binary categorical outcomes. Further motivation for this is provided below.

This concludes the factor analysis assumptions prior to conducting EFA for Model B.

7.7.3 Reliability assessment

Table 7.21 presents the Cronbach alpha value for Model B. The Cronbach alpha value for the actual use construct was 0.377, indicating low and unsatisfactory internal consistency (Hair *et al.*, 2013:166). This indicates that it is not possible to work with this construct as a latent construct made up of five items as the various items do not constitute a single construct. The study was therefore adjusted to represent the actual use construct as five unique binary categorical outcomes. This model was therefore analysed using a T-test analysis, as presented in the following section.

Table 7.21: Cronbach's alpha for Model B

Construct	**Scale items**	**Cronbach's alpha**
Actual use (AU)	AU1, AU2, AU3, AU4, AU5	0.377

7.7.4 Exploratory factor analysis (EFA)

The original construct for actual use (Model B) was created by combining five items from different studies. AU1 was sourced from Chopdar *et al.* (2018:123-124) and asked when last respondents used a mobile shopping app to purchase athleisure apparel. AU2 was developed by the researcher and aimed to understand how many items were actually bought. AU3 and AU4 were adapted from Klopping and McKinney (2004:48) and asked respondents how much time they spent shopping for athleisure apparel via mobile shopping apps per week and how many different mobile shopping apps they visited in a given month. The final item, AU5, was developed by the researcher to understand the value of athleisure apparel purchases. As discussed in the introduction of this chapter and section 7.7.3, Model B could not be measured as a latent variable made up of several different items. This led to the decision to analyse Model B using a T-test analysis, by breaking the dependent variable – actual use – into five different constructs, each functioning as new dependent variable. These five new constructs (functioning as 5 new dependent variables) were then linked to the constructs of facilitating conditions, habit, perceived risk and behavioural intention (as illustrated in Chapter 1, Figure 1.9). New hypotheses were formulated (see Table 7.24) and measured through T-test analysis (see Table 7.23). Table 7.22 details the new frequencies for the new actual use constructs.

Table 7.22: Actual use constructs – frequencies

AU1. WHEN LAST DID YOU USE A MOBILE SHOPPING APP TO PURCHASE ATHLEISURE APPAREL? (CHOOSE ONLY ONE).			
		Frequency	Valid %
	Over a month ago	118	47.2%
	Within last month	132	52.8%
	Total	250	100%
AU2. HOW MANY ATHLEISURE APPAREL ITEMS DID YOU PURCHASE DURING THIS TIME? (CHOOSE ONLY ONE).			
		Frequency	Valid %
	1 item	89	35.6%
	More than 1 item	161	64.4%
	Total	250	100%
AU3. IN GENERAL, HOW MUCH TIME DO YOU SPEND SHOPPING FOR ATHLEISURE APPAREL VIA MOBILE SHOPPING APPS PER WEEK? (CHOOSE ONLY ONE).			
		Frequency	Valid %
	Up to 15 mins	124	49.6%
	More than 15 mins	126	50.4%
	Total	250	100%
AU4. ON AVERAGE, HOW MANY DIFFERENT MOBILE SHOPPING APPS DO YOU VISIT IN A GIVEN MONTH? (CHOOSE ONLY ONE).			
		Frequency	Valid %
	1-2 apps	118	47.2%
	3 or more apps	132	52.8%
	Total	250	100%
AU5. WHAT WAS THE APPROXIMATE RAND VALUE OF YOUR MOST RECENT PURCHASE OF ATHLEISURE APPAREL? (CHOOSE ONLY ONE).			
		Frequency	Valid %
	Up to R500	100	40%
	R501 or more	150	60%
	Total	250	100%

The results of the T-test for each of the five constructs are summarised in Table 7.23. As is evident, for construct AU1, i.e. “When last did you use a mobile shopping app to purchase athleisure apparel?”, the p-values for performance expectancy, hedonic motivation, habit and behavioural intention were 0.013, 0.005, 0.000 and 0.012. All were thus <0.05, indicating that these four constructs exerted an influence on the last time consumers used their mobile shopping apps to purchase athleisure apparel. For construct AU2, i.e. “How many athleisure apparel items did you purchase during this time?”, the p-values for social influence and behavioural intention came to 0.034 and 0.005. As both were <0.05, it was evident that these constructs exerted an influence on the number of athleisure apparel items consumers purchased. For construct AU3, i.e. “In general, how much time do you spend shopping for athleisure apparel via mobile shopping apps per week?”, the p-values for effort expectancy and facilitating conditions were 0.007 and 0.004. Both were <0.05, indicating that these constructs exerted an influence on the amount of time consumers spent shopping for athleisure apparel items. For construct AU4, i.e. “On average, how many different mobile shopping apps do you visit in a given month?”, the p-values for hedonic motivation, habit and behavioural intention were 0.033, 0.003 and 0.031. As all were <0.05, it was evident that these three constructs all exerted an influence on the number of mobile shopping apps consumers used to purchase athleisure apparel. Lastly, for construct AU5, i.e. “What was the approximate Rand value of your most recent purchase of athleisure apparel?”, the p-value for behavioural intention came to 0.028. This was <0.05, indicating that behavioural intention exerted an influence on the Rand value consumers spend when shopping for athleisure apparel items.

Table 7.23: Actual use T-test analysis

AU1. When last did you use a mobile shopping app to purchase athleisure apparel? (Choose only one).

		Levene's test for equality of variances		T-test for equality of means						
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference	
									Lower	Upper
Performance expectancy	Equal variances assumed	0,066	0,798	2,501	248	0,013	0,25029	0,10008	0,05318	0,44740
	Equal variances not assumed			2,512	247,674	0,013	0,25029	0,09965	0,05402	0,44656
Hedonic motivation	Equal variances assumed	1,635	0,202	2,868	248	0,004	0,32829	0,11445	0,10288	0,55371
	Equal variances not assumed			2,854	238,154	0,005	0,32829	0,11504	0,10167	0,55491
Habit	Equal variances assumed	0,005	0,944	4,207	248	0,000	0,52263	0,12424	0,27794	0,76733
	Equal variances not assumed			4,204	244,275	0,000	0,52263	0,12431	0,27777	0,76750
Behavioural intention	Equal variances assumed	2,308	0,130	2,538	248	0,012	0,24792	0,09769	0,05551	0,44033
	Equal variances not assumed			2,525	238,509	0,012	0,24792	0,09817	0,05452	0,44132

AU2. How many athleisure apparel items did you purchase during this time? (Choose only one).

		Levene's test for equality of variances		T-test for equality of means						
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference	
									Lower	Upper
Social influence	Equal variances assumed	0,013	0,908	-2,146	248	0,033	-0,28264	0,13173	-0,54210	-0,02318
	Equal variances not assumed			-2,136	179,311	0,034	-0,28264	0,13232	-0,54374	-0,02155
Behavioural intention	Equal variances assumed	7,991	0,005	-3,043	248	0,003	-0,30824	0,10129	-0,50775	-0,10874
	Equal variances not assumed			-2,852	150,417	0,005	-0,30824	0,10806	-0,52176	-0,09473

AU3. In general, how much time do you spend shopping for athleisure apparel via mobile shopping apps per week? (Choose only one).

		Levene's test for equality of variances		T-test for equality of means						
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference	
									Lower	Upper
Effort expectancy	Equal variances assumed	1,736	0,189	-2,706	248	0,007	-0,25432	0,09399	-0,43945	-0,06919
	Equal variances not assumed			-2,701	234,950	0,007	-0,25432	0,09416	-0,43983	-0,06882
Facilitating conditions	Equal variances assumed	1,916	0,167	-2,942	248	0,004	-0,26658	0,09062	-0,44506	-0,08809
	Equal variances not assumed			-2,937	238,800	0,004	-0,26658	0,09075	-0,44536	-0,08780

AU4. On average, how many different mobile shopping apps do you visit in a given month? (Choose only one).

		Levene's test for equality of variances		**T-test for equality of means**						
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference	
									Lower	Upper
Hedonic motivation	Equal variances assumed	0,501	0,480	-2,152	248	0,032	-0,24804	0,11526	-0,47506	-0,02103
	Equal variances not assumed			-2,146	241,893	0,033	-0,24804	0,11556	-0,47568	-0,02041
Habit	Equal variances assumed	0,091	0,763	-3,026	248	0,003	-0,38219	0,12628	-0,63091	-0,13347
	Equal variances not assumed			-3,032	246,315	0,003	-0,38219	0,12607	-0,63051	-0,13388
Behavioural intention	Equal variances assumed	0,054	0,816	-2,169	248	0,031	-0,21261	0,09803	-0,40568	-0,01954
	Equal variances not assumed			-2,165	243,058	0,031	-0,21261	0,09819	-0,40602	-0,01919

AU5. What was the approximate Rand value of your most recent purchase of athleisure apparel? (Choose only one).

		Levene's test for equality of variances		**T-test for equality of means**						
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference	
									Lower	Upper
Behavioural intention	Equal variances assumed	7,163	0,008	-2,353	248	0,019	-0,23467	0,09973	-0,43108	-0,03825
	Equal variances not assumed			-2,217	169,029	0,028	-0,23467	0,10583	-0,44359	-0,02574

As discussed in section 7.7.3, the actual use construct could not be measured as a latent variable made up of several different items as the results showed that the items did not constitute a single factor. It was therefore decided to represent actual use as five unique binary categorical outcomes. As a result, the original hypotheses for Model B (actual use) (except for the trust hypothesis, i.e. H_{13}) were reformulated into five separate hypotheses as per the original hypotheses. Table 7.24 indicates how the different hypotheses were reformulated.

Table 7.24: Reformulated hypotheses for Model B

Original hypotheses		**Reformulated hypotheses**	
H_5	Facilitating conditions have a positive influence on consumers' actual use of mCommerce apps to purchase athleisure apparel	H_{5A}	Facilitating conditions have an influence on when last consumers used a mobile shopping app to purchase athleisure apparel (AU1)
		H_{5B}	Facilitating conditions have an influence on the amount of athleisure apparel items purchased (AU2)
		H_{5C}	Facilitating conditions have an influence on the amount of time spent shopping for athleisure apparel via mobile shopping apps per week (AU3)
		H_{5D}	Facilitating conditions have an influence on the number of mobile shopping apps visited in a given month (AU4)
		H_{5E}	Facilitating conditions have an influence on the approximate Rand value of athleisure apparel purchases (AU5)
H_9	Habit has a positive influence on consumers' actual use of mCommerce apps to purchase athleisure apparel	H_{9A}	Habit has an influence on when last consumers used a mobile shopping app to purchase athleisure apparel (AU1)
		H_{9B}	Habit has an influence on the amount of athleisure apparel items purchased (AU2)
		H_{9C}	Habit has an influence on the amount of time spent shopping for athleisure apparel via mobile shopping apps per week (AU3)
		H_{9D}	Habit has an influence on the number of mobile shopping apps visited in a given month (AU4)
		H_{9E}	Habit has an influence on the approximate Rand value of athleisure apparel purchases (AU5)
H_{11}	Perceived risk has a negative influence on consumers' actual use of mCommerce apps to purchase athleisure apparel	H_{11A}	Perceived risk has an influence on when last consumers used a mobile shopping app to purchase athleisure apparel (AU1)
		H_{11B}	Perceived risk has an influence on the amount of athleisure apparel items purchased (AU2)
		H_{11C}	Perceived risk has an influence on the amount of time spent shopping for athleisure apparel via mobile shopping apps per week (AU3)

		H_{11D}	Perceived risk has an influence on the number of mobile shopping apps visited in a given month (AU4)
		H_{11E}	Perceived risk has an influence on the approximate Rand value of athleisure apparel purchases (AU5)
H_{13}	Trust mediates the negative influence of perceived risk on consumers' actual use of mCommerce apps to purchase athleisure apparel	H_{13}	Trust mediates the negative influence of perceived risk on consumers' actual use of mCommerce apps to purchase athleisure apparel (no change)
H_{15}	Behavioural intention has a positive influence on consumers' actual use of mCommerce apps to purchase athleisure apparel	H_{15A}	Behavioural intention has an influence on when last consumers used a mobile shopping app to purchase athleisure apparel (AU1)
		H_{15B}	Behavioural intention has an influence on the amount of athleisure apparel items purchased (AU2)
		H_{15C}	Behavioural intention has an influence on the amount of time spent shopping for athleisure apparel via mobile shopping apps per week (AU3)
		H_{15D}	Behavioural intention has an influence on the number of mobile shopping apps visited in a given month (AU4)
		H_{15E}	Behavioural intention has an influence on the approximate Rand value of athleisure apparel purchases (AU5)

When controlling for all significant factors in a logistic regression, the data analysis revealed strongly correlated relationships between specific UTAUT2 constructs and actual use constructs. Main findings 31, 32, 33, 34 and 35 are summarised below.

Main finding 31:
Facilitating conditions have a borderline significant influence on the amount of time spent shopping for athleisure apparel via mobile shopping apps per week (AU3). It can be inferred that, if consumers have a working Internet connection to access and use the mobile shopping app, as well as the access to online customer support, increased time will be spent shopping for athleisure apparel via mobile shopping apps per week.

Main finding 32:
Habit has a significant influence on when last consumers used a mobile shopping app to purchase athleisure apparel (AU1). It can be inferred that habitual mCommerce app use influences usage frequency.

Main finding 33:
Habit has a borderline significant influence on the number of mobile shopping apps visited in a given month (AU4). It can be inferred that habitual mCommerce app use influences the number of mCommerce apps used per month.

Main finding 34:
Behavioural intention has a significant influence on the amount of athleisure apparel items purchased (AU2). This indicates that the more intent a consumer has for purchasing athleisure apparel via mCommerce apps, the greater the number of items he/she will purchase.

Main finding 35:
Behavioural intention has a significant influence on the approximate Rand value of athleisure apparel purchases (AU5), indicating that the greater the consumer's intent to purchase, the greater the amount spent.

In the following section, each hypothesis for Model B (actual use) presented in Chapter 1, Figure 1.9 and expanded on in Table 7.24 is discussed independently.

- **Hypothesis 5A: Facilitating conditions have an influence on when last consumers used a mobile shopping app to purchase athleisure apparel (AU1)**
- **Hypothesis 5B: Facilitating conditions have an influence on the amount of athleisure apparel items purchased (AU2)**
- **Hypothesis 5C: Facilitating conditions have an influence on the amount of time spent shopping for athleisure apparel via mobile shopping apps per week (AU3)**
- **Hypothesis 5D: Facilitating conditions have an influence on the number of mobile shopping apps visited in a given month (AU4)**
- **Hypothesis 5E: Facilitating conditions have an influence on the approximate Rand value of athleisure apparel purchases (AU5)**

Based on the discussion preceding this section, hypothesis 5C was **accepted**. Facilitating conditions, in their entirety, were not found to have a positive influence on actual use, which is a contradictory finding to the UTAUT2 (Venkatesh *et al.*, 2012). However, this finding is consistent with those of other studies, including Chopdar *et al.* (2018) and Alkhunaizan and Love (2012). Aligned to the findings reported for hypothesis 4, a possible reason for this may be the fact that the majority of the respondents (56.8%) were between the ages of 18-24. These consumers are known to be very comfortable with technology and very accepting of technological innovations (Savitz, 2012). When analysing the data for Model B, facilitating conditions were found to have a borderline significant influence on construct AU3, i.e. "In general, how much time do you spend shopping for athleisure apparel via mobile shopping apps per week?". It can be inferred that consumers' perceptions of the available resources and support when wanting to shop via mCommerce apps impacts the amount of time they end up spending on these apps per week.

- **Hypothesis 9A: Habit has an influence on when last consumers used a mobile shopping app to purchase athleisure apparel (AU1)**
- **Hypothesis 9B: Habit has an influence on the amount of athleisure apparel items purchased (AU2)**
- **Hypothesis 9C: Habit has an influence on the amount of time spent shopping for athleisure apparel via mobile shopping apps per week (AU3)**
- **Hypothesis 9D: Habit has an influence on the number of mobile shopping apps visited in a given month (AU4)**
- **Hypothesis 9E: Habit has an influence on the approximate Rand value of athleisure apparel purchases (AU5)**

Based on the discussion preceding this section, hypotheses 9A and 9D were **accepted**. The data revealed that (i) habit has a significant influence on construct AU1, i.e. "When last did you use a mobile shopping app to purchase athleisure apparel?", meaning that the more habitual mCommerce app usage is, the more often consumers will use mCommerce apps and (ii) habit has a borderline significant influence on construct AU4, i.e. "On average, how many different mobile shopping apps do you visit in a given month?”. It can be inferred that habitual mCommerce app use does marginally influence the number of mCommerce apps consumers use.

- **Hypothesis 11A: Perceived risk has an influence on when last consumers used a mobile shopping app to purchase athleisure apparel (AU1)**
- **Hypothesis 11B: Perceived risk has an influence on the amount of athleisure apparel items purchased (AU2)**
- **Hypothesis 11C: Perceived risk has an influence on the amount of time spent shopping for athleisure apparel via mobile shopping apps per week (AU3)**
- **Hypothesis 11D: Perceived risk has an influence on the number of mobile shopping apps visited in a given month (AU4)**
- **Hypothesis 11E: Perceived risk has an influence on the approximate Rand value of athleisure apparel purchases (AU5)**

Based on the discussion preceding this section, hypotheses 11A to 11E were all **rejected**. The data did not reveal perceived risk to have a negative influence on consumers’ actual use of mCommerce apps – a contradictory finding to the research done by Wu and Wang (2005:726). Aligned to the findings reported for hypothesis 10, this could be an indication that younger South African consumers are less risk-averse to potential risks associated with shopping for athleisure apparel online or via a mobile phone.

- **Hypothesis 13: Trust mediates the negative influence of perceived risk on consumers’ actual use of mCommerce apps to purchase athleisure apparel**

Based on the discussion preceding this section, hypothesis 13 was **rejected**. Trust was not found to mediate the negative influence of perceived risk on consumers’ actual use of mCommerce apps. This finding is in contrast to those of Farivar *et al.* (2017:587), Kesharwani and Bisht (2012:315-316) and Gao and Bai (2014:217). Aligned to the findings reported for hypothesis 12, although the data did not support this hypothesis, it was interesting to discover that perceived risk had a significant negative influence on trust (t=-5.736). Further details are provided in section 7.6.4.2.2, hypothesis 12.

- **Hypothesis 15A: Behavioural intention has an influence on when last consumers used a mobile shopping app to purchase athleisure apparel (AU1)**
- **Hypothesis 15B: Behavioural intention has an influence on the amount of athleisure apparel items purchased (AU2)**
- **Hypothesis 15C: Behavioural intention has an influence on the amount of time spent shopping for athleisure apparel via mobile shopping apps per week (AU3)**
- **Hypothesis 15D: Behavioural intention has an influence on the number of mobile shopping apps visited in a given month (AU4)**
- **Hypothesis 15E: Behavioural intention has an influence on the approximate Rand value of athleisure apparel purchases (AU5)**

Based on the discussion preceding this section, hypotheses 15B and 15E were **accepted**. The data revealed that (i) behavioural intention had a significant influence on construct AU2, i.e. “How many athleisure apparel items did you purchase during this time?”, meaning that the amount of items purchased is influenced by the consumer intending to purchase those items and (ii) behavioural intention had a significant influence on construct AU5, i.e. “What was the approximate Rand value of your most recent purchase of athleisure apparel?”. It can be inferred that consumers spend more on athleisure apparel if they first have an intention to purchase athleisure apparel.

A summary of the research hypotheses for Model B can be found in Table 7.25. A view of the final models with accepted relationships indicated in green for both Models A and B is presented in Figure 7.4.

Table 7.25: Reformulated Model B hypotheses

Reformulated hypotheses		Accepted
H_{5A}	Facilitating conditions have an influence on when last consumers used a mobile shopping app to purchase athleisure apparel (AU1)	No
H_{5B}	Facilitating conditions have an influence on the amount of athleisure apparel items purchased (AU2)	No
H_{5C}	Facilitating conditions have an influence on the amount of time spent shopping for athleisure apparel via mobile shopping apps per week (AU3)	Yes
H_{5D}	Facilitating conditions have an influence on the number of mobile shopping apps visited in a given month (AU4)	No
H_{5E}	Facilitating conditions have an influence on the approximate Rand value of athleisure apparel purchases (AU5)	No
H_{9A}	Habit has an influence on when last consumers used a mobile shopping app to purchase athleisure apparel (AU1)	Yes
H_{9B}	Habit has an influence on the amount of athleisure apparel items purchased (AU2)	No
H_{9C}	Habit has an influence on the amount of time spent shopping for athleisure apparel via mobile shopping apps per week (AU3)	No
H_{9D}	Habit has an influence on the number of mobile shopping apps visited in a given month (AU4)	Yes
H_{9E}	Habit has an influence on the approximate Rand value of athleisure apparel purchases (AU5)	No
H_{11A}	Perceived risk has an influence on when last consumers used a mobile shopping app to purchase athleisure apparel (AU1)	No
H_{11B}	Perceived risk has an influence on the amount of athleisure apparel items purchased (AU2)	No
H_{11C}	Perceived risk has an influence on the amount of time spent shopping for athleisure apparel via mobile shopping apps per week (AU3)	No
H_{11D}	Perceived risk has an influence on the number of mobile shopping apps visited in a given month (AU4)	No
H_{11E}	Perceived risk has an influence on the approximate Rand value of athleisure apparel purchases (AU5)	No
H_{13}	Trust mediates the negative influence of perceived risk on consumers' actual use of mCommerce apps to purchase athleisure apparel (no change)	No
H_{15A}	Behavioural intention has an influence on when last consumers used a mobile shopping app to purchase athleisure apparel (AU1)	No
H_{15B}	Behavioural intention has an influence on the amount of athleisure apparel items purchased (AU2)	Yes
H_{15C}	Behavioural intention has an influence on the amount of time spent shopping for athleisure apparel via mobile shopping apps per week (AU3)	No
H_{15D}	Behavioural intention has an influence on the number of mobile shopping apps visited in a given month (AU4)	No
H_{15E}	Behavioural intention has an influence on the approximate Rand value of athleisure apparel purchases (AU5)	Yes

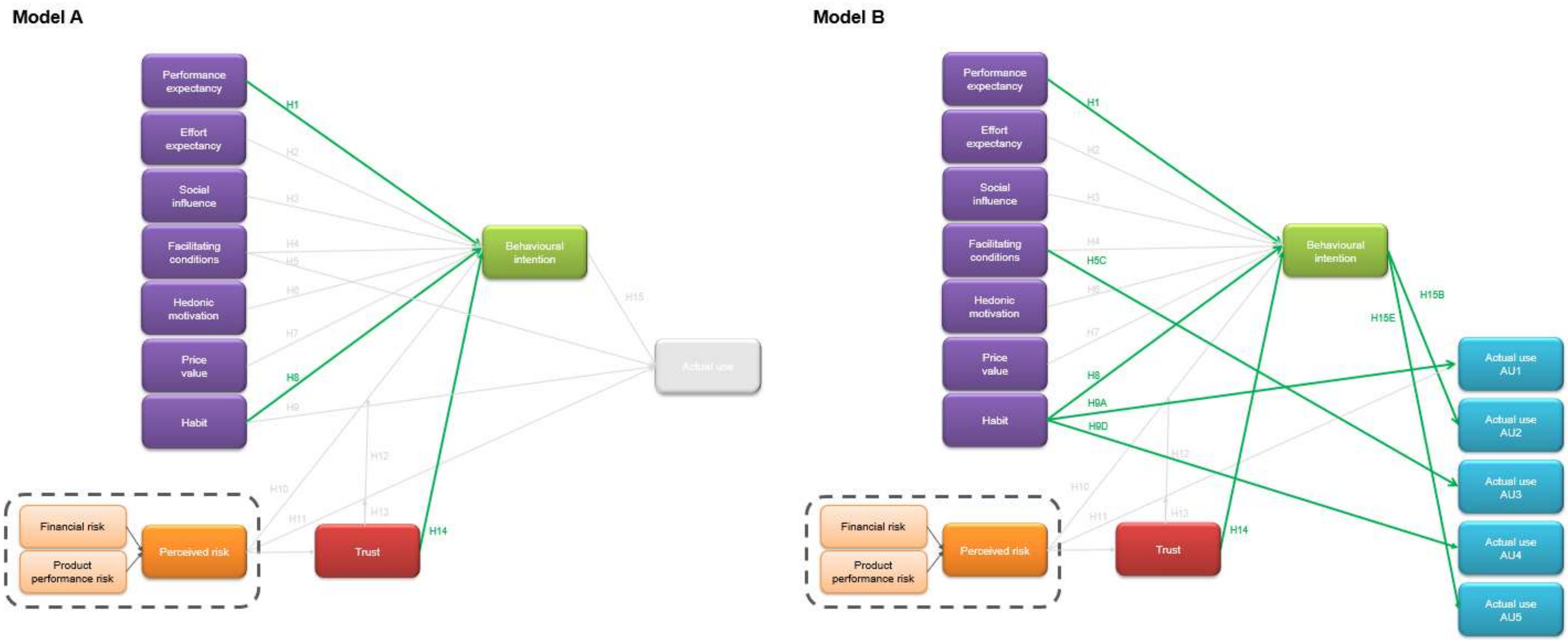


Figure 7.4: Models A and B with accepted relationships indicated in green

***Source**: Researcher's own construct*

Even though the data analysis resulted in only three out of ten hypotheses being accepted for Model A (30%) and five out of 21 for Model B (24%), this is the case with most of the studies referenced in the literature review sections of this study (see Chapters 1, 3, 4 and 5). Johns (2006:386-387; 389) states that context is probably the reason for variations in findings from one study to the next. Miladinovic and Xiang (2018:49) and Verkijika (2018:1672) concur, stating that different cultural and technological contexts yield different results on the acceptance and use of technology such as mobile shopping. New or different contexts can result in several changes to theories, including changing the directions of relationships between variables, rendering specific relationships insignificant, changing the significance of relationships and highlighting new relationships (Venkatesh *et al.*, 2012:158). Variations in research findings should therefore be seen as positive. Conducting empirical research to critically reflect on specific theories in new markets or cultures enhances researchers' ability to challenge those theories, explore potential weaknesses and encourage the rethinking of those theories. This leads to the creation of new knowledge (Alvesson & Kärreman, 2007:1265; 1278).

Consider Chopdar *et al.*'s (2018:120-121) cross-country study between India and the US. In India, performance expectancy, effort expectancy, facilitating conditions, hedonic motivation, price value and habit were all found to influence behavioural intention. Social influence had no impact. In the US, on the other hand, performance expectancy, facilitating conditions and hedonic motivation were found to influence behavioural intention, yet effort expectancy, social influence, price value and habit were not found to have a statistically significant influence on behavioural intention. The same model was tested in both countries, but due to cultural and technological differences, a vastly different model was arrived at. Figure 7.5 depicts the final research model for the present study.

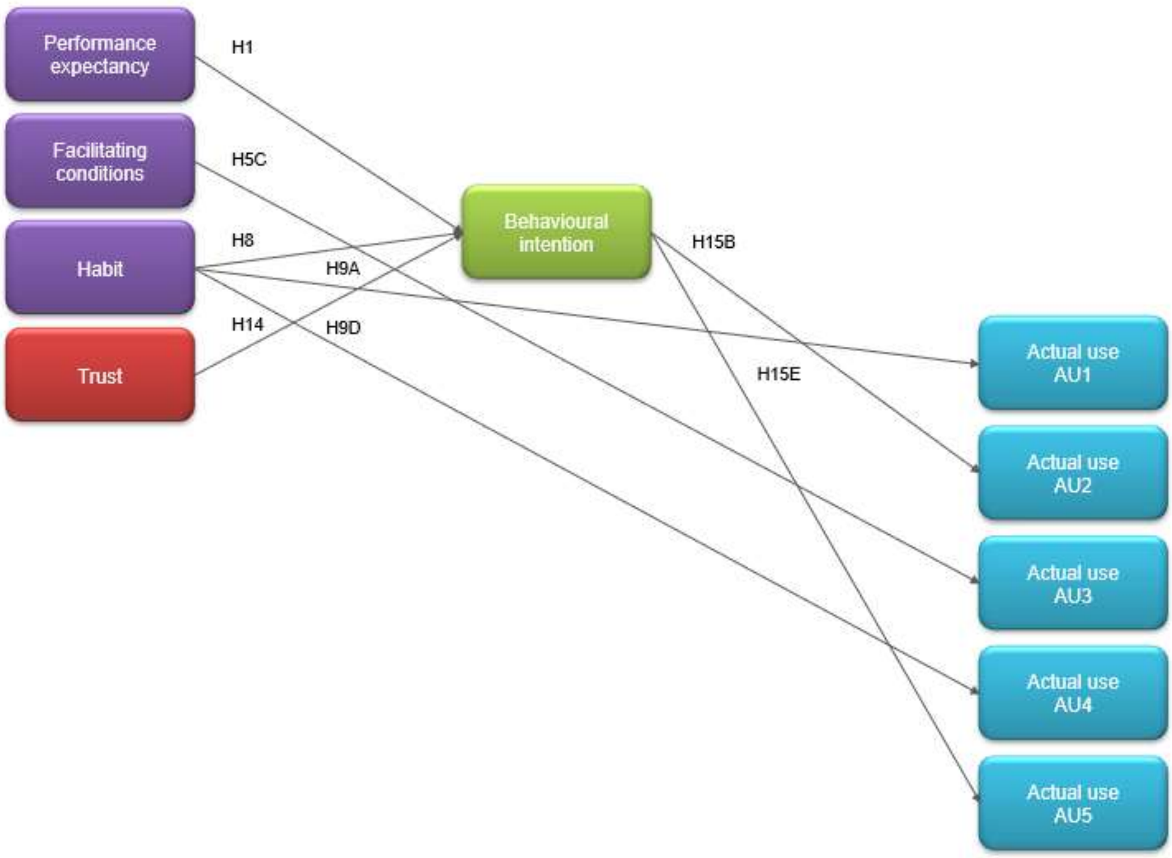


Figure 7.5: Final research model

***Source**: Researcher's own construct*

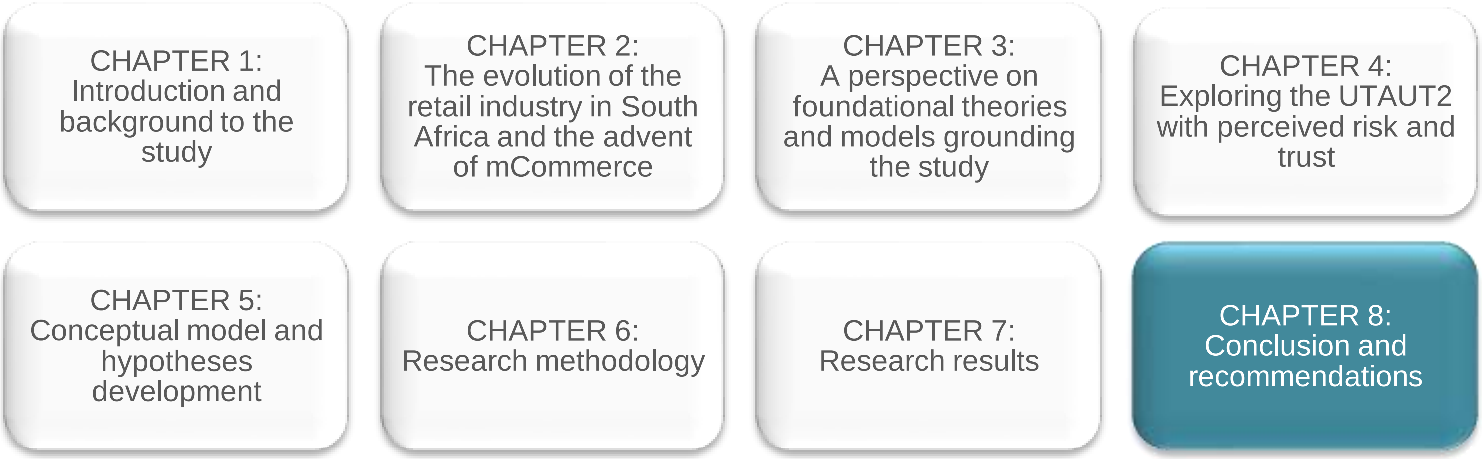
7.8 Conclusion

Chapter 7 presented detailed feedback on the results of the data analysis. The chapter provided an in-depth account of the descriptive statistics for both models, factor analyses, SEM and EFA, concluding with a summary of the accepted research hypotheses and the final research model.

The next chapter, Chapter 8, concludes the study, providing an overview of the findings, implications and recommendations for the industry, as well as detailed strategies based on the results of the data analysis. The chapter also covers the study's limitations and makes suggestions for future research.

CHAPTER 8

CONCLUSION AND RECOMMENDATIONS



8.1 Introduction

Chapter 7 provided a detailed account of the analysis conducted in this study. Models A and B were analysed separately, with structural equation modelling (SEM) being applied to the former and multiple regression to the latter. Data analysis of Model A revealed that performance expectancy, habit and trust have a significant influence on behavioural intention. The analysis further revealed perceived risk to have a significant negative influence on trust. For Model B, the outcome variable (actual use) was changed to be represented as five unique binary categorical outcomes (refer to Chapter 7, sections 7.6.2 and 7.6.3 for the reasoning behind this). Data analysis of this model revealed that facilitating conditions have a borderline significant influence on the amount of time spent shopping for athleisure apparel via mobile shopping apps per week, habit has a significant influence on when consumers last used a mobile shopping app to purchase athleisure apparel, habit has a borderline significant influence on the number of mobile shopping apps visited in a given month, behavioural intention has a significant influence on the amount of athleisure apparel items purchased and behavioural intention has a significant influence on the approximate Rand value of athleisure apparel purchases.

Chapter 8 concludes the study by reviewing all the information collected and providing recommendations. The chapter is split according to each secondary objective, commencing with an overview of the findings for each objective and referencing the results of the data analysis. Implications are then provided, followed by recommendations for industry. The chapter then moves on to highlight key strategies for each of the affirmed objectives and closes with the limitations of the study and suggestions for future research.

8.2 Brief overview of the study

Chapter 1 summarised the entire study. It commenced with background information, laying the foundation of the study. This can be summarised as follows: Most South Africans use their mobile phones to access the Internet (Space Station, 2017) and have a preference for shopping via apps (Business Tech, 2015), yet the category of clothing and accessories does not feature prominently in their shopping selection (Erken, 2017; Goldstuck, 2014:27). Seeing that the athleisure category has become a major trend impacting global and local growth in the fashion industry (Amed et al., 2017:12; Euromonitor International, 2017b), it is essential for South African fashion retailers selling athleisure apparel to understand the reasons for this low purchasing behaviour. From this information, the research problem became clear: To provide insights into this phenomenon by determining the constructs that influence consumers' acceptance and use of mobile commerce (mCommerce) apps to purchase athleisure apparel in South Africa. In order to address the research problem, information was needed on technology acceptance and use. A brief overview of the different theoretical paradigms underpinning the study was provided in Chapter 1, including technology acceptance and use theories and models as well as relationship-building theories. For the former, the discussion focused on the Innovation Diffusion Theory (IDT), the Theory of Reasoned Action (TRA), the Social Cognitive Theory (SCT), the Technology Acceptance Model (TAM), the Theory of Planned Behaviour (TPB) and the Unified Theory of Acceptance and Use of Technology 1 and 2 (UTAUT and UTAUT2). For the latter, the discussion focused on the Social Exchange Theory (SET) and the Transaction Cost Theory (TCT). The UTAUT2 forms the foundation of the study's conceptual model (refer to Chapter 1, Figure 1.9), with the added constructs of perceived risk and trust. Chapter 1 justified the inclusion of these two constructs based on extensive literature support.

Chapter 2 reviewed the retail industry in South Africa and the advent of mCommerce. The chapter covered changes in the buying habits of South African retail consumers, looked at the emergence of electronic commerce (eCommerce) and mCommerce, explored the athleisure apparel industry in South Africa as well as examining mCommerce integration into the athleisure apparel industry. Chapter 3 gave a detailed account of the foundational theories and models grounding the study. Chapter 4 focused on the UTAUT2, discussing each of its constructs in detail along with the added constructs of perceived risk and trust. In Chapter 5, the conceptual models were presented alongside the research hypotheses. Each of the 15 hypotheses was discussed in detail. Chapter 6 outlined the research methodology based on the 'research onion' of Saunders et al. (2016:124) (refer to Chapter 1, Figure 1.10). Chapter 7 provided detailed feedback on the analysis of the collected data.

The primary objective of this study was to determine the constructs that influence consumers' acceptance and use of mCommerce apps to purchase athleisure apparel in South Africa. The following sections comment on the results for each of the secondary objectives that fulfil the primary objective, highlighting the key constructs that influence consumers' acceptance and use of mCommerce apps to purchase athleisure apparel in South Africa.

8.3 Conclusions and recommendations for the secondary objectives

This section discusses each of the eight secondary objectives of the study. Each objective is listed, including the theoretical background, the study findings, the main conclusion as well as the recommendations.

8.3.1 Secondary objective 1

The first secondary objective for this study is as follows:

Secondary objective 1
To determine whether performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, habit, and trust have a positive influence on the behavioural intention of consumers to use mCommerce apps to purchase athleisure apparel.

As the first secondary objective combines numerous constructs, these are discussed individually. Each section commences with an overview of the findings for this particular objective, referencing the theoretical background provided in previous chapters as well as the results of the data analysis conducted in Chapter 7. It then provides the main conclusion as well as recommendations for the industry.

8.3.1.1 To determine whether performance expectancy influences behavioural intention

As per the definitions provided in Chapter 1, section 1.7.4.1 and Chapter 4, section 4.2.1, the construct of performance expectancy is described as the degree to which the use of a certain technology, such as shopping via a mobile app, is of benefit to a consumer (Venkatesh *et al.*, 2012:159). Research suggests that consumers are more likely to use technology that they deem to be useful or from which they derive benefit (Gupta *et al.*, 2018:140). In the context of this study, performance expectancy refers to a consumer having the ability to shop via their mobile phone at any time of day or at any location of their choice (Alalwan *et al.*, 2018:128; Tarhini *et al.*, 2016:834; Hyben *et al.*, 2015:3; eMarketer, 2013). In addition, an app reduces waiting time on the consumer's part as they are quick to open and load (Graybill, 2015).

As per the discussion in Chapter 7, section 7.6.1.2.1 (main finding 4), the majority of the respondents agreed that the use of mCommerce apps would provide a benefit to them when purchasing athleisure apparel. In addition, as per Chapter 7, section

7.6.4.2.2 (main finding 22), performance expectancy was found to positively influence behavioural intention (β=0.169, t=2.099, $p<0.05$), in line with the UTAUT2 (Venkatesh *et al.*, 2012). Other researchers, referenced in previous chapters (refer to Chapter 1, section 1.7.4.1, Chapter 3, section 3.3.7, Chapter 4, section 4.2.1 and Chapter 5, section 5.4.1.1), also found this construct to influence behavioural intention, including Alalwan *et al.* (2018), Chopdar *et al.* (2018), Gupta *et al.* (2018), Chaouali *et al.* (2016), Madan and Yadav (2016), Miladinovic and Xiang (2016), Oliveira *et al.* (2016), Tarhini *et al.* (2016), Hew *et al.* (2015), Martins *et al.* (2014), Akbar (2013), Alkhunaizan and Love (2012), Fai (2011) and AbuShanab and Pearson (2007).

The results thus provided support for the positive relationship between performance expectancy and consumers' behavioural intention. Consumers are therefore more likely to use mCommerce apps to purchase athleisure apparel if they perceive that the app offers useful functions such as greater efficiency or improved productivity (Shaw & Sergueeva, 2019:51; Miladinovic & Xiang, 2016:49; Hew *et al.*, 2015:1284).

The implications of this are twofold. The likelihood of consumers using mCommerce apps to purchase athleisure apparel will increase if they believe the app offers useful functions. Conversely, their behavioural intention will be reduced if the app is prone to errors or technological breakdowns (Chaouali *et al.*, 2016:216). Several recommendations with actionable strategies can be formulated from this insight and are elaborated below.

Recommendation 1
Design an app for a smartphone and leverage the capabilities of a smartphone.

As described in Chapter 1, section 1.2, in essence, mobile apps are pieces of software that run on a smartphone and provide users with a similar experience to a traditional desktop computer (Techopedia, 2020; Miladinovic & Xiang, 2016:7). mCommerce app owners or developers should design their shopping apps to leverage smartphone capabilities to the fullest extent, thereby increasing utility for the consumer. For example, the customer could be given the ability to leverage the smartphone's camera in the app to scan the garment's barcode and find additional sizes; the phone's GPS service could be used to locate stores nearby or alert a customer that they are in the vicinity of a physical store with an in-store sale; or allow the customer to create a profile to receive personalised alerts of new athleisure items that match their profile (Miladinovic & Xiang, 2016:54). In addition, it is imperative that mCommerce app owners or developers design apps with the smartphone screen size in mind. Given the small screen size, the app experience should be carefully thought through and designed, allowing for simple browsing and navigation by one hand and one thumb only. Payments should also be streamlined (Hew *et al.*, 2015:1286; Persson & Berndtsson, 2015:65; Yang, 2010:267).

Recommendation 2
Ensure app stability and guaranteed up-time.

Consumers' behavioural intention can also be reduced if a particular app is prone to errors or technological breakdowns (Chaouali *et al.*, 2016:216). It is imperative for mCommerce app owners and developers to ensure that apps are built with stability in mind and are able to handle a large volume of customers at the same time to ensure the app is available at all times (IBM, 2020). mCommerce app owners and developers should aim for 99.9% uptime, an industry standard (Intelliwave Technologies, 2019). Should an error or technological breakdown occur, mCommerce app owners should be transparent, issue an apology and state how the problem will be rectified to reassure customers (Weinhouse, 2018).

Recommendation 3
Regularly release new and improved app functionalities that make the app more useful for consumers.

mCommerce app owners and developers should regularly release new and improved functionalities on the app, enticing existing customers to make repeat use of it and encouraging new customers to download it (Chopdar *et al.*, 2018:122). An example of this includes improving convenience by allowing for quicker payment (Chaouali *et al.*, 2016:216). Another example to entice usage of the app is to offer certain products exclusively for sale via the app (Martins *et al.*, 2014:10). An excellent source of suggestions as to what improvements are needed in an app are the customers themselves. mCommerce app owners should have a permanent app review function or built-in survey in the app that asks customers to rate certain functions after use and make suggestions for improvement. These suggestions can then be prioritised and actioned accordingly (Tarhini *et al*., 2016:842).

Recommendation 4
Advertise the app and releases of new and improved app versions.

mCommerce app owners should invest in advertising their apps, highlighting useful functions, efficiency through shortened shopping times and convenience through access anywhere and at any time (Oliveira *et al.*, 2016:411). In addition, with each of the new and improved app version releases, mCommerce app owners should advertise these releases to consumers, emphasising the benefit each new release will bring to the customer (AbuShanab & Pearson, 2007:93). In order to do this, different marketing communication channels should be leveraged. The releases could be pushed out via the Apple App Store or the Google Play Store, as well as app push notifications straight to consumers' mobile phones that already have the app installed. In addition, mCommerce app owners could advertise new functionalities using social media, the company website or direct marketing by means of SMS and email (Alalwan *et al.*, 2018:134; Tarhini *et al.*, 2016:843). These marketing activities will create awareness of the new functions and entice consumers to use them (Verkijika, 2018:1673).

8.3.1.2 To determine whether effort expectancy influences behavioural intention

Venkatesh *et al.* (2012:159) describe effort expectancy as the level of ease associated with consumers' use of a specific technology. Contextually, in relation to this study, this can be interpreted in two ways. Firstly, effort expectancy relates to the ease of use provided by a touchscreen phone when using an app. Less effort is required on the consumer's part as a touchscreen allows for faster, more intuitive use of the app (Sky Technology, 2016). Secondly, it relates to efficiency of the activity of shopping which motivates consumers to use their mobile phones for shopping purposes (Parker & Wang, 2016:490). This description is provided in Chapter 1, section 1.7.4.2 and again in Chapter 4, section 4.2.2. The ease of using a mobile shopping app should, theoretically, be a motivating factor for consumers to adopt mobile shopping in an emerging market such as South Africa as less effort should lead to improved adoption (Chaouali *et al.*, 2016:212). However, in terms of this study, this was not the case.

As per the discussion in Chapter 7, section 7.6.4.2.2, this study found no relationship between effort expectancy and behavioural intention (β=0.137, t=1.491), contradicting the UTAUT2 (Venkatesh *et al.*, 2012) and numerous other studies referenced in previous chapters (refer to Chapter 1, section 1.7.4.2, Chapter 3, section 3.3.7, Chapter 4, section 4.2.2 and Chapter 5, section 5.4.1.2), including Alalwan *et al.* (2018), Lee *et al.* (2018), Hew *et al.* (2015), Persson and Berndtsson (2015), Fai (2011) and Wang and Wang (2010). A number of other researchers, however, support this finding and also did not find a relationship to exist between effort expectancy and behavioural intention including Shaw and Sergueeva (2019), Chopdar *et al.* (2018), Gupta *et al.* (2018), Verkijika (2018), Chaouali *et al.* (2016), Madan and Yadav (2016), Miladinovic and Xiang (2016), Oliveira *et al.* (2016) and Tarhini *et al.* (2016).

Although the results of this study did not support a relationship between effort expectancy and consumers' behavioural intention, as per the discussion in Chapter 7, section 7.6.1.2.2 (main finding 5), the majority of the respondents did agree that it was easy for them to use mCommerce apps. mCommerce app owners and developers can ensure that this continues by actioning the recommendation below.

Recommendation 5
Design an intuitive, easy-to-use app.

Aligned with recommendation 1 in section 8.3.1.1 above, in order to avoid effort expectancy impacting behavioural intention, mCommerce app owners and developers should ensure that app experiences are well-designed, allowing for easy navigation and simple browsing by one hand and one thumb only, requiring minimal effort, both physically and mentally (Chopdar *et al.*, 2018:122; Hew *et al.*, 2015:1286; Persson &

Berndtsson, 2015:65; Yang, 2010:267). Given the ubiquity of smartphones today, if these mCommerce app owners and developers align with best practice, i.e. design app functions and features to be similar to other popular apps, the app will be more intuitive and easier to use as the consumer will already be more familiar with the design elements (Shaw & Sergueeva, 2019:51; Tarhini *et al.*, 2016:843). Hew *et al.* (2015:1286) recommend simplified language and the use of icons to further simplify the use of apps. In addition, a fast app response time is required to ensure the benefit of using the app is not decreased (Wang & Wang, 2010:422).

8.3.1.3 To determine whether social influence positively influences behavioural intention

As per the definition provided in Chapter 1, section 1.7.4.3 and in Chapter 4, section 4.2.3, social influence refers to a consumer's belief that their friends and/or family believe they should use a specific technology, such as mobile shopping through an app (Venkatesh *et al.,* 2012:159). In the context of this study, this may refer to the social pressures exerted on an individual to adopt a new technology. That being said, in an emerging country such as South Africa, the Internet and mCommerce are only gradually penetrating the market. This means that consumers are also gradually introduced to these innovations. As a result, they are able to build trust in the technology over time (Chaouali *et al.*, 2016:210).

As per the discussion in Chapter 7, section 7.6.4.2.2, this study found no relationship between social influence and behavioural intention (β=-0.017, t=-0.321). This contradicts the UTAUT2 (Venkatesh *et al.*, 2012) and numerous other studies referenced in previous chapters (refer to Chapter 1, section 1.7.4.3, Chapter 3, section 3.3.7, Chapter 4, section 4.2.3 and Chapter 5, section 5.4.1.3), including Gupta *et al.* (2018), Lee *et al.* (2018), Verkijika (2018), Madan and Yadav (2016), Tarhini *et al.* (2016), Fai (2011), Yang (2010) and AbuShanab and Pearson (2007). Various other researchers, however, support this finding and also report no relationship between social influence and behavioural intention. These include Shaw and Sergueeva (2019), Alalwan *et al.* (2018), Chopdar *et al.* (2018), Chaouali *et al.* (2016), Miladinovic and Xiang (2016), Hew *et al.* (2015) and Alkhunaizan and Love (2012).

Although the results of this study do not support a relationship between social influence and behavioural intention to use mCommerce apps and the majority of the respondents felt impartial as to the influence of their family and friends (refer to main finding 6 in Chapter 7, section 7.6.1.2.3), mCommerce app owners and developers nonetheless need to ensure that this continues. Two recommendations with actionable strategies to assist in this regard are discussed below.

Recommendation 6
Incorporate social interaction into mCommerce apps.

As stated in Chapter 7, section 7.6.4.2.2, mCommerce can be seen as a personal activity – a potential reason for the results not finding a relationship between social influence and behavioural intention. Nevertheless, this does not negate the need to integrate social interaction into mCommerce apps. Social media has become increasingly more prolific over the last few years, with platforms such as Facebook growing its South African users by 14% from 2017 to 2020, with this figure projected to grow by another 12.5% by 2023 (Statista, 2019f). Instagram exhibited a phenomenal growth rate of 73% in South Africa between 2018 and 2019 alone (Javan, 2019). Integrating social interaction into mobile shopping apps increases sharing and word-of-mouth amongst consumers, which not only drives new users to the platform, but also increases usage from existing users (Chopdar *et al.*, 2018:122; Verkijika, 2018:1673). It is also a cost-effective way of advertising the app to new and existing customers, reinforcing recommendation 4 in section 8.3.1.1 above (Alalwan *et al.*, 2018:134).

Recommendation 7
Incorporate customer reviews into mCommerce apps.

Aligned with recommendation 3 in section 8.3.1.1 above, mCommerce app owners and developers should incorporate customer reviews into apps, allowing customers to rate their overall experience and provide suggestions for improvement. Reviews have increased in popularity and trustworthiness over the last few years and have been shown to exert significant influence over consumers' purchasing decisions (Li, Xie &

Zhang, 2020:1; Xu 2020:2; Oliveira *et al.*, 2016:411; Yang, 2010:267). Madan and Yadav (2016:239) support this, stating that there is a perception that online reviews are more credible than other sources of information. Researchers have also found online reviews to assist in reducing perceived risk (Xu, 2020:4). As discussed in Chapter 7, section 7.6.4.2.2, even though this study did not find social influence from family and friends to influence behavioural intention, consumers may be more inclined to reference reviews as opposed to the opinions of their inner circle when making decisions regarding the purchase of athleisure apparel (Miladinovic & Xiang, 2016:51).

8.3.1.4 To determine whether facilitating conditions influence behavioural intention

Facilitating conditions are described as the consumer's perception of available support and resources when performing a certain behaviour (Venkatesh *et al.*, 2012:159) (refer to Chapter 1, section 1.7.4.4 and Chapter 4, section 4.2.4). In the context of this study, this construct can be understood as an available Internet connection for the consumer to access and use the mobile shopping app, as well as the availability of online customer support, for example, frequently asked questions on the app or company's website and an email address and/or contact number (Miladinovic & Xiang, 2016:22). In theory, if consumers have support at their disposal, there should be an increased willingness to adopt and use a specific technology. This was not the case, however.

As per the discussion in Chapter 7, section 7.6.4.2.2, this study found no relationship between facilitating conditions and behavioural intention (β=0.127, t=1.301). This contradicts the UTAUT2 (Venkatesh *et al.*, 2012) and numerous other studies referenced in previous chapters (refer to Chapter 1, section 1.7.4.4, Chapter 3, section 3.3.7, Chapter 4, section 4.2.4 and Chapter 5, section 5.4.1.4), including Chopdar *et al.* (2018), Madan and Yadav (2016), Verkijika (2018) and Yang (2010). However, Shaw and Sergueeva (2019), Gupta *et al*. (2018) and Oliveira *et al.* (2016) also found no relationship between facilitating conditions and behavioural intention, supporting this study's findings.

Although the results of this study found no evidence of a relationship between facilitating conditions and consumers' behavioural intention, as per the discussion in

Chapter 7, section 7.6.1.2.4 (main finding 7), the majority of the respondents felt that they were well-equipped and had the necessary resources to use mCommerce apps. mCommerce app owners and developers can ensure that this continues by actioning the recommendations below.

Recommendation 8
Zero-rate data usage for mCommerce apps.

To make sure that facilitating conditions (such as Internet connectivity and the availability of customer support) do not undermine behavioural intention, mCommerce app owners can implement zero-rate data usage for their apps. This means that consumers would not incur any data costs for using the apps (Yang, 2010:267). This can be arranged via a third party or with mobile telephone networks directly.

Recommendation 9
Ensure that the app is compressed in size to allow for speedy response.

Another element of facilitating conditions that has been reported as significant in prior mCommerce studies is the speed in app response time. Considering that mobile response speeds are often determined by the mobile network provider and the location of the customer, it is still imperative that mCommerce app owners and developers make their apps as small and compressed as possible to ensure limited data consumption and quick response times (Madan & Yadav, 2016:239). Slow response times have been shown to have a severe negative impact on customer experience. A 2015 study by Apteligent revealed that 48% of consumers will stop using an app or even uninstall it due to slow speeds (Matheny, 2015). Research indicates that the ideal response time is as low as two seconds, with every additional second resulting in a 7% impact on conversion rate (Mehul, 2018). Designing a small, compressed app that has a fast response time will allow users to browse the app quickly and efficiently, creating a positive customer experience.

Recommendation 10
Provide 24/7 customer support and frequently asked questions (FAQs) via a service chatbot.

With an increasing number of customers accessing digital platforms to engage with organisations, these organisations have had to investigate innovative, more cost-effective means of customer service to keep up with the increased demand (Verkijika, 2018:1673; Miladinovic & Xiang, 2016:50). Chatbots are one such innovation. Chatbots are able to provide customers with automated, personalised service anywhere and at any time and at a much lower price than employing a team of customer service representatives. Chatbots can be built to solve customer problems, save time and, in instances where it cannot provide the required assistance itself, hand over seamlessly to a human consultant for intervention (Chung, Ko, Joung & Kim, 2018:1). mCommerce app owners can leverage chatbot technology to assist customers with their service enquiries. A simple chatbot can be built by leveraging FAQs and exposing them to customers via a website, app, instant messaging apps such as WhatsApp or on social media channels such as Facebook. As new questions are posed by customers, the business can answer these questions and publish the information through the chatbot. As it sits centrally, all the channels it is exposed through will benefit from the additional questions and answers being uploaded. In addition, artificial intelligence can be leveraged by the developers building the chatbot to enable it to learn over time and become smarter at understanding and interpreting customers' different questions, leading to improved first-call resolution.

8.3.1.5 To determine whether hedonic motivation positively influences behavioural intention

As per the definition provided in Chapter 1, section 1.7.4.5 and in Chapter 4, section 4.2.5, hedonic motivation refers to the enjoyment associated with using a specific technology (Venkatesh *et al.,* 2012:161). In the context of this study, this refers to a feeling of joy, pleasure or playfulness experienced by the consumer when engaging with technology such as a mobile shopping app (Alalwan *et al.*, 2018:128).

As per the discussion in Chapter 7, section 7.6.4.2.2, no relationship was found between hedonic motivation and behavioural intention (β=0.051, t=1.124). This contradicts the UTAUT2 (Venkatesh *et al.*, 2012) and other studies referenced in previous chapters (refer to Chapter 1, section 1.7.4.5, Chapter 3, section 3.3.7, Chapter 4, section 4.2.5 and Chapter 5, section 5.4.1.5), including Shaw and Sergueeva (2019), Alalwan *et al.* (2018), Chopdar *et al.* (2018), Verkijika (2018), Miladinovic and Xiang (2016) and Hew *et al.* (2015). Gupta *et al.* (2018) and Oliveira *et al.* (2016), however, did not find a relationship between hedonic motivation and behavioural intention, supporting this study's finding.

Although the results of this study did not reveal a relationship between hedonic motivation and consumers' behavioural intention, the majority of the respondents were of the opinion that using mCommerce apps brought them joy and entertainment (refer to main finding 8 in Chapter 7, section 7.6.1.2.5). mCommerce app owners and developers can ensure that this continues by actioning the recommendation below.

Recommendation 11
Create an enjoyable app experience.

In order to ensure hedonic motivation does not exert a negative influence on behavioural intention, mCommerce app owners and developers should ensure that, whilst developing a well-designed, intuitive app, they should also make the experience an enjoyable one for consumers by incorporating interactive features that keep the customer engaged and augment the overall shopping experience (Shaw & Sergueeva, 2019:51; Chopdar *et al*., 2018:122; Verkijika, 2018:1673; Miladinovic & Xiang, 2016:54). This is aligned with recommendations 1 and 3 in section 8.3.1.1, recommendation 5 in section 8.3.1.2 and recommendation 6 in section 8.3.1.3. Examples of this include enabling augmented reality which would allow the customer to virtually try on a clothing item; allowing the customer to find a size in a store located in close proximity and placing that item on hold in the store pending their arrival; giving the customer access to the latest in fashion trends; providing the customer with information on community exercise and wellbeing events close to their home or place of work; or inspiration for specific exercise ensembles such as apparel for yoga versus running versus Pilates versus spinning (ChargeItSpot, 2019).

8.3.1.6 To determine whether price value positively influences behavioural intention

Venkatesh *et al.* (2012:161) describe price value as the cognitive trade-off a consumer makes between the benefit they perceive will be gained from using the technology against the monetary cost of using it. This description is provided in Chapter 1, section 1.7.4.6 and again in Chapter 4, section 4.2.6. As discussed in the aforementioned sections, mCommerce app owners do not maintain a physical store presence, do not pay monthly salaries to salespeople, do not pay rent, etc. and are therefore able to pass these overhead savings on to the customer in the form of attractive discounts on items. This can have a significant influence on the customer's behavioural intention to use the technology (Jao, 2015).

As per the discussion in Chapter 7, section 7.6.4.2.2, this study found no relationship between price value and behavioural intention (β=0.027, t=0.439). This was in contradiction to the UTAUT2 (Venkatesh *et al.*, 2012) and other studies referenced in previous chapters (refer to Chapter 1, section 1.7.4.6, Chapter 3, section 3.3.7, Chapter 4, section 4.2.6 and Chapter 5, section 5.4.1.6), including Alalwan *et al.* (2018) and the Indian results of Chopdar *et al.*'s (2018) study. The American results, however, do support the findings of this study, i.e. no relationship was found between price value and behavioural intention. As stated in Chapter 7, section 7.6.4.2.2, this study has shown synergies with the American portion of Chopdar *et al.*'s (2018) research, specifically in relation to performance expectancy, effort expectancy and perceived risk as well as these constructs' influence on behavioural intention. Various other researchers also confirm this finding, notably, Verkijika (2018), Miladinovic and Xiang (2016), Oliveira *et al.* (2016) and Hew *et al.* (2015).

Although the results of this study did not support a relationship between price value and consumers' behavioural intention, the majority of the respondents agreed that mCommerce apps offer athleisure apparel at good prices (refer to main finding 9 in Chapter 7, section 7.6.1.2.6). mCommerce app owners and developers can capitalise on this. Two recommendations with actionable strategies to assist in this regard are described below.

Recommendation 12
Offer attractive discounts.

One of the greatest benefits of maintaining an mCommerce store is the fact that such retailers are not required to maintain a physical store which costs a significant amount of capital outlay to establish and maintain, including leasing the premises, hiring and paying monthly salaries for salespeople, etc. (Jao, 2015). These savings can be passed on to customers in the form of attractive discounts on athleisure apparel.

Recommendation 13
Ensure the utility offered by the app outweighs the cost of using it.

Even though the questionnaire did not measure customers' opinions regarding data usage in relation to browsing or shopping via mCommerce apps, mCommerce app owners can nonetheless ensure that price sensitivity does not undermine behavioural intention. It is recommended that mCommerce app owners, aligned with recommendation 8 in section 8.3.1.4 above, zero-rate the data usage for the app. This means that consumers would only incur a charge for downloading the app, but not for using it. South African consumers are known to be price-sensitive. In fact, Nielsen (2019) reports that South Africa is the second most price-sensitive country in the world. If the utility of the app outweighs the monetary cost of using it, it will encourage repeat use from existing customers as well as new customers (Alalwan *et al.*, 2018:133). In addition, many apps charge a fee for using the app (over and above the data costs incurred for downloading and using it). mCommerce app owners should refrain from this as it may deter consumers from using the app. It is recommended that owners consider monetising apps in different ways, for example, by selling advertising space on the app (Hew *et al.*, 2015:1286).

8.3.1.7 To determine whether habit has a positive influence on behavioural intention

As per the definition provided in Chapter 1, section 1.7.4.7 and in Chapter 4, section 4.2.7, the construct of habit is described as the automatic execution of a specific behaviour as a result of prior learning (Venkatesh *et al.,* 2012:161). In the context of this study, smartphone and app usage today occurs habitually or naturally as it is repeated so often (Lipsman, 2015; Chou *et al.*, 2013:4). The more habitual the performance of a task, the less choice is needed and the lesser the influence of external factors (Miladinovic & Xiang, 2016:24).

As per the discussion in Chapter 7, section 7.6.4.2.2 (main finding 23), this study found habit to positively influence behavioural intention ($\beta=0.163$, $t=3.117$, $p<0.05$). This finding is aligned with the UTAUT2 (Venkatesh *et al.*, 2012). Other researchers, referenced in previous chapters (refer to Chapter 1, section 1.7.4.7, Chapter 3, section 3.3.7, Chapter 4, section 4.2.7 and Chapter 5, section 5.4.1.7) also found this construct to influence behavioural intention, including Chopdar *et al.* (2018), Gupta *et al.* (2018), Miladinovic and Xiang (2016) and Hew *et al.*, (2015).

The results of this study thus reveal a positive relationship between habit and consumers' behavioural intention. Consumers are therefore more likely to use mCommerce apps to purchase athleisure apparel if they have already formulated habitual behaviour of shopping via their mobile phones (Alalwan *et al.*, 2018:134). Several recommendations with actionable strategies can be formulated from this insight, as discussed below.

Recommendation 14
Design an app that feels familiar.

Aligned with recommendation 5 in section 8.3.1.2, mCommerce app owners and developers should design apps that feel familiar to consumers. Developers should reference the design thinking applied in top-downloaded and most-used apps to ensure the app feels familiar and intuitive to users. In addition, developers should ensure alignment to best practice, i.e. leveraging functions, features, iconography and user journeys that are similar to other popular apps (Shaw & Sergueeva, 2019:51; Tarhini *et al.*, 2016:843). This will ensure the design of an easy-to-use, intuitive app whose usage will thus become routine and habitual far more quickly (Miladinovic & Xiang, 2016:54).

Recommendation 15
Create a rewards programme to encourage frequent use of the app.

Habitual behaviour can be encouraged through the creation of a rewards programme where frequent app users are incentivised for continued usage. A rewards programme, also referred to as a loyalty programme, is described as a marketing programme designed to incentivise profitable customers to increase loyalty (Hwang & Choi, 2020:366). Examples of rewards that can be offered via such a programme include exclusive access to special offers, tailored discounts based on past purchases, general prizes as well as contributions to social responsibility programmes (Hwang & Choi, 2020:366; Farivar *et al*. 2017:599). Increased app usage frequency leads to the creation of habit which, in turn, bolsters behavioural intention (Miladinovic & Xiang, 2016:50).

Recommendation 16
Leverage push notifications.

Aligned with recommendation 1 in section 8.3.1.1 and recommendation 15 above, app users should be incentivised to create profiles and share information about themselves. mCommerce app owners and developers can leverage this information to segment the user base into groups and send tailored offers, personalised discounts and new product announcements to these groups. Users can be alerted to these offers, discounts and rewards by means of push notifications via the app which will also encourage repeat use.

8.3.1.8 To determine whether trust positively influences behavioural intention

As per the definition in Chapter 1, section 1.7.4.9 and Chapter 4, section 4.4, the construct of trust is described as the level of confidence a consumer has in an online or mobile exchange (Ribbink *et al.*, 2004:447). Kesharwani and Bisht (2012:309-310) describe this as the degree to which a consumer feels confident about relying on an eCommerce or mCommerce retailer. This construct has been shown to have a significant influence on behavioural intention (Farivar *et al.,* 2017:597; Joubert & van Belle, 2013:29; Ribbink *et al.,* 2004:446).

As discussed in Chapter 7, section 7.6.4.2.2 (main finding 25), this study found trust to positively influence behavioural intention ($\beta=0.532$, $t=7.834$, $p<0.05$). Other researchers, referenced in previous chapters (refer to Chapter 1, section 1.7.4.9, Chapter 4, section 4.4 and Chapter 5, section 5.4.7) reported the same results, including Chin *et al.* (2018), Gupta *et al.* (2018), Marriott and Williams (2018), Verkijika (2018), Chaouali *et al.* (2016), Suh *et al.* (2015), Gao *et al.* (2014), Vasileiadis (2014), Chong (2013) and Joubert and van Belle (2013).

The results of this study therefore confirm a positive relationship between trust and consumers' behavioural intention. This means that consumers are more likely to use mCommerce apps to purchase athleisure apparel if they trust the platform. Several recommendations with actionable strategies can be formulated from this insight, as described below.

Recommendation 17
Design a professional, credible-looking app.

Reinforcing the recommendations made in sections 8.3.1.1 (recommendation 1) and 8.3.1.2 (recommendation 5), it is imperative for the app to be well-designed as this will reflect the credibility and professional image of the organisation. Quality perception related to an app or website, according to Chang and Chen (2008:831) and McKnight *et al.* (2002:316), has an influence on initial trust. Consumers visiting the app for the first time will make a judgement call based on the app's look and feel. This impression will determine whether they proceed to purchase or not. Kesharwani and Bisht (2012:316) support this view, emphasising the positive impact of well-designed websites and apps on initial consumer trust and behavioural intention to purchase.

Recommendation 18
Offer credible, well-known payment options.

Just as mCommerce app owners and developers should design apps that feel familiar to consumers (refer to recommendation 5 in section 8.3.1.2 and recommendation 14 in section 8.3.1.7), they should also leverage familiar payment facilitators. There are numerous credible payment options available in the market that customers have come to know and trust. A good point of departure is to select the payment facilitators used by top-downloaded and most-used apps (Persson & Berndtsson, 2015:77). Examples include offering debit and credit card payment solutions, electronic funds transfers (EFTs), PayFast as well as digital payment solutions such Zapper and SnapScan. These are well-known payment solutions used by a number of eCommerce and mCommerce retailers in South Africa (Euromonitor International, 2017). Leveraging these existing, well-known payment solutions lends credibility to the organisation and assists in establishing trust as consumers will have been exposed to these payment facilitators via other platforms.

Recommendation 19
Surface security accreditations on the app.

As stated in Chapter 1, section 1.7.4.8 and Chapter 4, section 4.3, South Africans' concerns about online security have been increasing year on year (Swiegers, 2018:18; Goldstuck, 2014:13; 17). mCommerce app owners and developers should apply for a Secure Socket Layer (SSL) certificate – a mandatory requirement if the app accepts major credit cards – from trusted security entities such as Thawte, Entrust, Geotrust or VeriSign (Low, 2020; Farivar *et al.*, 2017:599; Ribbink *et al.*, 2004:453; McKnight *et al*., 2002:317). The entity's logo should be featured prominently on the app, especially during the payment process, to address any doubts in security from customers upfront (Rouibah *et al.*, 2016:38). Chin *et al.* (2018:55) and Vasileiadis (2014:188) support this view, stating that increased efforts towards improving security measures and prominently displaying such improvements can lead to increased profitability for mCommerce app owners. D'Allesandro *et al.* (2012:450-451) concur, stating that having the appropriate security measures in place increases consumer trust and decreases perceived risk.

Recommendation 20
Establish an easy and convenient returns and refund policy.

In order to instil trust in customers and enhance behavioural intention to purchase athleisure apparel, mCommerce app owners should allow for an easy and convenient returns and refund policy should the ordered item not be suitable to the customer (Verkijika, 2018:1673; Farivar *et al.*, 2017:599). A money-back guarantee could also be considered (Farivar *et al.*, 2017:599; Suh *et al.*, 2015:138; Martins *et al.*, 2014:10; Vasileiadis, 2014:188).

Recommendation 21
Establish a truthful and transparent complaints handling procedure.

mCommerce app owners should create a culture of truthfulness and transparency. When mistakes are made, customer service agents should be empowered to admit to those mistakes and put the necessary measures in place to address them. The customer should be kept up to speed on progress made on the complaint. Such measures assist in developing customer trust (Verkijika, 2018:1673; Farivar *et al.*, 2017:599). In addition, and reinforcing recommendation 10 in section 8.3.1.4, a customer service chatbot should appear to customers on their channels of choice (e.g. website, app, WhatsApp or Facebook) to ensure prompt assistance (Farivar *et al.*, 2017:599; Suh *et al.*, 2015:138).

Recommendation 22
If a physical store presence is maintained, leverage it.

A study by Chaouali *et al.* (2016:216) proved how impactful a physical store presence can be in enhancing trust in an online store presence. If mCommerce app owners are in the fortunate position of having a physical store as well, they are in the unique position of being able to leverage the trust built with customers in those physical stores in the digital space. Chang and Chen (2008:833) corroborate this. Evans and Schmalensee (2016) and Jao (2015) concur, stating that leveraging both bricks and clicks environments creates more meaningful relationships with consumers.

Recommendation 23
Leverage online reviews to build trust.

Aligned with recommendation 7 in section 8.3.1.3, online reviews have increased in popularity, trustworthiness and credibility over the last few years (Li *et al.*, 2020:1; Xu 2020:2; Madan & Yadav, 2016:239; Oliveira *et al.*, 2016:411; Yang, 2010:267). mCommerce app owners should invite both positive and negative product reviews from customers, praising the positive and addressing the negative as speedily as possible, indicating to customers that constant improvement is important to the organisation (Persson & Berndtsson, 2015:77). In addition, McKnight *et al*. (2002:316) state that online reviews provide new customers with a gauge of the organisation's reputation based on others' experience, which assists in establishing initial trust.

Recommendation 24
Include trust elements in advertising campaigns.

Aligned with recommendation 4 in section 8.3.1.1, mCommerce app owners should constantly advertise the app to encourage new users to sign up and existing users to use the app more frequently. Messages and 'proof points' that build trust, for example, 'Verified by VeriSign' or 'Secured by Thawte', should be included in the advertising to instil confidence in customers (Marriott & Williams, 2018:141; Verkijika, 2018:1673; Rouibah *et al.*, 2016:38; Martins *et al.*, 2014:10).

8.3.2 Secondary objective 2

The second secondary objective for this study is described as follows:

Secondary objective 2
To establish whether facilitating conditions and habit have a positive influence on consumers' actual use of mCommerce apps to purchase athleisure apparel.

As the second secondary objective combines two constructs, each is discussed individually. Each section commences with an overview of the findings for this particular objective, referencing the theoretical background from previous chapters as well as the results of the data analysis conducted in Chapter 7. It then provides the main conclusion as well as recommendations for the industry.

8.3.2.1 To determine whether facilitating conditions have a positive influence on actual use

Venkatesh *et al.* (2012:159) describe facilitating conditions as the consumer's perception of available support and resources when performing a certain behaviour (refer to Chapter 1, section 1.7.4.4 and Chapter 4, section 4.2.4). As discussed in section 8.3.1.4 above, in the context of this study, facilitating conditions refer to an available Internet connection to access and use the mobile shopping app as well as the availability of online customer support, for example, frequently asked questions on the app or company website or an email address and/or contact number (Miladinovic & Xiang, 2016:22). Based on the literature, if consumers have support at their disposal, there should be an increased willingness to adopt and use a specific technology.

As discussed in Chapter 7, section 7.7.4, the hypothesis formulated to answer this objective was split into five separate hypotheses (refer to Chapter 7, Table 7.24). Of these five hypotheses, one was accepted, i.e. "Facilitating conditions have an influence on the amount of time spent shopping for athleisure apparel via mobile shopping apps per week" (refer to main finding 31 in Chapter 7, section 7.7.4). As discussed in Chapter 7, section 7.7.4, consumers' perception of the available resources and support when wanting to shop via mCommerce apps may have an influence on the amount of time they end up spending on these apps per week. Interestingly, studies differ on this finding. Alalwan *et al.* (2018:131), for example, found this construct to influence actual use. In their study, the actual use construct was measured as a latent construct made up of five items that specifically asked respondents what they used Internet banking for. Similarly, Akbar (2013:22) also found facilitating conditions to influence actual use. Here, the researcher measured the actual use construct through two statements relating to usage frequency. Tarhini *et al.* (2016:842) concur.

In contrast, however, Chopdar *et al*. (2018:117; 119) did not find facilitating conditions to impact actual use in both the US and India. The actual use construct was measured as a latent construct made up of four items that specifically positioned statements to respondents relating to the usage of their mobile phone for shopping purposes. Lee *et al.* (2018:34) study also found no relationship between these two constructs. These researchers measured actual use as a single construct made up of three items, all measuring future usage. Martins *et al*. (2014:9) concur, reporting no relationship between facilitating conditions and actual use. These researchers measured the actual use construct through one statement relating to usage frequency. Finally, Alkhunaizan and Love's (2012:93) results are aligned with the aforementioned studies, with no relationship presenting itself between facilitating conditions and actual use.

Be that as it may, this study found a positive relationship between facilitating conditions and the amount of time spent shopping for athleisure apparel via mobile shopping apps per week. Elements such as an available Internet connection to access and use the mobile shopping app as well as the availability of online customer support will therefore lead to increased time being spent shopping via mobile shopping apps per week (Miladinovic & Xiang, 2016:22). With this in mind, recommendations 8, 9 and 10 in section 8.3.1.4 are of significance here as well, i.e. 8: Zero-rate data usage for mCommerce apps, 9: Ensure that the app is compressed in size to allow for speedy response and 10: Provide 24/7 customer support and FAQs.

8.3.2.2 To establish whether habit positively influences actual use

As per Chapter 1, section 1.7.4.7 and Chapter 4, section 4.2.7, Venkatesh *et al.* (2012:161) describe habit as the automatic execution of a specific behaviour due to prior learning. As discussed in section 8.3.1.1.7 above, in the context of this study, the use of smartphones and apps today occurs habitually as it is repeated so often (Lipsman, 2015; Chou *et al.*, 2013:4). Miladinovic and Xiang (2016:24) state that the more habitual the performance of a task, the less choice is needed and the lesser the impact of external factors.

As per Chapter 7, section 7.7.4, the hypothesis formulated to answer this objective was split into five separate hypotheses (refer to Chapter 7, Table 7.24). Of these five hypotheses, two were accepted, i.e. “Habit has an influence on when last consumers used a mobile shopping app to purchase athleisure apparel” (refer to main finding 32 in Chapter 7, section 7.7.4) and “Habit has an influence on the number of mobile shopping apps visited in a given month” (refer to main finding 33 in Chapter 7, section 7.7.4). As discussed in Chapter 7, section 7.7.4, one can infer that habitual mCommerce app use influences usage frequency and the number of mCommerce apps used. Alalwan *et al.* (2018:131) corroborate this view, reporting a strong relationship between habit and actual use. These researchers measured actual use as a latent construct made up of five items, asking respondents what they used Internet banking for. This is affirmed by Chopdar *et al.* (2018:117; 119) in their findings for both India and the US. These researchers measured actual use using items relating to the usage of mobile phones for shopping purposes. Finally, Gupta *et al.* (2018:9) also support a strong relationship between these two constructs.

The results of this study therefore provide evidence of a positive relationship between habit and when consumers last used a mobile shopping app as well as the number of mobile shopping apps visited in a given month. Consumers are therefore more likely to frequently use mCommerce apps or various other apps if they have already formed habitual behaviour of shopping via their mobile phones (Alalwan *et al.*, 2018:134). With this in mind, recommendations 14, 15 and 16 in section 8.3.1.7 are of significance here as well, i.e. 14: Design an app that feels familiar, 15: Create a rewards programme to encourage frequent use of the app and 16: Leverage push notifications.

8.3.3 Secondary objective 3

The third secondary objective for this study is described as follows:

Secondary objective 3
To investigate whether perceived risk has a negative influence on the behavioural intention of consumers to use mCommerce apps to purchase athleisure apparel.

This section commences with an overview of the findings for this particular objective, referencing the theoretical background provided in previous chapters as well as the results of the data analysis conducted in Chapter 7. It then provides the main conclusion and recommendations for the industry.

As described in Chapter 1, section 1.7.4.8 and Chapter 4, section 4.3, perceived risk refers to the nature and amount of risk assessed by a consumer in planning a purchase decision (Chen, 2013:316; Forsythe & Shi, 2003:869). Four types of risk have been identified as being relevant in the online or mobile shopping domain. These include financial risk, product performance risk, privacy risk and time/convenience risk. However, for the purposes of this study, only financial risk and product performance risk were focused on (Forsythe *et al.*, 2006:57; Wu & Wang, 2005:722). This decision was supported by Farivar *et al.* (2017:591), Yang *et al.* (2015:261), Ueltschy *et al.* (2004:71) and Featherman and Pavlou (2003:460), all of whom found financial risk and product performance risk to be the two primary risk types influencing consumers' online and/or mobile purchasing behaviour.

As per the discussion in Chapter 7, section 7.6.4.2.2, this study found no relationship between perceived risk and behavioural intention (β=0.022, t=0.445). This contradicts the aforementioned researchers as well as the other studies referenced in previous chapters (refer to Chapter 1, section 1.7.4.8, Chapter 4, section 4.3 and Chapter 5, section 5.4.3), including Alalwan *et al.* (2018), Gupta *et al.* (2018), Verkijika (2018), Martins *et al.* (2014) and Groß (2016), among others. It also contradicts main finding 11 (refer to Chapter 7, section 7.6.1.2.8) which highlighted that the majority of the respondents agreed that they felt exposed to certain risks when transacting via mCommerce apps. Interestingly, the highest level of agreement was with the statement regarding consumers' ability to examine products before purchasing. A number of other studies, however, concur with this study's findings and did not find a relationship between perceived risk and behavioural intention. These include Chin *et al.* (2018), Chopdar *et al.* (2018), Marriott and Williams (2018) and Li (2017).

Although the results of this study do not provide evidence of a relationship between perceived risk and consumers' behavioural intention, mCommerce app owners and developers can ensure this continues by implementing the recommendations stated above, and in particular, recommendation 21 in section 8.3.1.8, which would assist in reducing product performance risk. If customers are aware of a transparent returns and refund policy and a potential money-back guarantee, it greatly reduces product performance risk perceptions (Farivar *et al.*, 2017:599; Martins *et al.*, 2014:10; Featherman & Pavlou, 2003:469). Similarly, recommendations 7 (in section 8.3.1.3) and 24 (in section 8.3.1.8) can assist in reducing financial risk as online reviews boost customer confidence, comfort and feelings of safety (Martins *et al.*, 2014:10; Featherman & Pavlou, 2003:469). Additional recommendations with actionable strategies to assist in this regard are elaborated on below.

Recommendation 25
Ensure excellent security measures.

Reinforcing recommendations 18 and 19 in section 8.3.1.8, to attenuate perceived risk (particularly financial risk), mCommerce app owners and developers should offer credible, well-known payment options and prominently feature security accreditation on the app (Chopdar *et al.*, 2018:122; Lu, 2017:46; Madan & Yadav, 2016:239; Featherman & Pavlou, 2003:469). In addition, mCommerce app owners and developers should employ two-factor authentication (2FA), which provides an extra layer of security to customers (Bashir & Madhavaiah, 2015:92). A customer will typically be able to check out their basket in an mCommerce app to proceed to payment by logging in with their username and password. With 2FA, another piece of information is required after the login step, for example, a unique PIN sent to a different device, a unique keystroke pattern or an answer to a secret question. 2FA protects both the user and the merchant (Authy, 2020). Ensuring excellent security measures has been shown to increase profitability for mCommerce app owners (Chin *et al.*, 2018:55; Vasileiadis, 2014:188). D'Allesandro *et al.* (2012:450-451) add that having the appropriate security measures in place bolsters consumer trust while decreasing perceived risk.

It is also imperative to ensure the communication of security measures in advertising campaigns on the company website and on the app itself. Aligned with recommendation 4 in section 8.3.1.1 and recommendation 24 in section 8.3.1.8, messages emphasising security measures and the protection of customer information, for example, 'This app is verified by VeriSign' or 'This website is secured by Thawte', should be included in the advertising to instil confidence in customers (Marriott & Williams, 2018:141; Verkijika, 2018:1673; Martins *et al.*, 2014:10).

Recommendation 26
Distribute athleisure apparel via other established mCommerce businesses.

Consumers' perceived risk is reduced, according to D'Allesandro *et al.* (2012:451), when products they are interested in are sold via more than one channel. mCommerce app owners looking to sell athleisure apparel via their apps should approach other established mCommerce businesses such as Takealot.com, Zando or Superbalist.com to sell their athleisure apparel items. As discussed in Chapter 2, section 2.2.5, a company such as Takealot.com for example, is well-established and sees an annual turnover of billions of Rands, making it and other similar brands, reputable and credible distribution partners for a new mCommerce business looking to sell athleisure apparel (Mybroadband, 2017a).

Recommendation 27
Use real, high-quality images of athleisure apparel.

As discussed in Chapter 1, section 1.7.4.8 and Chapter 4, section 4.3, researchers have found product performance risk to be heightened in online or mobile environments if the quality, size or material of the products cannot be accurately judged (Marriott & Williams, 2018:136; Lee & Stoel, 2014:403). This was proven true for this study as well, considering that the highest level of agreement was with the statement regarding consumers' ability to examine products before purchasing. mCommerce app owners and developers can combat this by using real, high-quality images of athleisure apparel. If customers are able to zoom in on the image without distortion, they are able to evaluate it better (Marriott & Williams, 2018:142). In addition, reinforcing recommendation 11 in section 8.3.1.5, mCommerce app owners and developers can leverage augmented reality by allowing customers to virtually try on the athleisure item they are interested in.

8.3.4 Secondary objective 4

The fourth secondary objective for this study is described as follows:

Secondary objective 4
To determine whether perceived risk has a negative influence on consumers' actual use of mCommerce apps to purchase athleisure apparel.

This section commences with an overview of the findings for this particular objective, referencing the theoretical background provided in previous chapters as well as the results of the data analysis conducted in Chapter 7. It then provides the main conclusion as well as recommendations for the industry.

Perceived risk was described in section 8.3.3 above as well as in Chapter 1, section 1.7.4.8 and Chapter 4, section 4.3. As discussed in Chapter 7, section 7.7.4, the hypothesis formulated to answer this objective was split into five separate hypotheses (refer to Chapter 7, Table 7.24), all of which were rejected. Chopdar *et al.*'s (2018:119) American results support this finding, suggesting that younger South African consumers are less risk-averse to potential risks associated with shopping for athleisure apparel online or via a mobile phone.

Although this study did not find evidence of a relationship between perceived risk and actual use of mCommerce apps, mCommerce app owners and developers can ensure that this continues by actioning the recommendations below, notably, recommendations 18, 19, 20 and 23 in section 8.3.1.8.

- Recommendation 18: Offer credible, well-known payment options on the app such as EFT, PayFast, Zapper and SnapScan.
- Recommendation 19: Highlight security accreditations on the app from trusted security entities such as Thawte, Entrust, Geotrust or VeriSign.
- Recommendation 20: Establish an easy and convenient returns and refund policy and consider a money-back guarantee.
- Recommendation 23: Leverage online reviews as this assists new customers with a view of the reputation an organisation or mCommerce apparel store has prior to purchasing.

In addition, recommendations 25, 26 and 27 in section 8.3.3 can also be employed.

- Recommendation 25: Ensure excellent security measures, reinforcing the above discussion on recommendation 19.
- Recommendation 26: Distribute athleisure apparel via other established mCommerce businesses. Leveraging the reputation of well-established businesses such as Takealot.com or Zando can assist in lending credibility to a new mCommerce business looking to sell athleisure apparel.
- Recommendation 27: Use real, high-quality images of athleisure apparel. mCommerce app owners can combat heightened product performance risk by offering high-quality imagery of athleisure apparel on the mCommerce app to assist customers in zooming in and evaluating the apparel piece better.

8.3.5 Secondary objective 5

The fifth secondary objective for this study is described as follows:

Secondary objective 5
To establish whether trust mediates the influence of perceived risk on the behavioural intention of consumers, and consumers' actual use of mCommerce apps to purchase athleisure apparel.

This section commences with an overview of the findings for this particular objective, referencing the theoretical background provided in previous chapters as well as the results of the data analysis conducted in Chapter 7. It then provides the main conclusion as well as recommendations for the industry.

Trust was described in section 8.3.1.8 above as well as in Chapter 1, section 1.7.4.9 and Chapter 4, section 4.4. Research shows that trust has a mediating effect on the relationship between perceived risk and behavioural intention (Farivar *et al.,* 2017:597; Joubert & van Belle, 2013:29; Amoroso & Hunsinger 2009:25; Ribbink *et al.,* 2004:446) as well as the relationship between perceived risk and actual use (Farivar *et al.*, 2017:587; Kesharwani & Bisht, 2012:315-316); Gao & Bai, 2014:217). The findings of this study, however, did not support this outcome.

As noted in Chapter 7, sections 7.5.4.2.2 and 7.6.4, this study found no mediating relationship between trust, perceived risk and behavioural intention, nor was any relationship found between trust, perceived risk and actual use. Kim and Koo (2016:1021) and Mayer *et al.* (1995:711) report much confusion as to the directionality of the relationship between perceived risk and trust. In this study, although trust was not proven to be a mediating construct, a new relationship emerged from the data: perceived risk was shown to have a marked negative influence on trust (refer to main finding 24 in Chapter 7, section 7.6.4.2.2). Various studies support this, including D'Allesandro *et al.* (2012), Chang and Chen (2008), Lee and Lee (2007), Corritore *et al.* (2003) and De Ruyter *et al.* (2000). It is therefore important for mCommerce app owners and developers to employ the recommendations given in sections 8.3.1.8 and 8.3.3 to mitigate perceived risk and increase trust. These include designing a professional, credible-looking app; offering credible, well-known payment options; prominently featuring security accreditations on the app; establishing an easy and convenient returns and refund policy; establishing a truthful and transparent complaints handling procedure; leveraging physical store presence (if available); leveraging online reviews; including trust elements in advertising campaigns; ensuring excellent security measures; distributing athleisure apparel via other established mCommerce businesses; and using real, high-quality images of athleisure apparel.

8.3.6 Secondary objective 6

The sixth secondary objective for this study is described as follows:

Secondary objective 6
To determine whether behavioural intention has a positive influence on consumers' actual use of mCommerce apps to purchase athleisure apparel.

This section commences with an overview of the findings for this particular objective, referencing the theoretical background provided in previous chapters, as well as the results of the data analysis conducted in Chapter 7. It then provides the main conclusion as well as recommendations for the industry.

As described in Chapter 1, section 1.7.4.10 and Chapter 4, section 4.2.8, Miladinovic and Xiang (2016:12) state that behavioural intention refers to an individual's willingness to use or accept a particular technology, for example, a mobile shopping app. Various researchers, including Miladinovic and Xiang (2016:12), Tarhini *et al.* (2016:842), Persson and Berndtsson (2015:28), Williams *et al.* (2015:464), Venkatesh *et al.* (2012:157) and Wu and Wang (2005:726) state that the behavioural intention to use a certain technology is a strong predictor and determining factor of the user actually using the technology.

As argued in Chapter 7, section 7.7.4, the hypothesis formulated to answer this objective was split into five separate hypotheses (refer to Chapter 7, Table 7.24). Of these five hypotheses, two were accepted, i.e. "Behavioural intention has an influence on the amount of athleisure apparel items purchased" (refer to main finding 34 in Chapter 7, section 7.7.4) and "Behavioural intention has an influence on the approximate Rand value of athleisure apparel purchases" (refer to main finding 35 in Chapter 7, section 7.7.4). Various research studies referenced in this study (refer to Chapter 1, section 1.7.4.10, Chapter 4, section 4.2.8 and Chapter 5, section 5.4.8) support the finding that behavioural intention influences actual use, including Alalwan *et al.* (2018), Chopdar *et al.* (2018), Gupta *et al.* (2018), Lee *et al.* (2018), Tarhini *et* *al.* (2016), Persson and Berndtsson (2015), Martins *et al.* (2014), Vasileiadis (2014), Akbar (2013), Alkhunaizan and Love (2012) and Wu and Wang (2005).

The results of this study confirm a positive relationship between behavioural intention and the amount of athleisure apparel items purchased, as well as the approximate Rand value of these purchases. Consumers are therefore likely to purchase more athleisure apparel items at a greater value if they have the behavioural intention to do so (Alalwan *et al.*, 2018; Chopdar *et al.*, 2018; Gupta *et al.*, 2018; Lee *et al.*, 2018; Tarhini *et al.*, 2016; Persson & Berndtsson, 2015; Martins *et al.*, 2014; Vasileiadis, 2014; Akbar, 2013; Alkhunaizan & Love, 2012; Wu & Wang, 2005). In addition, main finding 13 (refer to Chapter 7, section 7.6.1.2.10) indicates that the majority of the respondents agreed that they would either start using or continue using mCommerce apps in the future. All recommendations provided and discussed thus far have the potential to lead to behavioural intention, which, in turn, will lead to actual use.

8.3.7 Secondary objective 7

The seventh secondary objective for this study is described as follows:

Secondary objective 7
To determine which of the independent variables has the largest influence on the behavioural intention of consumers to use mCommerce apps to purchase athleisure apparel.

As outlined in section 7.6.4.2.2 in Chapter 7, the variable with the greatest influence on behavioural intention is trust ($\beta=0.532$, $t=7.834$, $p<0.05$), followed by performance expectancy ($\beta=0.169$, $t=2.099$, $p<0.05$) and habit ($\beta=0.163$, $t=3.117$, $p<0.05$). This finding makes a valuable contribution to the mobile shopping literature in South Africa and justifies the inclusion of this additional construct in the existing UTAUT2 model by proving its significant influence over behavioural intention. mCommerce app owners and developers should therefore action the recommendations in section 8.3.1.8 to increase trust. These include designing a professional, credible-looking app; offering credible, well-known payment options; prominently featuring security accreditations on the app; establishing an easy and convenient returns and refund policy; establishing a truthful and transparent complaints handling procedure; leveraging a physical store presence (if available); leveraging online reviews to build trust; and including trust elements in advertising campaigns.

8.3.8 Secondary objective 8

The eighth and final secondary objective for this study is described as follows:

Secondary objective 8
To determine which of the independent variables has the largest influence on consumers' actual use of mCommerce apps to purchase athleisure apparel.

As per section 7.7.4 in Chapter 7, the variable with the greatest influence on construct AU1, i.e. "When last did you use a mobile shopping app to purchase athleisure apparel?" is habit ($p=0.000$ which is <0.05). The variable with the greatest influence on construct AU2, i.e. "How many athleisure apparel items did you purchase during this time?" is behavioural intention ($p=0.003$ which is <0.05). The variable with the greatest influence on construct AU3, i.e. "In general, how much time do you spend shopping for athleisure apparel via mobile shopping apps per week?" is facilitating conditions ($p=0.004$ which is <0.05). The variable with the greatest influence on construct AU4, i.e. "On average, how many different mobile shopping apps do you visit in a given month?" is habit ($p=0.000$ which is <0.05). Finally, the variable with the greatest influence on construct AU5, i.e. "What was the approximate Rand value of your most recent purchase of athleisure apparel?" is behavioural intention ($p=0.019$ which is <0.05). These findings again make a significant contribution to the mobile shopping literature in South Africa. mCommerce app owners and developers are encouraged to action the recommendations in sections 8.3.1.7 and 8.3.2.2, i.e. design an app that feels familiar; create a rewards programme to encourage frequent use of the app; and leverage push notifications. The recommendations in sections 8.3.1.4 and 8.3.2.1 are also significant here, i.e. zero-rate data usage for mCommerce apps; ensure that the app is compressed in size to allow for speedy response; and provide 24/7 customer support and FAQs. Finally, as discussed in section 8.3.6, all recommendations provided and discussed in this study have the potential to lead to behavioural intention which, in turn, will lead to actual use.

This concludes the conclusions and recommendations section of the study. The following section links the secondary objectives of this study to the research results reported in Chapter 7 to determine whether the primary objective of the study was achieved.

8.4 Linking the research study

Table 8.1 below links the eight secondary objectives of this study to the results presented in Chapter 7 to determine whether the primary objective of the study was achieved. The table presents the linkages between the primary research objective (see Chapter 1, section 1.5), the secondary research objectives (see Chapter 1, section 1.5), the hypotheses (see Chapter 1, section 1.7.4), the theoretical chapters (see Chapters 3, 4 and 5), the questionnaire (see Annexure 7), the main findings (see Chapter 7) and the recommendations (this chapter, Chapter 8).

Table 8.1: Linking the research study

Objectives		Hypotheses	Theoretical chapters	Questionnaire	Research results	Recommendations
Primary objective	Secondary objective 1	H1 H2 H3 H4 H6 H7 H8 H14	Ch 3 Ch 4 Ch 5	Section B	Main finding 4 Main finding 5 Main finding 6 Main finding 7 Main finding 8 Main finding 9 Main finding 10 Main finding 22 Main finding 23	Recommendations 1-24
	Secondary objective 2	H5 H9	Ch 3 Ch 4 Ch 5	Section B Section C	Main finding 31 Main finding 32 Main finding 33	Recommendations 8-10 Recommendations 14-16
	Secondary objective 3	H10	Ch 4 Ch 5	Section B	Main finding 11	Recommendations 25-27
	Secondary objective 4	H11	Ch 4 Ch 5	Section B Section C		Recommendations 18-20 Recommendation 23 Recommendations 25-27
	Secondary objective 5	H12 H13	Ch 4 Ch 5	Section B Section C	Main finding 12 Main finding 25	Recommendations 17-27
	Secondary objective 6	H15	Ch 3 Ch 4 Ch 5	Section B Section C	Main finding 13 Main finding 34 Main finding 35	Recommendations 1-27
	Secondary objective 7					Recommendations 17-24
	Secondary objective 8					Recommendations 8-10 Recommendations 14-16

Based on the aforementioned table and linkages, it is evident that the study has addressed its primary objective of determining the constructs that influence consumers' acceptance and use of mCommerce apps to purchase athleisure apparel in South Africa. The following section details the academic and industry contribution of the study.

8.5 Academic and industry contribution of the study

8.5.1 Academic contribution

The significance of this research was briefly discussed in Chapter 1, section 1.6. From an academic standpoint, the study tested an adapted version of the UTAUT2 in South Africa. Similar studies in emerging African economies such as South Africa have not yet been conducted and therefore, this study adds to the existing body of knowledge. The seven original constructs of the UTAUT2 (performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value and habit) were tested, along with two additional constructs – perceived risk and trust. The inclusion of these two additional constructs was informed by research conducted by Farivar *et al*. (2017:597), Dai and Chen (2015:42), Wu and Wang (2005:726) and Lim (2003:218), which identified these as two key variables impacting consumers' use of mCommerce.

The results revealed that the UTAUT2 cannot be applied as is to the South African market. This is because out of the seven constructs of the model, only performance expectancy and habit were shown to influence behavioural intention (Model A) while facilitating conditions and habit were shown to influence separated actual use constructs (Model B). The addition of trust, which does not feature in the original UTAUT2, turned out to be an essential addition in the South African context as it was found to be a key determining factor of behavioural intention, alongside performance expectancy and habit.

The separation of the actual use construct into five separate constructs represents a further contribution to the academic literature for the application of the UTAUT2 in emerging African economies such as South Africa. Based on the low, unsatisfactory internal consistency achieved for this construct (Cronbach's alpha = 0.377; refer to Chapter 7, section 7.7.3), it was not possible to work with this construct as a latent construct made up of five items. This was because the various items did not constitute a single construct. The study was therefore adjusted to represent the actual use construct as five unique binary categorical outcomes. It is interesting to note that at present, the outcome of this adjustment is only applicable to South Africa. Habit was shown to exert an influence on when consumers last used a mobile shopping app to purchase athleisure apparel (AU1). It can be inferred that habitual mCommerce app use in South Africa influences usage frequency. Behavioural intention was shown to have an influence on the amount of athleisure apparel items purchased (AU2). This indicates that the greater the intent of a South African consumer to purchase athleisure apparel via mCommerce apps, the greater the number of items they will purchase. Facilitating conditions were found to influence the amount of time spent shopping for athleisure apparel via mobile shopping apps per week (AU3). It can be inferred that if South African consumers have a working Internet connection to access and use the mobile shopping app as well as access to online customer support, greater time will be spent shopping for athleisure apparel via mobile shopping apps per week. Habit was shown to influence the number of mobile shopping apps visited in a given month (AU4). It can be inferred that habitual mCommerce app use influences the number of mCommerce apps used per month in South Africa. Finally, behavioural intention was shown to exert an influence on the approximate Rand value of athleisure apparel purchases (AU5), indicating that the greater the consumer's intent to purchase, the greater the amount spent.

The study further also made significant contributions to industry, elaborated on below.

8.5.2 Industry contribution

From the perspective of industry knowledge, there is limited research in the field of mCommerce in emerging African economies such as South Africa (Magan, 2016:12). The data gathered from this study sheds light on mCommerce and provides South African business owners with a more in-depth understanding of the factors that stimulate consumers' desire to use mCommerce apps as well as those which drive them to ultimately purchase athleisure apparel.

As discussed in section 8.5.1, the research results revealed that the original UTAUT2 cannot be applied in its current form to an emerging economy such as the South African market. The reason being is that, out of the seven hypothesised relationships, only two – i.e. performance expectancy and habit – were shown to influence behavioural intention. In addition, the added construct of trust, which does not form part of the original UTAUT2 but which was added by the researcher, was found to influence behavioural intention. This provides industry professionals with great insight into focus areas to attract consumers to mCommerce environments and encourage conversion to purchase. Extensive recommendations have been provided in section 8.3 to assist with this. However, in order to realise the majority of these recommendations, a few key strategies are essential for professionals already in industry as well as those looking to venture into the industry of mCommerce.

- Firstly, it is necessary to gain a thorough understanding of the digital landscape. The digital realm has developed significantly over the last few years, with many organisations today investing more and more into this domain to leverage the untapped opportunities it holds for brands. Understanding which channels are available, how they work and what they are best leveraged for will stand individuals looking to venture into this space in good stead, enabling them to build an approach that best addresses their specific objectives.
- Secondly, an in-depth understanding of the app environment is essential. mCommerce app owners are encouraged to employ professional developers or partner with expert agencies which specialise in app development. Such specialists could design an intuitive user experience and build an app that provides utility to the end user. Furthermore, even though the research results revealed younger South African consumers to be less risk averse, trust is nonetheless imperative and very influential in the decision-making process. Therefore mCommerce app owners should gain a thorough understanding of security requirements to ensure adequate implementation and adherence.
- Thirdly, expert partnerships should be leveraged. Once the app is designed, it needs to be advertised to the public. Partnering with a media agency that understands the advertising landscape and can leverage group-buying discounts could assist in realising a number of the recommendations presented in section 8.3 and would be

able to provide mCommerce app owners with the right level of expertise to meet targets, in line with budgetary restrictions.

- Fourthly, an iterative process should be followed. The digital realm is ever-changing. The right tracking, metrics and measures need to be put in place and reviewed on a continuous basis to adjust the approach accordingly.

The following section discusses limitations of the study and provides opportunities for future research to address these limitations.

8.6 Limitations of the study and opportunities for future research

This study successfully utilised the UTAUT2 of Venkatesh *et al.* (2012) as the foundation model to determine the constructs that influence consumers' acceptance and use of mCommerce apps to purchase athleisure apparel in South Africa. The added constructs of perceived risk and trust were also investigated. The findings from the research model augment the existing body of knowledge in mobile shopping, shedding light on mobile shopping via apps in emerging markets such as South Africa. The insights gained from this study provide South African business owners with a more in-depth understanding of the factors which stimulate consumers' desire to use mCommerce apps as well as those which drive them to ultimately purchase athleisure apparel. The study does, however, have certain limitations that can be addressed in future research. These limitations with suggestions for future research opportunities are elaborated on below.

The majority of the sample (76.6%) was below the age of 30, an age group classified as Millennials. The findings of the research are therefore limited to this cohort in South Africa. In addition, the entire sample was drawn from the province of Gauteng, and specifically, the cities of Johannesburg and Tshwane. Even though Gauteng is home to the largest percentage of online shoppers in South Africa (43%), the Western Cape and KwaZulu Natal should also be considered for inclusion as the next two largest provinces (Effective Measure, 2017a:5). Future research should extend age and location to target the more general South African, thereby providing more accurate generalised data for the broader South African population (Chopdar *et al.*, 2018:123; Yang, 2010:267).

This study was quantitative in nature and even though the sample size is considered significant (n=500), a qualitative or mixed-method (quantitative and qualitative) investigation into the reasons why South Africans do not purchase clothing and accessories via their mobile phones may provide greater understanding into this phenomenon and provide greater insights for mCommerce app owners (Alalwan *et al.*, 2018:135; Verkijika, 2018:1674; Tarhini *et al.*, 2016:844).

Venkatesh *et al*. (2012:159) argue that age, gender and experience moderate the influence of all the different variables on behavioural intention while experience specifically moderates the influence of behavioural intention on actual use. This study did not evaluate the moderating effects of those variables. Although there have been studies that have not found these variables to moderate these relationships (e.g. Martins *et al.*, 2014:9), future research could look at these moderating effects, specifically in South Africa.

Many studies applying the UTAUT2 have only focused on consumers' behavioural intention, not actual use (Shaw & Sergueeva, 2019; Gupta *et al.*, 2018; Verkijika, 2018; Chaouali *et al.*, 2016; Madan & Yadav, 2016; Miladinovic & Xiang, 2016; Hew *et al.*, 2015). This study examines both consumers' behavioural intention and actual use of mCommerce apps to purchase athleisure apparel. Future research could extend the model even further by investigating continued usage to better understand loyalty and return behaviour (Chong, 2013:529).

Finally, this study was cross-sectional in nature. A longitudinal study could provide additional insights for researchers and industry as it would evaluate the changes in consumers' behaviour over time (Chopdar *et al.*, 2018:123; Verkijika, 2018:1673; Farivar *et al.*, 2017:599; Chaouali *et al.*, 2016:216; Bashir & Madhavaiah, 2015:92; Hew *et al*., 2015:1286).

8.7 Conclusion

Chapter 8 is the final chapter and concludes the study. This chapter commenced with a brief overview of the entire study, providing a summary of each of the seven preceding chapters. It then proceeded to provie detailed conclusions and recommendations structured around the eight secondary objectives of the study, all of which together, achieve the primary objective of the study.

The study delivered a valid and reliable model that assists in better understanding the factors that influence South African consumers' behavioural intention and actual use of mCommerce apps to purchase athleisure apparel. Performance expectancy, habit and trust were found to have significant influence over behavioural intention. Furthermore, habit was found to have a significant influence on when consumers last used a mobile shopping app to purchase athleisure apparel, behavioural intention was found to have a significant influence on the amount of items purchased, facilitating conditions was found to have a borderline significant influence on the amount of time spent shopping per week, habit was found to have a borderline significant influence on the number of mobile shopping apps visited in a given month and behavioural intention was found to have a significant influence on the approximate Rand value of the purchases.

Twenty-seven actionable recommendations and several overarching strategies were provided to assist South African fashion retailers and mCommerce app owners to adjust their business strategies accordingly in an effort to secure a stronger relational focus, with a beneficial value-add for all parties to the relationship.

A number of limitations to the study were then discussed, and the chapter concluded with suggestions for future research.

REFERENCE LIST

Aaker, D.A., Kumar, V., Leone, R.P. & Day, G.S. (2013). *Marketing research*. 11th ed. Singapore: John Wiley & Sons.

Abdulai, R.T. & Owusu-Ansah, A. (2014). Essential ingredients of a good research proposal for undergraduate and postgraduate students in the social sciences. *SAGE Open*:1-15.

AbuShanab, E. & Pearson, J.M. (2007). Internet banking in Jordan: The unified theory of acceptance and use of technology (UTAUT) perspective. *Journal of Systems and Information Technology*, 9(1):78-97.

Agrebi, S. & Jallais, J. (2015). Explain the intention to use smartphones for mobile shopping. *Journal of Retailing and Consumer Services*, 22:16-23.

Agudo-Peregrina, A.F., Hernández-García, A. & Pascual-Miguel, F.J. (2014). Behavioral intention, use behavior and the acceptance of electronic learning systems: Differences between higher education and lifelong learning. *Computers in Human Behavior*, 34:301-314.

Ajzen, I. (1991). The theory of planned behavior. *Organizational behavior and human decision processes*, 50:179-211.

Akar, E. & Dalgic, T. (2018). Understanding online consumers' purchase intentions: A contribution from social network theory. *Behaviour & Information Technology*, 37(5):473-487.

Akbar, F. (2013). *What affects students' acceptance and use of technology?* Honours Thesis. Pennsylvania, USA: Carnegie Mellon University.

Akbar, Y.H. & Tracogna, A. (2018). The sharing economy and the future of the hotel industry: Transaction cost theory and platform economics. *International Journal of Hospitality Management*, 71:91-101.

Al-Debei, M.M., Akroush, M.N. & Ashouri, M.I. (2015). Consumer attitudes towards online shopping: The effects of trust, perceived benefits and perceived web quality. *Internet Research*, 25(5):707-733.

Alaghehband, F.K., Rivard, S., Wub, S. & Goyette, S. (2011). An assessment of the use of Transaction Cost Theory in information technology outsourcing. *Journal of Strategic Information Systems*, 20:125-138.

Alalwan, A.A., Dwivedi, Y.K, Rana, N.P. & Algharabat, R. (2018). Examining factors influencing Jordanian customers' intentions and adoption of internet banking: Extending UTAUT2 with risk. *Journal of Retailing and Consumer Services*, 40:125-138.

AlHinai, Y.S. (2009). *The adoption of advanced mobile commerce services by individuals: Investigating the impact of the interaction between the consumer and the mobile service provider*. Doctoral dissertation. Melbourne, Australia: University of Melbourne.

Aliyu, A.A., Singhry, I.M., Adamu, H. & Abubakar, M.M. (2015). *Ontology,* Epistemology and Axiology in quantitative and qualitative research: Elucidation of the research philosophical misconception. *Proceedings of the Academic Conference: Mediterranean Publications & Research International on New Direction and Uncommon, 2(1),* University of Agric, Abeokuta, Ogun State, Nigeria, 22 December.

Allen, I.E. & Seaman, C.A. (2007). *Likert Scales and Data Analyses*. Available from: http://rube.asq.org/quality-progress/2007/07/statistics/likert-scales-and-data-analyses.html

Alkhunaizan, A. & Love, S. (2012). What drives mobile commerce? An empirical evaluation of the revised UTAUT model. *International Journal of Management and Marketing Academy*, 2(1):82-99.

Alumran, A., Hou, X.Y., Sun, J., Yousef, A.A. & Hurst, C. (2014). Assessing the construct validity and reliability of the parental perception on antibiotics (PAPA) scales. *BMC Public Health*, 14(73):1-9.

Alvesson, M. & Kärreman, D. (2007). Constructing mystery: Empirical matters in theory development. *The Academy of Management Review*, 32(4):1265-1281.

Amed, I., Andersson, J., Berg, A., Drageset, M., Hedrich, S. & Kappelmark, S. (2018). *The state of fashion 2018*. Available from: https://cdn.businessoffashion.com/reports/The_State_of_Fashion_2018_v2.pdf

Amed, I., Berg, A., Balchandani, A., Andersson, J., Hedrich, S. & Young, R. (2019). *The state of fashion 2019.* Available from: https://www.mckinsey.com/~/media/McKinsey/Industries/Retail/Our%20Insights/The%20influence%20of%20woke%20consumers%20on%20fashion/The-State-of-Fashion-2019.ashx

Amed, I., Berg, A., Brantberg, L. & Hedrich, S. (2017). *The state of fashion*. Available from: http://www.mckinsey.com/industries/retail/our-insights/the-state-of-fashion

Amoroso, D.L. & Hunsinger, D.S. (2009). Understanding consumers' acceptance of online purchasing. *Journal of Information Technology Management*, 1:15-41.

Argyros, T. (2017). *The Evolution of Retail: The Effect of Automation and AI.* Available from: https://www.forbes.com/sites/forbestechcouncil/2017/11/03/the-evolution-of-retail-the-effect-of-automation-and-ai/#717cc8a714a1

Attuquayefio, S.N. & Addo, H. (2014). Using the UTAUT model to analyze students' ICT adoption. *International Journal of Education and Development Using Information and Communication Technology*, 10(3):75-86.

Authy. (2020). *What is Two-Factor Authentication (2FA)?* Available from: https://authy.com/what-is-2fa/

Awang, Z. (2012). *A Handbook on SEM*. 2nd ed. Terengganu, Malaysia: Universiti Sultan Zainal Abidin.

Bandura, A. (1989). Social cognitive theory. *Annals of Child Development*, 6:1-85.

Bashir, I. & Madhavaiah, C. (2015). Consumer attitude and behavioural intention towards Internet banking adoption in India. *Journal of Indian Business Research*, 7(1):67-102.

Baymard Institute. (2013). *Mobile commerce spending patterns (2013 survey results)*. Available from: https://baymard.com/blog/mcommerce-spending-patterns-2013

Belkhamza, Z. & Niasin, M.A.F. (2017). *The effect of privacy concerns on smartphone app purchase in Malaysia: Extending the theory of planned behavior*. Kota Kinabalu, Malaysia: Universiti Malaysia Sabah.

Beneke, J., Greene, A., Lok, I. & Mallett, K. (2012). The influence of perceived risk on purchase intent – the case of premium grocery private label brands in South Africa. *Journal of Product & Brand Management*, 21(1):4-14.

Benzo, R., Mohsen, M.G. & Fourali, C. (2018). *Marketing research: Planning, process, practice*. London, UK: SAGE Publications.

Bhatnagar, A. & Ghose, S. (2004). Segmenting consumers based on the benefits and risks of Internet shopping. *Journal of Business Research*, 57:1352-1360.

Bisht, P. (2017). *Sports Apparel Market by End User (Men, Women, Kids) and Mode of Sale (Retail stores, Supermarkets, Brand outlets, Discount stores, Online stores) - Global Opportunity Analysis and Industry Forecast, 2014 – 2020*. Available from: https://www.alliedmarketresearch.com/sports-apparel-market

BizCommunity. (2017a). *Google reveals findings of the 2017 Connected Consumer Study*. Available from: http://www.bizcommunity.com/Article/196/16/170329.html

BizCommunity. (2017b). *Spree, 24.com record double-digit growth but Media24 profit drops*. Available from: http://www.bizcommunity.com/Article/196/15/163770.html

Bloomenthal, A. (2019a). *Electronic commerce (e-commerce)*. Available from: https://www.investopedia.com/terms/e/ecommerce.asp

Bloomenthal, A. (2019b). *Mobile commerce*. Available from: http://www.investopedia.com/terms/m/mobile-commerce.asp

Boateng, H., Adam, D.R., Okoe, A.F. & Anning-Dorson, T. (2016). Assessing the determinants of internet banking adoption intentions: A social cognitive theory perspective. *Computers in Human Behavior*, 65:468-478.

Bojang, I. (2017). Determinants of trust in B2C e-commerce and their relationship with consumer online trust: A case of Ekaterinburg, Russian Federation. *Journal of Internet Banking and Commerce*, 22(S8):1-59.

Brand South Africa. (2014). *South African shopping mall development shows strong growth*. Available from: https://www.brandsouthafrica.com/south-africa-fast-facts/news-facts/sa-shopping-malls

Bratt, M. (2018). *Online shopping growing in popularity in SA, but lags global pace*. Available from: http://themediaonline.co.za/2018/01/48086/

Braun, S. (2015). *The History of Retail: A Timeline*. Available from: https://www.lightspeedhq.com/blog/2015/05/the-history-of-retail-a-timeline/

Brown, A. (2017). Africa's fashion industry: Challenges, opportunities. Available from: http://www.africastrictlybusiness.com/news-analysis/africas-fashion-industry-challenges-opportunities

Brown, H. (2016). Online apparel consumer behavior: Hedonic motivation & post-purchase communication. *Major Papers by Master of Science Students*, 5:1-37.

Bryman, A. & Bell, E. (2011). *Research methodology: Business and management contexts*. 3rd ed. Southern Africa: Oxford University Press.

Burns, A.C. & Bush, R.F. (2006). *Marketing research*. 5th ed. Upper Saddle River, NJ: Pearson Education.

Business Tech. (2015). *What's driving online shopping in SA?* Available from: https://businesstech.co.za/news/internet/82863/whats-driving-online-shopping-in-sa/

Business Tech. (2018a). *South Africa's economy expected to grow at 1.9% in 2018.* Available from: https://businesstech.co.za/news/finance/231297/south-africas-economy-expected-to-grow-at-1-9-in-2018/

Business Tech. (2018b). *The biggest players in South Africa's retail industry.* Available from: https://businesstech.co.za/news/business/242127/the-biggest-players-in-south-africas-retail-industry/

Busser, J.A. & Shulga, L.V. (2018). Co-created value: Multidimensional scale and nomological network. *Tourism Management*, 65:69-86.

Cangur, S. & Ercan, I. (2015). Comparison of model fit indices used in structural equation modeling under multivariate normality. *Journal of Modern Applied Statistical Methods*, 14(1):152-167.

Cassavoy, L. (2017). *What makes a smartphone smart?* Available from: https://www.lifewire.com/what-makes-a-smartphone-smart-579597

Çelik, H.E. & Yilmaz, V. (2011). Extending the technology acceptance model for adoption of e-shopping by consumers in Turkey. *Journal of Electronic Commerce Research*, 12(2):152-164.

Center for Innovation in Research and Teaching. (2019). *Analyzing Quantitative Research*. Available from: https://cirt.gcu.edu/research/developmentresources/research_ready/quantresearch/analyze_data

Chan, L.L. & Idris, N. (2017). Validity and reliability of the instrument using exploratory factor analysis and Cronbach's alpha. *International Journal of Academic Research in Business and Social Sciences*, 7(10):400-410.

Chang, H.H. & Chen, S.W. (2008). The impact of online store environment cues on purchase intention: Trust and perceived risk as a mediator. *Online Information Review*, 32(6): 818-841.

Chaouali, W., Yahia, I.B. & Souiden, N. (2016). The interplay of counter-conformity motivation, social influence and trust in customers' intention to adopt Internet banking services: The case of an emerging country. *Journal of Retailing and Consumer Services*, 28:209-218.

ChargeItSpot. (2019). *10 best retail apps of 2019*. Available from: https://chargeitspot.com/10-best-retail-apps-of-2019/

Che, T., Peng, Z., Lim, K.H. & Hua, Z. (2015). Antecedents of consumers' intention to revisit an online group-buying website: a transaction cost perspective. *Information & Management*, 52:588-598.

Chen, C. (2013). Perceived risk, usage frequency of mobile banking services. *Managing Service Quality: An International Journal*, 23(5):410-436.

Chen, C. (2015). PRIS: A multiple-item scale for measuring perceived risk of internet shopping. *The Journal of International Management Studies*, 10(2):61-77.

Chen, R. (2013). Member use of social networking sites — an empirical examination. *Decision Support Systems*, 54:1219-1227.

Cheung, M.F.A. & To, W.M. (2017). The influence of the propensity to trust on mobile users' attitudes toward in-app advertisements: An extension of the theory of planned behavior. *Computers in Human Behavior*, 76:102-111.

Chilisa, B. & Kawulich, B. (2012). *Doing social research: A global context*. Europe, Middle East & Africa: McGraw-Hill.

Chong, A.Y.L. (2013). A two-staged SEM-neural network approach for understanding and predicting the determinants of m-Commerce adoption. *Expert Systems with Applications*, 40:1240-1247.

Chopdar, P.K., Korfiatis, N., Sivakumar, V.J. & Lytras, M.D. (2018). Mobile shopping apps adoption and perceived risks: A cross-country perspective utilizing the Unified Theory of Acceptance and Use of Technology. *Computers in Human Behavior*, 86:109-128.

Choudrie, J., Junior, C.A., McKenna, B. & Richter, S. (2018). Understanding and conceptualising the adoption, use and diffusion of mobile banking in older adults: A research agenda and conceptual framework. *Journal of Business Research*, 88:449-465.

Chou, C.H., Chiu, C.H., Ho, C.Y. & Lee, J.C. (2013). Understanding mobile apps continuance usage behaviour and habit: An expectance-confirmation theory. *Proceedings of the Pacific Asia Conference on Information Systems (PACIS) Conference*.

Chou, S.W. & Hsu, C.S. (2018). An empirical investigation on knowledge use in virtual communities – A relationship development perspective. *International Journal of Information Management,* 38:243-255.

Chung, K.C. & Holdsworth, D.K. (2012). Culture and behavioural intent to adopt mobile commerce among the Y Generation: Comparative analyses between Kazakhstan, Morocco and Singapore. *Young Consumers*, 13(3):224-241.

Chung, M., Ko, E., Joung, H. & Kim, S.J. (2018). Chatbot e-service and customer satisfaction regarding luxury brands. *Journal of Business Research*, 1-9.

Cigdem, H. & Ozturk, M. (2016). Factors Affecting Students' Behavioral Intention to Use LMS at a Turkish Post-Secondary Vocational School. *International Review of Research in Open and Distributed Learning*. Available from: http://www.irrodl.org/index.php/irrodl/article/view/2253/3697

City Press. (2017, May 21). *Edcon's new management team has articulated a coherent strategy to reduce space given to international brands and reprioritise private labels.* Available from: https://www.pressreader.com/south-africa/citypress/20170521/282303910073370

Compeau, D.R. & Higgins, C.A. (1995). Computer self-efficacy: Development of a measure and initial test. *MIS Quarterly*, 189-211.

ComScore.com. (2011). *Mobile shopping goes mainstream: Majority of U.S. smartphone owners performed shopping activities on their phone in September*. Available from: http://www.comscore.com/Insights/Press-Releases/2011/12/Mobile-Shopping-Goes-Mainstream

Consumer Barometer. (2017). *Consumer Barometer with Google*. Available from: https://www.consumerbarometer.com/en/graph-builder/?question=V1&filter=country:south_africa

Cooke, R. (2018). *#MobileCommerce: The rise of mobile shopping and its impact on business.* Available from: http://www.bizcommunity.com/Article/196/822/178956.html

Corritore, C.L., Kracher, B. & Wiedenbeck, S. (2003). On-line trust: Concepts, evolving themes, a model. *International Journal of Human-Computer Studies*, 58(6):737-758.

Cropanzano, R., Anthony, E.L., Daniels, S.R. & Hall, A.V. (2016). Social exchange theory: A critical review with theoretical remedies. *Academy of Management Annals*, 11(1):1-107.

Dai, B., Forsythe, S. & Kwon, W.S. (2014). The impact of online shopping experience on risk perceptions and online purchase intentions: Does product category matter? *Journal of Electronic Commerce Research*, 15(1):13-24.

Dai, H. & Chen, Y. (2015). Effects of exchange benefits, security concerns and situational privacy concerns on mobile commerce adoption. *Journal of International Technology and Information Management*, 24(3):40-56.

Daud, D. & Hassan, P.F. (2011). Perceived Risk, Perceived Technology, Online Trust for the Online Purchase Intention in Malaysia. *International Journal of Business and Management*, 6(6):167-182.

Davis, F.D.D. (1986). *A technology acceptance model for empirically testing new end-user information systems: Theory and results*. Doctoral thesis. Boston, MA: Massachusetts Institute of Technology.

De Bruyn, P. & Freathy, P. (2011). Retailing in post-apartheid South Africa: The strategic positioning of Boardmans*.* *International Journal of Retail & Distribution Management*, 39(7):538-554.

De Ruyter, K., Wetzels, M. & Kleijnen, M. (2000). Customer adoption of e-service: An experimental study. *International Journal of Service Industry Management*, 12(2):184-207.

du Plessis, G. (2018). *#MobileCommerce: The growth of mobile shopping in South Africa*. Available from: http://www.bizcommunity.com/Article/196/822/179452.html

du Plessis, S. & Smit, B. (2006). *Economic growth in South Africa since 1994*. Stellenbosch, South Africa: University of Stellenbosch.

Debter, L. (2019). *Amazon surpasses Walmart as the world's largest retailer*. Available from: https://www.forbes.com/sites/laurendebter/2019/05/15/worlds-largest-retailers-2019-amazon-walmart-alibaba/#1a4812e34171

Deloitte. (2014). *From bricks to clicks. Generating global growth through eCommerce expansion*. Available from: https://www2.deloitte.com/content/dam/Deloitte/za/Documents/consumer-business/za_generating_growth_through_ecommerce_24112014.pdf

Deloitte. (2015). *South Africa dominates Africa/Middle East Region in 2015 Deloitte Global Retailing Survey*. Available from: https://www2.deloitte.com/za/en/pages/consumer-business/articles/global-powers-of-retailing-survey-2015.html

Devaraj, S., Fan, M. & Kohli, R. (2002). Antecedents of B2C channel satisfaction and preference: Validating e-commerce metrics. *Information Systems Research*, 13(3):316-333.

Devaraj, S., Fan, M. & Kohli, R. (2006). Examination of online channel preference: Using the structure-conduct-outcome framework. *Decision Support Systems*, 42:1089-1103.

Dicey, L. (2017). *SA consumers change their shopping habits*. Available from: https://www.businesslive.co.za/redzone/news-insights/2017-10-04-sa-consumers-change-their-shopping-habits/

Dirk, N. (2015). *SA's men are the big spenders*. Available from: https://www.iol.co.za/business-report/economy/sas-men-are-the-big-spenders-1872410

Dlodlo, N. & Mafini, C. (2013). The relationship between technology acceptance and frequency of mobile commerce use amongst Generation Y consumers. *Acta Commercii*, 13(1):1-8.

eCommerce DB. (2018). *Top online stores by revenue: global eCommerce market.* Available from: https://ecommercedb.com/en/ranking/ww/all

Effective Measure. (2017a). *eCommerce industry report 2017.* Available from: http://hello.effectivemeasure.com/za-ecommerce-2017

Effective Measure. (2017b). *South Africa Mobile in 2017*. Available from: http://hello.effectivemeasure.com/za-mobile-2017

Eiriz, V. & Wilson, D. (2004). Research in relationship marketing: Antecedents, traditions and integration. *European Journal of Marketing*, 40(3/4):275-291.

eMarketer. (2013). *Smartphones, tablets drive faster growth in eCommerce sales*. Available from: https://www.emarketer.com/Article/Smartphones-Tablets-Drive-Faster-Growth-Ecommerce-Sales/1009835

Erken, F. (2017). *Mobile shopping in South Africa*. Available from: http://www.itnewsafrica.com/2017/06/mobile-shopping-in-south-africa/

eShop World. (2018). *South Africa eCommerce Insights* | *24.79 Million Online Shoppers by 2021*. Available from: https://www.eshopworld.com/blog-articles/south-africa-ecommerce-insights-2017/

Euler Hermes Economic Research Report. (2018). *Global Sector Report: Retail*. Available from: http://www.eulerhermes.com/economic-research/blog/EconomicPublications/retail-global-sector-report-feb18.pdf

Euromonitor International. (2013). *How BRICS consumers behave*. Available from: https://www.euromonitor.com/how-brics-consumers-behave/report

Euromonitor International. (2016). *How to meet the connected consumer's need for a seamless mobile commerce experience*. Available from: http://www.euromonitor.com/how-to-meet-the-connected-consumers-need-for-a-seamless-mobile-commerce-experience/report

Euromonitor International. (2017a). *Apparel and footwear in South Africa*. Available from: http://www.euromonitor.com/apparel-and-footwear-in-south-africa/report

Euromonitor International. (2017b). *Sportswear in South Africa*. Available from: http://www.euromonitor.com/sportswear-in-south-africa/report

Euromonitor International. (2017c). *The growth of Internet retail in South Africa.* Available from: https://blog.euromonitor.com/2017/10/growth-internet-retail-south-africa.html

Euromonitor International. (2019). *Apparel and footwear in South Africa*. Available from: http://www.euromonitor.com/apparel-and-footwear-in-south-africa/report

Evans, D.S. & Schmalensee, R. (2016). *The best retailers combine bricks and clicks*. Available from: https://hbr.org/2016/05/the-best-retailers-combine-bricks-and-clicks

Fai, L.C. (2011). *Extended UTAUT model of mobile commerce: An empirical study of negative user acceptance behaviours of mobile commerce in Hong Kong*. Doctoral thesis. Sydney, Australia: Macquarie University.

Faqih, K.M.S. & Jaradat, M.I.R.M. (2015). Assessing the moderating effect of gender differences and individualism-collectivism at individual-level on the adoption of mobile commerce technology: TAM3 perspective. *Journal of Retailing and Consumer Services*, 22:37-52.

Farfan, B. (2018). *Definition, types, and examples of retailing: Why retailing is important to end user customers*. Available from: https://www.thebalancesmb.com/what-is-retail-2892238

Farivar, S., Turel, O. & Yuan, Y. (2017). A trust-risk perspective on social commerce use: An examination of the biasing role of habit. *Internet Research*, 27(3):586-607.

Fashion United. (2019). *Global fashion industry statistics - International apparel*. Available from: https://fashionunited.com/global-fashion-industry-statistics

Fávero, L.P. & Belfiore, P. (2019). *Data science for business and decision-making*. London, UK: Academic Press, Elsevier.

Featherman, M.S. & Pavlou, P.A. (2003). Predicting e-services adoption: A perceived risk facets perspective. *International Journal of Human Computer Studies*, 59:451-474.

Fibre Processing and Manufacturing Sector Education and Training Authority (FPM SETA). (2014). *Clothing, textiles, footwear and leather sectors: A profile of the clothing, textiles, footwear and leather sub-sectors*. Available from: http://www.fpmseta.org.za/downloads/FPM_sub-sector_clothing_textiles_footwear_leather_final.pdf

Fishbein, M. & Middlestadt, S.E. (1987). Using the theory of reasoned action to develop educational interventions: Applications to illicit drug use. *Health Education Research*, 2(4):361-371.

Flanders Investments & Trade. (2016). *South African retail fact sheet*. Available from: https://www.flandersinvestmentandtrade.com/export/sites/trade/files/market_studies/SOUTH%20AFRICAN%20RETAIL%20FACT%20SHEET%20-%20APPAREL%20SHORT%20VERSION%20%282016%29.docx

Forsythe, S.M. & Shi, B. (2003). Consumer patronage and risk perceptions in Internet shopping. *Journal of Business Research*, 56:865-875.

Forsythe, S., Liu, C., Shannon, D. & Gardner, L.C. (2006). Development of a scale to measure the perceived benefits and risks of online shopping. *Journal of Interactive Marketing*, 20(2):55-75.

Foss, N.J. & Klein, P.G. (2010). *Critiques of transaction cost economics: An overview*. Available from: https://www.researchgate.net/publication/287167160_Critiques_of_transaction_cost_economics_An_overview

Fuentes, C. & Svingstedt, A. (2017). Mobile phones and the practice of shopping: A study of how young adults use smartphones to shop. *Journal of Retailing and Consumer Services*, 38:137-146.

Galarnyk, M. (2018). *Understanding boxplots*. Available from: https://towardsdatascience.com/understanding-boxplots-5e2df7bcbd51

Gao, L. & Bai, X. (2014). A unified perspective on the factors influencing consumer acceptance of internet of things technology. *Asia Pacific Journal of Marketing and Logistics*, 26(2):211-231.

Gao, S., Krogstie, J. & Siau, K. (2014). Adoption of mobile information services: An empirical study. *Mobile Information Systems*, 10:147-171.

Gauteng Province Quarterly Bulletin. (2012). *The retail industry on the rise in South Africa.* Available from:

http://www.gauteng.gov.za/government/departments/provincial-treasury/Documents/QB1%20The%20Retail%20Industry%20on%20the%20Rise.pdf

Gensler, L. (2017). *The world's largest retailers 2017: Amazon & Alibaba are closing in on Wal-Mart.* Available from: https://www.forbes.com/sites/laurengensler/2017/05/24/the-worlds-largest-retailers-2017-walmart-cvs-amazon/#2c23cf320b50

Gerber, C., Ward, S. & Goedhals-Gerber, L. (2014). The impact of perceived risk on on-line purchase behaviour. *Risk Governance & Control: Financial Markets & Institutions*, 4(4):99-106.

Ghoshal, S. & Moran, P. (1996). Bad for practice: A critique of the transaction cost theory. *The Academy of Management Review*, 21(1):13-47.

Gilbert, P. (2016). *Sub-Saharan Africa has highest mobile subs growth rate*. Available from: http://www.itweb.co.za/index.php?option=com_content&view=article&id=157599:Sub-Saharan-Africa-has-highest-mobile-subs-growth-rate&catid=260

Gilbert, P. (2019). *SA smartphone penetration now at over 80%, says ICASA*. Available from: https://www.itweb.co.za/content/GxwQDM1AYy8MlPVo

Goko, C. (2017). *Clothing retailers at the sharp end of SA's political and economic turmoil*. Available from: http://www.fastmoving.co.za/news/retailer-news-16/clothing-retailers-at-the-sharp-end-of-sa-s-political-and-economic-turmoil-10280

Goldstuck, A. (2014). *2014 MasterCard online shopping behaviour study*. Available from: http://www.marketingmixconferences.co.za/wp-content/uploads/2014/03/Arthur-Goldstuck-MasterCard-presentation.pdf

Golson, J. (2016). *Apple's app store now has over 2 million apps*. Available from: http://www.theverge.com/2016/6/13/11922926/apple-apps-2-million-wwdc-2016

Graybill, S. (2015). *Consumers' undying love for apps, and 25 reasons your brand needs one*. Available from: https://www.linkedin.com/pulse/consumers-undying-love-apps-25-reasons-your-brand-needs-graybill

Green, D. (2017). *How athleisure overtook fashion to become the dominant way that Americans dress*. Available from: http://www.businessinsider.com/athleisure-is-more-than-a-trend-2017-3?IR=T

Groß, M. (2015). Mobile shopping: A classification framework and literature review. *International Journal of Retail & Distribution Management*, 43(3):221-241.

Groß, M. (2016). Impediments to mobile shopping continued usage intention: A trust-risk-relationship. *Journal of Retailing and Consumer Services,* 33:109-119.

Gummerus, J., von Koskull, C. & Kowalkowski, C. (2017). Guest editorial: Relationship marketing – past, present and future. *Journal of Services Marketing*, 31(1):1-5.

Gummesson, E. (2017). From relationship marketing to total relationship marketing and beyond. *Journal of Services Marketing*, 31(1):16-19.

Gupta, A. & Arora, N. (2017). Understanding determinants and barriers of mobile shopping adoption using behavioral reasoning theory*. Journal of Retailing and Consumer Services*, 36:1-7.

Gupta, A., Dogra, N. & George, B. (2018). What determines tourist adoption of smartphone apps? An analysis based on the UTAUT-2 framework*. Journal of Hospitality and Tourism Technology*, 1-27.

Hair, J.F., Black, W.C., Babin, B.J., Anderson, R.E. & Tatham, R.L. (2006). *Multivariate data analysis.* 6th ed. Upper Saddle River, NJ: Pearson Prentice Hall.

Hair, J.F., Black, W.C., Babin, B.J. & Anderson, R.E. (2010). *Multivariate data analysis.* 7th ed. Upper Saddle River, NJ: Pearson Prentice Hall.

Hair, J.F., Celsi, M.W., Ortinau, D.J. & Bush, R.P. (2013). *Essentials of marketing research*. 3rd ed. New York, NY: McGraw-Hill.

Hartmans, A. (2017). *15 fascinating facts you probably didn't know about Amazon*. Available from: http://www.businessinsider.com/jeff-bezos-amazon-history-facts-2017-4?IR=T

Hattingh, D., Magnus, K.H. & Ramlakan, S. (2016). *South Africa's cautious consumer*. Available from: https://www.mckinsey.com/industries/consumer-packaged-goods/our-insights/south-africas-cautious-consumer

Herhausen, D., Binder, J., Schoegel, M. & Herrmann, A. (2014). Integrating bricks with clicks: Retailer-level and channel-level outcomes of online-offline channel integration. *Journal of Retailing*, 91(2):309-325.

Hew, J.J., Lee, V.H., Ooi, K.B. & Wei, J. (2015). What catalyses mobile apps usage intention: An empirical analysis. *Industrial Management & Data Systems*, 115(7):1269-1291.

Hodgson, G.M. (2010). *Limits of transaction cost analysis*. Available from: https://pdfs.semanticscholar.org/e2cb/bffc39cff517534f2f1c4a311a4360e38b7b.pdf

Hoffmann, V., Probst, K. & Christinck, A. (2007). *Farmers and researchers: How can collaborative advantages be created in participatory research and technology development?* Germany: Universität Hohenheim.

Holmes, A., Byrne, A. & Rowley, J. (2013). Mobile shopping behaviour: Insights into attitudes, shopping process involvement and location. *International Journal of Retail & Distribution Management*, 42(1):25-39.

Holder, J. & Hern, A. (2018). *Bezos's empire: How Amazon became the world's most valuable retailer*. Available from: https://www.theguardian.com/technology/ng-interactive/2018/apr/24/bezoss-empire-how-amazon-became-the-worlds-biggest-retailer

Hooper, D., Coughlan, J. & Mullen, M.R. (2008). Structural equation modelling: Guidelines for determining model fit. *The Electronic Journal of Business Research Methods*, 6(1):53-60.

Hoque, R. & Sorwar, G. (2017). Understanding factors influencing the adoption of mHealth by the elderly: An extension of the UTAUT model. *International Journal of Medical Informatics*, 101:75-84.

Hox, J.J. & Bechger, T.M. (1999). An Introduction to Structural Equation Modeling. *Family Science Review*, 11:354-373.

Huang, H.C., Cheng, T.C.E., Huang, W.F. & Teng, C.I. (2018). Impact of online gamers' personality traits on interdependence, network convergence, and continuance intention: Perspective of social exchange theory. *International Journal of Information Management*, 38:232-242.

Huang, Y. & Oppewal, H. (2006). Why consumers hesitate to shop online: An experimental choice analysis of grocery shopping and the role of delivery fees. *International Journal of Retail & Distribution Management*, 24(4/5):334-353.

Hubert, M., Blut, M., Brock, C., Backhaus, C. & Eberhardt, T. (2017). Acceptance of smartphone-based mobile shopping: Mobile benefits, customer characteristics, perceived risks, and the impact of application context. *Psychology & Marketing*, 34(2):175-194.

Huo, C., Zhang, M. & Ma, F. (2018). Factors influencing people's health knowledge adoption in social media: The mediating effect of trust and the moderating effect of health threat. *Library Hi Tech*, 36(1):129-151.

Hwang, J. & Choi, L. (2020). Having fun while receiving rewards?: Exploration of gamification in loyalty programs for consumer loyalty. *Journal of Business Research*, 106:365-376.

Hyben, B., Mladenow, A., Novak, N.M. & Strauss, C. (2015). Consumer acceptance on mobile shopping of textile goods in Austria: Modelling an empirical study. In M. Indrawan-Santiago, M. Steinbauer, A.M. Tjoa, I. Khalil & G. Anderst-Kotsis (Eds.). *Proceedings of the 13th International Conference on Advances in Mobile Computing and Multimedia (MoMM2015).*

IBM. (2020). *IBM Cloud Availability Monitoring: Ensure app uptime*. Available from: https://www.ibm.com/garage/method/practices/manage/tool_bluemix_availability_monitoring/

Ifinedo, P. (2017). Examining students' intention to continue using blogs for learning: Perspectives from technology acceptance, motivational and social-cognitive frameworks. *Computers in Human Behavior*, 72:189-199.

Im, J.Y. & Hancer, M. (2014). Shaping travelers' attitude toward travel mobile applications. *Journal of Hospitality and Tourism Technology*, 5(2):177-193.

Im, I., Kim, Y. & Han, H.J. (2008). The effects of perceived risk and technology type on users' acceptance of technologies. *Information & Management*, 45:1-9.

Information Technology Laboratory, National Institute of Standards and Technology. (2019). *What are outliers in the data?* Available from: https://www.itl.nist.gov/div898/handbook/prc/section1/prc16.htm

Intelliwave Technologies. (2019). *Maintaining 99.9% uptime in the cloud: Reliability, security, monitoring and recovery.* Available from: https://www.intelliwavetechnologies.com/maintaining-99-9-uptime-in-the-cloud-reliability-security-monitoring-and-recovery/

IT News Africa. (2016). *Online shoppers in Sub-Saharan Africa still don't trust e-commerce sites*. Available from: http://www.itnewsafrica.com/2016/12/online-shoppers-in-sub-saharan-africa-still-dont-trust-e-commerce-sites/

IT News Africa. (2017). *Online shopping trends in 2017*. Available from: http://www.itnewsafrica.com/2017/06/online-shopping-in-2017/

ITWeb. (2018). *Spree, Superbalist merger to create online retail giant*. Available from: https://www.itweb.co.za/content/rxP3jMBpepmvA2ye

Jacoby, J. & Kaplan, L.B. (1972). The components of perceived risk. *Proceedings of the 3rd Annual Conference of the Association for Consumer Research.*

Jak, S. (2015). *Meta-analytics structural equation modelling*. Utrecht, The Netherlands: Springer International Publishing.

Jao, J. (2015). *The marriage of clicks and bricks*. Available from: https://www.entrepreneur.com/article/243121

Jarvenpaa, S.L., Tractinsky, N. & Vitale, M. (2000). Consumer trust in an Internet store. *Information Technology and Management*, 1:45-71.

Javadi, M.H.M., Dolatabadi, H.R., Nourbakhsh, M., Poursaeedi, A. & Asadollahi, A.R. (2012). An analysis of factors affecting on online shopping behavior of consumers. *International Journal of Marketing Studies*, 4(5):81-98.

Javan, M. (2019). *Everything you need to launch an Instagram profile for your business*. Available from: https://smesouthafrica.co.za/grow-engagement-instagram-profile/

Jeong, M. & Oh, H. (2017). Business-to-business social exchange relationship beyond trust and commitment. *International Journal of Hospitality Management*, 65:115-124.

Johns, G. (2006). The essential impact of context on organizational behavior. *Academy of Management Review*, 31(2):386-408.

Joubert, J. & van Belle, J.P. (2013). The role of trust and risk in mobile commerce adoption within South Africa. *International Journal of Business, Humanities and Technology*, 3(2):27-38.

June, L. (2014). Are personal innovativeness and social influence critical to continue with mobile commerce? *Internet Research*, 24(2):134-159.

Kahn, U. (2015). *Why fashion retailers can't afford to ignore mobile*. Available from: https://buildfire.com/fashion-retailers-mobile-apps/

Kaldi, A., Aghaie, A. & Khoshalhan, F. (2008). KMS Adoption in Organizations. *Proceedings of the 2008 IEEE IEEM.*

Kell, J. (2016). *A bunch of new brands are joining the athleisure wear craze*. Available from: http://fortune.com/2016/10/22/fashion-brands-athleisure-trend/

Kesharwani, A. & Bisht, S.S. (2012). The impact of trust and perceived risk on internet banking adoption in India: An extension of technology acceptance model. *International Journal of Bank Marketing*, 30(4):303-322.

Khalifa, M. & Shen, K.N. (2008). Explaining the adoption of transactional B2C mobile commerce. *Journal of Enterprise Information Management*, 21(2):110-124.

Khawtom, M. (2017). *A history of athleisure*. Available from: http://www.maekhawtom.com/a-history-of-athleisure

Kimani, N. (2017). *South African athleisure brands you need to know.* Available from: http://tdsblog.com/south-african-athleisure-brands/

Kim, G. & Koo, H. (2016). The causal relationship between risk and trust in the online market place: A bidirectional perspective. *Computers in Human Behavior*, 55:1020-1029.

Kim, H.Y. (2013). Statistical notes for clinical researchers: Assessing normal distribution (2) using skewness and kurtosis. *The Korean Academy of Conservative Dentistry*, 52-54.

Kim, J., Ma, Y.J. & Park, J. (2009). Are US consumers ready to adopt mobile technology for fashion goods?: An integrated theoretical approach. *Journal of Fashion Marketing and Management: An International Journal*, 13(2):215-230.

King, A.P. & Eckersley, R.J. (2019). *Statistics for biomedical engineers and scientists: How to visualize and analyze data*. London, UK: Academic Press, Elsevier Ltd.

Klein, M. (2017). *The big chance for Takealot*. Available from: https://www.fin24.com/Finweek/Featured/the-big-chance-for-takealot-20170531

Kline, R.B. (2011). *Principles and practice of structural equation modeling*. 3rd ed. New York, NY: The Guilford Press.

Klopping, I.M. & McKinney, E. (2004). Extending the Technology Acceptance Model and the Task-Technology Fit Model to Consumer E-Commerce. *Information Technology, Learning, and Performance Journal*, 22(1):35-48.

Kolowich, L. (2016). *How is mobile commerce growing around the world?* Available from: https://blog.hubspot.com/marketing/mobile-commerce-growth-global#sm.0000mcig9r13cyew8v321jgzhwrj9

Kootstra, G.J. (2004). *Exploratory factor analysis: Theory and application.* Available from: http://www.let.rug.nl/nerbonne/teach/rema-stats-meth-seminar/Factor-Analysis-Kootstra-04.PDF

Koubaa, J., Tabbane, R.S. & Jallouli, C. (2013). On the use of structural equation modeling in marketing image research. *Asia Pacific Journal of Marketing and Logistics*, 26(2):315-338.

Kundu, M.G., Mishra, S. & Khare, D. (2002). Specificity and sensitivity of normality tests. *Proceedings of the VI International Symposium on Optimization and Statistics, Aligarh Muslim University, India.*

Kwahk, K.Y., Ahn, H. & Ryu, Y.U. (2018). Understanding mandatory IS use behavior: How outcome expectations affect conative IS use. *International Journal of Information Management*, 38:64-76.

Lacity, M.C., Willcocks, L.P. & Khan, S. (2011). Beyond Transaction Cost Economics: Towards an endogenous theory of Information Technology Outsourcing. *Journal of Strategic Information Systems*, 20:139-157.

Lai, P.C. (2016). The literature review of technology adoption models and theories for the novelty technology. *Journal of Information Systems and Technology Management*, 14(1):21-38.

Lavrakas, P.J. (2008). *Cover Letter.* Available from: http://methods.sagepub.com/reference/encyclopedia-of-survey-research-methods/n116.xml

Learning Theories. (2014). *Social Cognitive Theory*. Available from: https://www.learning-theories.org/doku.php?id=learning_theories:social_cognitive_learning_theory

Lee, D., Park, J. & Ahn, J. (2001). On the explanation of factors affecting e-commerce adoption. *Proceedings of the 22nd International Conference on Information Systems.*

Lee, H.S., Kim, T.G. & Choi, J.Y. (2012). A study on the factors affecting smart phone application acceptance. *Proceedings of the 3rd International Conference on e-Education, e-Business, e-Management and e-Learning*. Singapore: IACSIT Press.

Lee, J.E. & Stoel, L. (2014). High versus low online price discounts: Effects on customers' perception of risks. *Journal of Product & Brand Management*, 23(6):401-412.

Lee, K.S. & Lee, H.S. (2007). Factors influencing the adoption behavior of mobile banking: A South Korean perspective. *Journal of Internet Banking and Commerce*, 12(2):1-9.

Lee, S., Park, E.A., Cho, M. & Jin, B. (2018). Factors affecting tablet computer users' intention to purchase mobile applications. *Social Behavior and Personality*, 46(1):25-38.

Leibowitz, J. (2013). *How did we get here? A short history of retail*. Available from: https://www.linkedin.com/pulse/20130607115409-12921524-how-did-we-get-here-a-short-history-of-retail/

Leke, A., Fine, D., Dobbs, R., Magwentshu, N., Lund, S., Wu, C. & Jacobson, P. (2015). *South Africa's bold priorities for inclusive growth*. Available from: https://www.mckinsey.com/global-themes/middle-east-and-africa/south-africas-bold-priorities-for-inclusive-growth

Leung, L. & Chen, C. (2017). Extending the theory of planned behavior: A study of lifestyles, contextual factors, mobile viewing habits, TV content interest and intention to adopt mobile TV. *Telematics and Informatics*, 34:1638-1649.

Lexico powered by Oxford. (2020a). *Activewear*. Available from: https://www.lexico.com/en/definition/activewear

Lexico powered by Oxford. (2020b). *Retailer*. Available from: https://www.lexico.com/definition/retailer

Li, H., Xie, K.L. & Zhang, Z. (2020). The effects of consumer experience and disconfirmation on the timing of online review: Field evidence from the restaurant business. *International Journal of Hospitality Management*, 84:1-11.

Liang, T.P. & Huang, J.S. (1998). An empirical study on consumer acceptance of products in electronic markets: A transaction cost model. *Decision Support Systems*, 24:29-43.

Liao, C., Huang, Y.J., To, P.L. & Lu, Y.T. (2017). Factors driving digital music purchases. *Social Behavior and Personality*, 45(4):583-598.

Liébana-Cabanillas, F., Marinković, V. & Kalinić, Z. (2017). A SEM-neural network approach for predicting antecedents of m-commerce acceptance. *International Journal of Information Management*, 37:14-24.

Lim, J.S. & Noh, G.Y. Effects of gain-versus loss-framed performance feedback on the use of fitness apps: Mediating role of exercise self-efficacy and outcome expectations of exercise. *Computers in Human Behavior*, 77:249-257.

Lim, N. (2003). Consumers' perceived risk: Sources versus consequences. *Electronic Commerce Research and Applications*, 2:216-228.

Lin, J.S.C. & Chang, H.S. (2011). The role of technology readiness in self-service technology acceptance. *Managing Service Quality: An International Journal*, 21(4):424-444.

Lin, K.Y. & Lu, H.S. (2015). Predicting mobile social network acceptance based on mobile value and social influence. *Internet Research*, 25(1):107-130.

Lipsman, A. (2015). *How the power of habit drives mobile app usage*. Available from: https://www.comscore.com/Insights/Blog/How-the-Power-of-Habit-Drives-Mobile-App-Usage

Liu, C. & Forsythe, S. (2010). Sustaining online shopping: Moderating role of online shopping motives. *Journal of Internet Commerce*, 9:83-103.

Lorna Jane SA. (2020). *Our Founder*. Available from: https://lornajane.co.za/our-founder/

Low, J. (2020). *SSL certificate buyer's guide: FAQ & compare best SSL certificate providers (prices updated 2020)*. Available from: https://www.buildthis.io/buy-ssl-certificate/

Lu, D. (2017). *How do trust and risk affect customers' online purchase intention? A study of trust and risk in the online shopping context*. Master's dissertation. Ontario, Canada: University of Guelph.

Lucintel. (2012). *Global retail industry 2012-2017: trends, profits and forecast analysis*. Available from: https://www.researchandmarkets.com/reports/2173102/global_retail_industry_20122017_trends_profits

Lumen Learning. (2018). *Social-Cognitive Perspectives on Personality*. Available from: https://courses.lumenlearning.com/boundless-psychology/chapter/social-cognitive-perspectives-on-personality/

Lyytinen, K. & Damsgaard, J. (2001). *What's wrong with the diffusion of innovation theory? The case of a complex and networked technology.* Available from: https://pdfs.semanticscholar.org/53a7/a96149bae64041338fc58b281a6eef7d9912.pdf

Madan, K. & Yadav, R. (2016). Behavioural intention to adopt mobile wallet: A developing country perspective. *Journal of Indian Business Research*, 8(3):227-244.

Madan, K. & Yadav, R. (2018). Understanding and predicting antecedents of mobile shopping adoption: A developing country perspective. *Asia Pacific Journal of Marketing and Logistics*, 30(1):139-162.

Magan, B. (2016). *Factors influencing mobile commerce acceptance and adoption in South Africa*. Master's dissertation. Johannesburg, South Africa: University of the Witwatersrand.

Magni, M., Martinez, A. & Motiwala, R. (2016). *Saving, scrimping, and … splurging? New insights into consumer behavior*. Available from: http://www.mckinsey.com/industries/consumer-packaged-goods/our-insights/saving-scrimping-and-splurging-new-insights-into-consumer-behavior

Malhotra, N.K. (2007). *Marketing research: An applied orientation*. 5th ed. Upper Saddle River, NJ: Pearson Education International.

Malhotra, N.K., Birks, D.F. & Wills, P. (2012). *Marketing research: An applied approach*. 4th ed. Essex, England: Pearson Education.

Manson, H. (2012). *Zando rockets into SA ecommerce space*. Available from: http://www.bizcommunity.com/Article/196/16/74204.html

Manson, H. (2016). *Superbalist.com — where millennials shop*. Available from: http://www.marklives.com/2016/09/superbalist-where-millennials-shop/

Marriott, H.R. & Williams, M.D. (2016). Developing a theoretical model to examine consumer acceptance behaviour of mobile shopping. In Y.K. Dwivedi, M. Mäntymäki, M.N. Ravishankar, M. Janssen, M. Clement, E.L. Slade, N.P. Rana, S. Al-Sharhan & A.C. Simintiras (Eds.). *Proceedings of the 15th Conference on e-Business, e-Services and e-Society (I3E).* United Kingdom: Springer International Publishing.

Marriott, H.R. & Williams, M.D. (2018). Exploring consumers perceived risk and trust for mobile shopping: A theoretical framework and empirical study. *Journal of Retailing and Consumer Services*, 42:133-146.

Martins, C., Oliveira, T. & Popovič, A. (2014). Understanding the Internet banking adoption: A unified theory of acceptance and use of technology and perceived risk application. *International Journal of Information Management*, 34:1-13.

Matheny, M. (2015). *Latency impacts user experience, 48 percent of consumers uninstall or stop app-use due to slow speeds, Apteligent report reveals*. Available from: http://www.apteligent.com/news-press/latency-impacts-user-experience-48-percent-of-consumers-uninstall-or-stop-app-use-due-to-slow-speeds-crittercism-report-reveals/

Matikiti, R., Roberts-Lombard, M. & Mpinganjira, M. (2016). Drivers of the use of social networking sites for travel arrangements in South Africa: Test of the social exchange theory. *Journal of Global Business and Technology*, 12(2):28-44.

Maydon, T. (2017). *The history of fashion retail credit in South Africa*. Available from: https://insights.principa.co.za/the-history-of-fashion-retail-credit-in-south-africa

Mayer, R.C., Davis, J.H. & Schoorman, F.D. (1995). An integrative model of organizational trust. *The Academy of Management Review*, 20(3):709-734.

Mazzocchi, M. (2008). *Statistics for marketing and consumer research*. London, UK: SAGE Publications.

McKnight, D.H., Choudhury, V. & Kacmar, C. (2002). The impact of initial consumer trust on intentions to transact with a web site: A trust building model. *Journal of Strategic Information Systems*, 11:297-323.

McNair, C. & Pearl, M. (2018). *Worldwide retail and eCommerce sales: eMarketer's updated forecast and new mCommerce estimates for 2016—2021*. Available from: https://www.emarketer.com/Report/Worldwide-Retail-Ecommerce-Sales-eMarketers-Updated-Forecast-New-Mcommerce-Estimates-20162021/2002182

Media24. (2018). *Spree*. Available from: http://www.media24.com/online-shops/spree/

Mehul, R. (2018). *Top reasons why your mobile app is slow and how to fix it.* Available from: https://www.freecodecamp.org/news/top-reasons-why-your-mobile-app-is-slow-and-how-to-fix-it-f0f7ce524934/

Merriam Webster. (2020a). *Sportswear.* Available from: https://www.merriam-webster.com/dictionary/sportswear

Merriam Webster. (2020b). *The 'athleisure' trend.* Available from: https://www.merriam-webster.com/words-at-play/athleisure-words-were-watching

Miladinovic, J. & Xiang, H. (2016). *A study on factors affecting the behavioural intention to use mobile shopping fashion apps in Sweden*. Master's dissertation. Sweden: Jönköping University.

Miotto, A.P. & Parente, J.G. (2015). Retail evolution model in emerging markets: Apparel store formats in Brazil. *International Journal of Retail & Distribution Management*, 43(3):242-260.

Mitchell, R., Schuster, L. & Jin, H.S. (2018). Gamification and the impact of extrinsic motivation on needs satisfaction: Making work fun? *Journal of Business Research*, 1-8.

Moneyweb. (2017). *Growth in mobile e-commerce 'immense' opportunity for retailers*. Available from: https://www.moneyweb.co.za/news/tech/big-growth-in-online-shopping-in-sa/

Monsuwé, T.P., Dellaert, B.G.C. & de Ruyter, K. (2004). What drives consumers to shop online? A literature review. *International Journal of Service Industry Management*, 15(1):102-121.

Montazemi, A.R. & Qahri-Saremi, H. (2015). Factors affecting adoption of online banking: A meta-analytic structural equation modeling study. *Information & Management*, 52:210-226.

Mooi, E. & Sarstedt, M. (2011). *A concise guide to market research*. Heidelberg, Berlin: Springer-Verlag.

Morgan, R.M. & Hunt, S.D. (1994). The Commitment-Trust Theory of Relationship Marketing. *Journal of Marketing*, 58:20-38.

Morosan, C. & DeFranco, A. (2016). It's about time: Revisiting UTAUT2 to examine consumers' intentions to use NFC mobile payments in hotels. *International Journal of Hospitality Management*, 53:17-29.

Mou, J., Shin, D.H. & Cohen, J. (2017). Understanding trust and perceived usefulness in the consumer acceptance of an e-service: A longitudinal investigation. *Behaviour & Information Technology*, 36(2):125-139.

MovePretty. (2020). *About*. Available from: https://www.movepretty.com/pages/about

Mybroadband. (2016). *Smartphone penetration in South Africa hits major milestone*. Available from: https://mybroadband.co.za/news/smartphones/180894-smartphone-penetration-in-south-africa-hits-major-milestone.html

Mybroadband. (2017a). *Takealot's plan to grow its R2.3-billion annual revenue*. Available from: https://mybroadband.co.za/news/business/229775-takealots-plan-to-grow-its-r2-3-billion-annual-revenue.html

Mybroadband. (2017b). *The battle to take on Takealot*. Available from: https://mybroadband.co.za/news/business/207408-the-battle-to-take-on-takealot.html

Nam, D., Lee, J. & Lee, H. (2018). Business analytics use in CRM: A nomological net from IT competence to CRM performance*. International Journal of Information Management*:1-13.

Nasri, W. & Charfeddine, L. (2012). Factors affecting the adoption of Internet banking in Tunisia: An integration theory of acceptance model and theory of planned behaviour. *Journal of High Technology Management Research*, 23:1-14.

Natarajan, T., Balasubramanian, S.A. & Kasilingam, D.L. (2017). Understanding the intention to use mobile shopping applications and its influence on price sensitivity. *Journal of Retailing and Consumer Services*, 37:8-22.

Netonomy. (2013). *Online shopping started in 1979. Birthplace: the UK*. Available from: http://netonomy.net/2013/10/30/online-shopping-started-in-1979-birthplace-the-uk/

Newsom, J.T. (2018). *Some clarifications and recommendations on fit indices, lecture notes.* Psy 523/623 Structural Equation Modeling, Portland State University, delivered Spring 2018. Available from: http://web.pdx.edu/~newsomj/semclass/ho_fit.pdf

Nielsen. (2014). *Age matters with digital shoppers*. Available from: http://www.nielsen.com/us/en/insights/news/2014/age-matters-with-digital-shoppers.html

Nielsen. (2017). *South African shoppers influenced by clicks and bricks*. Available from: http://www.nielsen.com/za/en/press-room/2017/south-african-shoppers-influenced-by-clicks-and-bricks.html

Nielsen. (2019). *South Africa is the second-most price sensitive country in the world*. Available from: https://www.nielsen.com/ssa/en/insights/article/2019/south-africa-is-the-second-most-price-sensitive-country-in-the-world/

Noble, B. (2017). *How digital opportunity is reshaping SA's shopping centres*. Available from: https://www.businesslive.co.za/fm/features/2017-09-14-how-digital-opportunity-is-reshaping-sas-shopping-centres/

OCS. (2016). *A brief history of retail*. Available from: https://www.ocsretailsupport.co.uk/latest-news/brief-history-retail/

Oliveira, T., Thomas, M., Baptista, G. & Campos, F. (2016). Mobile payment: Understanding the determinants of customer adoption and intention to recommend the technology. *Computers in Human Behavior*, 61:404-414.

Omarjee, L. (2017). *Challenged retail sector to be hit by downgrade – research*. Available from: https://www.fin24.com/Companies/Retail/challenged-retail-sector-to-be-hit-by-downgrade-research-20170412

Otieno, O.C., Liyala, S., Odongo, B.C. & Abeka, S. (2016). Theory of reasoned action as an underpinning to technological innovation adoption studies. *World Journal of Computer Application and Technology*, 4(1):1-7.

Oturakci, M. & Yuregir, O.H. (2018). New approach to Rogers' innovation characteristics and comparative implementation study. *Journal of Engineering and Technology Management*, 47:53-67.

Pajares, F. (1997). Current directions in self-efficacy research. In M. Maehr & P.R. Pintrich (Eds.). *Advances in motivation and achievement*. Greenwich, CT: JAI Press.

Pallant, J. (2016). *SPSS survival manual: A step by step guide to data analysis using SPSS program*. 6th ed. London, UK: McGraw-Hill Education.

Parker, C.J. & Wang, H. (2016). Examining hedonic and utilitarian motivations for m-Commerce fashion retail app engagement. *Journal of Fashion Marketing and Management: An International Journal*, 20(4):487-506.

Persson, J. & Berndtsson, J. (2015). *Determinants of smartphone shopping adoption: Key factors for online shopping of consumer goods through smartphones in Sweden.* Master's thesis. Sweden: Lund University.

Petro, G. (2015). *Lululemon, Nike and the rise of 'athleisure'*. Available from: https://www.forbes.com/sites/gregpetro/2015/09/16/lululemon-nike-and-the-rise-of-athleisure/3/#1ce0b1fb5a9a

Phong, N.D., Khoi, N.H. & Le, A.N. (2018). Factors affecting mobile shopping: A Vietnamese perspective. *Journal of Asian Business and Economic Studies*, 25(2):186-205.

Pikkarainen, T., Pikkarainen, K., Karjaluoto, H. & Pahnila, S. (2004). Consumer acceptance of online banking: An extension of the technology acceptance model. *Internet Research*, 14(3):224-235.

Pinho, J.C.M.R. & Soares, A.M. (2011). Examining the technology acceptance model in the adoption of social networks. *Journal of Research in Interactive Marketing*, 5(2/3):116-129.

Posey, C., Lowry, P.B., Roberts, T.L. & Ellis, S. (2010). Proposing the online community self-disclosure model: The case of working professionals in France and the U.K. who use online communities. *European Journal of Information Systems*, 19:181-195.

Prinsloo, D.A. (2016). *Retail trends in a very dynamic South African market.* Available from: http://urbanstudies.co.za/retail-trends-in-a-very-dynamic-south-african-market/

Pullen, J.P. (2015). Here's how Wi-Fi actually works. Available from: http://time.com/3834259/wifi-how-works/

PwC. (2012). *South African retail and consumer products outlook 2012-2016.* Available from: https://www.pwc.co.za/en/assets/pdf/retail-and-consumer-products-outlook-2012-2016.pdf

Quinlan, C., Babin, B., Carr, J., Griffin, M. & Zikmund, W.G. (2015). *Business Research Methods*. 1st ed. Hampshire, United Kingdom: Cengage Learning EMEA.

Ragab, M.A.F. & Arisha, A. (2018). Research methodology in business: A starter's guide. *Management and Organisational Studies*, 5(1):1-23.

Rangongo, T. (2018). *7 tricks used by card fraud criminals in South Africa – and how to protect yourself against them*. Available from: https://www.businessinsider.co.za/8-insane-tricks-used-by-card-fraud-criminals-in-south-africa-and-how-you-can-protect-yourself-against-them-2018-4

Ratten, V. (2011). Social cognitive theory in mobile banking innovation. *International Journal of E-Business Research*, 7(1):39-51.

Ratten, V. (2015). A cross-cultural comparison of online behavioural advertising knowledge, online privacy concerns and social networking using the technology acceptance model and social cognitive theory. *Journal of Science & Technology Policy Management*, 6(1):25-36.

Ratten, V. & Ratten, H. (2007). Social cognitive theory in technological innovation. *European Journal of Innovation Management*, 10(1):90-108.

Razali, N.M. & Wah, Y.B. (2011). Power comparisons of Shapiro-Wilk, Kolmogorov-Smirnov, Lilliefors and Anderson-Darling tests. *Journal of Statistical Modeling and Analytics*, 2(1):21-33.

Renaud, K. & van Biljon, J. (2008). Predicting technology acceptance and adoption by the elderly: A qualitative study. *SAICSIT* 2008, 1-10.

Reyhle, N. (2014). *The history of retail shopping: a millennium of change*. Available from: https://retailminded.com/the-history-of-retail-shopping/

Ribbink, D., van Riel, A.C.R., Liljander, V. & Streukens, S. (2004). Comfort your online customer: Quality, trust and loyalty on the internet. *Managing Service Quality*, 14(6):446-456.

Riffai, M.M.M.A., Grant, K. & Edgar, D. (2012). Big TAM in Oman: Exploring the promise of on-line banking, its adoption by customers and the challenges of banking in Oman. *International Journal of Information Management*, 32:239-250.

Rogers, E. (2003). *The diffusion of innovations*. 5th ed. New York, NY: The Free Press.

Rogers, M. (2010). *Consumers' attitudes, perceived risk, trust and internet banking adoption in Uganda.* Master's dissertation. Kampala, Uganda: University of Makerere.

Rondan-Cataluña, F.J., Arenas-Gaitán, J. & Ramírez-Correa, P.E. (2015). A comparison of the different versions of popular technology acceptance models: A non-linear perspective. *Kybernetes*, 44(5):788-805.

Rouibah, K., Lowry, P.B. & Hwang, Y. (2016). The effects of perceived enjoyment and perceived risks on trust formation and intentions to use online payment systems: New perspectives from an Arab country. *Electronic Commerce Research and Applications*, 19:33-43.

Ruane, L. & Wallace, E. (2013). Generation Y females online: Insights from brand narratives. *Qualitative Market Research: An International Journal*, 16(3):315-335.

SA History. (2015). *The first OK Bazaars opens on the corner of Eloff and President Street in Johannesburg*. Available from: http://www.sahistory.org.za/dated-event/first-ok-bazaars-opens-corner-eloff-and-president-street-johannesburg

SA Venues. (2020). *Johannesburg shopping, Johannesburg.* Available from: https://www.sa-venues.com/attractionsga/johannesburg-shopping.htm

Sair, S.H. & Danish, R.Q. (2018). Effect of performance expectancy and effort expectancy on the mobile commerce adoption intention through personal innovativeness among Pakistani consumers. *Pakistan Journal of Commerce and Social Sciences*, 12(2):501-520.

Saleh, K. (2017). *Global online retail spending – statistics and trends*. Available from: https://www.invespcro.com/blog/global-online-retail-spending-statistics-and-trends/

Sanne, P.N.C. & Wiese, M. (2018). The theory of planned behaviour and user engagement applied to Facebook advertising. *South African Journal of Information Management*, 20(1):1-10.

Saunders, M., Lewis, P. & Thornhill, A. (2016). *Research methods for business students.* 7th ed. Essex, United Kingdom: Pearson Education.

Savitz, E. (2012). *Generation gap: How technology has changed how we talk about work.* Available from: http://www.forbes.com/sites/ciocentral/2012/05/15/generation-gap-how-technology-has-changed-how-we-talk-about-work/#67850425271e

Shafinah, K., Sahari, N., Sulaiman, R., Yusoff, M.S.M. & Ikram, M.M. (2013). Determinants of user behavior intention (BI) on mobile services: A preliminary view. *Procedia Technology*, 11:127-133.

Shaikh, A.A. & Karjaluoto, H. (2015). Mobile banking adoption: A literature review. *Telematics and Informatics*, 32:129-142.

Shanmugam, A., Savarimuthu, M.T. & Wen, T.C. (2014). Factors affecting Malaysian behavioral intention to use mobile banking with mediating effects of attitude. *Academic Research International*, 5(2):236-253.

Sharma, R. & Mishra, R. (2014). A review of evolution of theories and models of technology adoption. *Indian Institute of Management*, 6(2):17-29.

Shaw, N. & Sergueeva, K. (2019). The non-monetary benefits of mobile commerce: Extending UTAUT2 with perceived value. *International Journal of Information Management,* 45:44-55.

Shezi, N. (2016). *The rise of athleisure*. Available from: http://www.elle.co.za/the-rise-of-the-athleisure/

Shiau, W.L. & Luo, M.M. (2012). Factors affecting online group buying intention and satisfaction: A social exchange theory perspective. *Computers in Human Behavior*, 28:2431-2444.

Shop Direct. (2018). *Online shopping in SA is poised for growth.* Available from: http://www.shopdirect.co.za/news/online-shopping-in-sa-is-poised-for-growth/

Sky Technology. (2016). *7 proven benefits of touch screens and touch screen technology*. Available from: http://www.sky-technology.eu/blog/article/item/7-proven-benefits-of-touch-screens-and-touch-screen-technology.html

Slade, E., Williams, M. & Dwivedi, Y. (2013). Extending UTAUT2 to explore consumer adoption of mobile payments*. Proceedings of the UK Academy for Information Systems Conference*.

Smith, C. (2017). *SA e-commerce growing by leaps and bounds*. Available from: https://www.fin24.com/Companies/Retail/sa-e-commerce-growing-by-leaps-and-bounds-20170222

Sniehotta, F.F., Presseau, J. & Araújo-Soares, V. (2014). Time to retire the theory of planned behaviour. *Health Psychology Review*, 8(1):1-7.

South African Embassy in the Netherlands. (2013). *South African automotive industry – profile.* Available from: https://www.zuidafrika.nl/automotive-industry

South African Market Insights. (2016). *South Africa's consumers spending patterns last updated (16 March 2016)*. Available from: https://www.southafricanmi.com/sa-consumer-spending-patterns.html

South African Market Insights. (2017). *Blog: 22 May 2017 (SA's retail trade data vs SA's economic growth rate).* Available from: https://www.southafricanmi.com/blog-22may2017.html

South African Treasury's Budget Review. (2019). *Economic overview*. Available from: http://www.treasury.gov.za/documents/national%20budget/2019/review/Chapter%202.pdf

Space Station. (2017). *How South Africans access the Internet.* Available from: http://www.thespacestation.co.za/how-south-africans-access-the-internet/

Spitzer, M., Wildenhain, J., Rappsilber, J. & Tyers, M. (2014). BoxPlotR: A web tool for generation of box plots. *Nature Methods*, 11(2):121-122.

Statista. (2017). *Cumulative number of apps downloaded from the Apple App Store from July 2008 to June 2017 (in billions)*. Available from: https://www.statista.com/statistics/263794/number-of-downloads-from-the-apple-app-store/

Statista. (2018a). *Total retail sales worldwide from 2015 to 2020 (in trillion U.S. dollars).* Available from: https://www.statista.com/statistics/443522/global-retail-sales/

Statista. (2018b). *Total revenue of the global sports apparel market from 2012 to 2024 (in billion U.S. dollars)*.* Available from: https://www.statista.com/statistics/254489/total-revenue-of-the-global-sports-apparel-market/

Statista. (2019a). *Number of smartphone users worldwide from 2016 to 2021 (in billions).* Available from: https://www.statista.com/statistics/330695/number-of-smartphone-users-worldwide/

Statista. (2019b*). Number of smartphone users in South Africa from 2014 to 2023 (in millions)*.* Available from: https://www.statista.com/statistics/488376/forecast-of-smartphone-users-in-south-africa/

Statista. (2019c). *Retail e-commerce sales worldwide from 2014 to 2023 (in billion U.S. dollars)*. Available from: https://www.statista.com/statistics/379046/worldwide-retail-e-commerce-sales/

Statista. (2019d). *Retail e-commerce sales CAGR forecast in selected countries from 2019 to 2023*. Available from: https://www.statista.com/statistics/220177/b2c-e-commerce-sales-cagr-forecast-for-selected-countries/

Statista. (2019e). *Fashion*. Available from: https://www.statista.com/outlook/244/112/fashion/south-africa#

Statista. (2019f). *Number of Facebook users in South Africa from 2017 to 2023 (in millions)*. Available from: https://www.statista.com/statistics/558248/number-of-facebook-users-in-south-africa/

Statistics South Africa (Stats SA). (2017). *Mid-year population estimates*. Available from: http://www.statssa.gov.za/publications/P0302/P03022017.pdf

Statistics South Africa (Stats SA). (2018a). *Five facts about the retail trade industry*. Available from: http://www.statssa.gov.za/?p=11101

Statistics South Africa (Stats SA). (2018b). *Retail trade sales (Preliminary) – March 2018*. Available from: http://www.statssa.gov.za/publications/P62421/P62421March2018.pdf

Straub, E.T. (2011). Understanding technology adoption: Theory and future directions for informal learning. *Review of Educational Research*, 79(2):625-649.

Su, P., Wang, L. & Yan, J. (2018). How users' Internet experience affects the adoption of mobile payment: a mediation model. *Technology Analysis & Strategic Management*, 30(2):186-197.

Suh, Y.I., Ahn, T. Lee, J.K. & Pedersen, P.M. (2015). Effect of trust and risk on purchase intentions in online secondary ticketing: Sport consumers and ticket reselling. *South African Journal for Research in Sport, Physical Education and Recreation*, 37(2):131-142.

Suhr, D.D. (2006). *Exploratory or Confirmatory Factor Analysis?* Available from: https://www.researchgate.net/profile/Grace_Rebekah/post/What_should_I_do_to_perform_a_confirmatory_factor_analysis_using_SPSS/attachment/59d62f0fc49f478072e9f7bc/AS:273523199676434@1442224420630/download/EFA+%26+CFA+materal+in+SAS.pdf

Sun, J. (2005). Assessing Goodness of Fit in Confirmatory Factor Analysis. *Measurement and Evaluation in Counselling and Development*, 37(4):240-256.

Sun, S., Lee, P. & Law, R. (2019). Impact of cultural values on technology acceptance and technology readiness. *International Journal of Hospitality Management*, 77:89-96.

Superbalist.com. (2016). *Lulama Wolf is athleisure*. Available from: https://superbalist.com/thewayofus/2016/05/16/lulama-wolf-is-athleisure/615

Superbalist.com. (2020). *Athleisure*. Available from: https://superbalist.com/search?q=athleisure

Survey Monkey. (2020). *Survey sample size*. Available from: https://www.surveymonkey.com/mp/sample-size/

Swiegers, L. (2018). *Perceived risk barriers to online shopping: Experiences of technologically enabled Generation Y consumers*. Master's dissertation. Stellenbosch, South Africa: University of Stellenbosch.

Taherdoost, H. (2016). Validity and reliability of the research instrument; how to test the validation of a questionnaire/survey in a research. *International Journal of Academic Research in Management*, 5(3):28-36.

Takealot.com. (2020a). *More about our journey*. Available from: https://www.takealot.com/about/our-journey

Takealot.com. (2020b). *Athleisure*. Available from: https://www.takealot.com/sport/athleisure-24658

Tanskanen, K. (2015). Who wins in a complex buyer-supplier relationship? A social exchange theory based dyadic study. *International Journal of Operations & Production Management*, 25(4):577-603.

Tan, G.W.H. & Ooi, K.B. (2018). Gender and age: Do they really moderate mobile tourism shopping behavior? *Telematics and Informatics*, 35:1617-1642.

Tarhini, A., El-Masri, M., Ali, M. & Serrano, A. (2016). Extending the UTAUT model to understand the customers' acceptance and use of internet banking in Lebanon: A structural equation modelling approach. *Information Technology & People*, 29(4):830-849.

Team, T. (2016). *The athleisure trend is here to stay*. Available from: https://www.forbes.com/sites/greatspeculations/2016/10/06/the-athleisure-trend-is-here-to-stay/#1b0f72ac28bd

Techopedia. (2020). *Mobile application (mobile app).* Available from: https://www.techopedia.com/definition/2953/mobile-application-mobile-app

Teo, T.S.H. & Yu, Y. (2004). Online buying behavior: A transaction cost economics perspective. *The International Journal of Management Science*, 33(5):451-465.

Ter Huurne, M., Ronteltap, A., Corten, R. & Buskens, V. (2017). Antecedents of trust in the sharing economy: A systematic review. *Consumer Behaviour*, 16:485-498.

Thakur, R. & Srivastava, M. (2013). Customer usage intention of mobile commerce in India: an empirical study. *Journal of Indian Business Research*, 5(1):52-72.

Thebe Tourism. (2017). *Travelport: The South African Digital Traveler Research*. Available from: http://www.thebetourism.co.za/wp-content/uploads/2017/11/Travelport-South-Africa-Report-FINAL.pdf

Ting, D.H., Lim, S.F., Patanmacia, T.S., Low, C.G. & Ker, G.C. (2011). Dependency on smartphone and the impact on purchase behaviour. *Young Consumers*, 12(3):193-203.

Ueltschy, L.C., Krampf, R.F. & Yannopoulos, P. (2004). A cross-national study of perceived consumer risk towards online (internet) purchasing. *The Multinational Business Review*, 12(2):59-82.

University of London. (2019). *Unit 1 Introduction to research*. Available from: https://www.soas.ac.uk/cedep-demos/000_P506_RM_3736-Demo/unit1/page_26.htm

University of Pretoria. (2016). *Innovate Issue 11*. Available from: http://www.up.ac.za/media/shared/130/ZP_Files/innovate-11_2016_exploring-sa-retail-landscape.zp111498.pdf

Upadhyay, T. (2016). *How mobile has revolutionised the way we shop.* Available from: http://brandequity.economictimes.indiatimes.com/news/digital/how-mobile-has-revolutionised-the-way-we-shop/55083562

Urbach, N. (2010). Structural equation modeling in information systems research using Partial Least Squares. *Journal of Information Technology Theory and Application*, 11(2):5-40.

van Slyke, C. (2008). *Information communication technologies: Concepts, methodologies, tools and applications*. Hershey, PA: IGI Global.

van Zyl, G. (2015). *Why the Kalahari brand was discontinued*. Available from: https://www.fin24.com/Tech/Companies/Why-the-Kalahari-brand-was-discontinued-20150505 van Zyl, L.E. (2014). *Research methodology for the economic and management sciences*. Essex, United Kingdom: Pearson Education.

Vasileiadis, A. (2014). Security concerns and trust in the adoption of m-commerce. *Social Technologies*, 4(1):179-191.

Vault. (2018). *Retail*. Available from: http://www.vault.com/industries-professions/industries/retail.aspx

Velarde, V.D.V. (2012). *Determinants of online purchasing behavior: an empirical investigation using an extension of the theory of planned behaviour.* Master's dissertation. Denmark: Aarhus University.

Venkatesh, V., Morris, M.G., Davis, G.B. & Davis, F.D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, 27(3):425-478.

Venkatesh, V., Thong, J.Y.L. & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the unified Theory of Acceptance and Use of Technology. *MIS Quarterly*, 36(1):157-178.

Venktess, K. (2016). *TIMELINE: Internet turns 25 in South Africa*. Available from: https://www.fin24.com/Tech/News/timeline-internet-turns-25-in-south-africa-20161111

Verkijika, S.F. (2018). Factors influencing the adoption of mobile commerce applications in Cameroon. *Telematics and Informatics*, 35:1665-1674.

Wang, H.Y. & Wang, S.H. (2010). User acceptance of mobile Internet based on the unified theory of acceptance and use of technology: Investigating the determinants and gender differences. *Social Behavior and Personality*, 38(3):415-426.

Wang, X., Yuen, K.F., Wong, Y.D. & Teo, C.C. (2018). An innovation diffusion perspective of e-consumers' initial adoption of self-collection service via automated parcel station. *The International Journal of Logistics Management*, 29(1):237-260.

Wang, Y., Min, Q. & Han, S. (2016). Understanding the effects of trust and risk on individual behavior toward social media platforms: A meta-analysis of the empirical evidence. *Computers in Human Behavior*, 56:34-44.

Ward, C. (2015). *Global retail sales set to reach $24 trillion in 2015.* Available from: https://www.mycustomer.com/selling/ecommerce/global-retail-sales-set-to-reach-24-trillion-in-2015

Weebly.com. (2018). *Social Cognitive Theory.* Available from: http://gavsappsychpersonalityjbd.weebly.com/social-cognitive-theory-and-its-criticisms.html

Wei, T.T., Marthandan, G., Chong, A.Y.L., Ooi, K.B. & Arumugam, S. (2009). What drives Malaysian m-commerce adoption? An empirical analysis. *Industrial Management & Data Systems*, 109(3):370-388.

Weinhouse, M. (2018). *Why you should be radically transparent with your customers*. Available from: https://www.forbes.com/sites/forbesagencycouncil/2018/04/16/why-you-should-be-radically-transparent-with-your-customers/#3da090467aef

Wells, P. & Nieuwenhuis, P. (2018). Over the hill? Exploring the other side of the Rogers' innovation diffusion model from a consumer and business model perspective. *Journal of Cleaner Production*, 194:444-451.

West, R. & Turner, L.H. (2018). *Social Exchange Theory*. Available from: http://highered.mheducation.com/sites/0767430344/student_view0/chapter11/index.html

Williams, M.D., Rana, N.P. & Dwivedi, Y.K. (2015). The unified theory of acceptance and use of technology (UTAUT): A literature review. *Journal of Enterprise Information Management*, 28(3):443-488.

Williamson, O.E. (1981). The economics of organization: The transaction cost approach. *The American Journal of Sociology*, 87(3):548-577.

Williamson, B. (2014). *South Africa's big ecommerce problem is supply, not demand*. Available from: http://ventureburn.com/2014/08/south-africas-big-ecommerce-problem-is-supply-not-demand/

Wood, B. (2015). *The history of online shopping*. Available from: https://purple.ai/blogs/the-history-of-online-shopping/

World Wide Worx. (2016). *Instagram, Facebook make waves in SA.* Available from: http://www.worldwideworx.com/socialsa2016/

World Wide Worx. (2019). *Online retail reaches 1.4% of SA's total retail*. Available from: http://www.worldwideworx.com/onlineretail2019/

Wu, C.H., Kao, S.C., Lin, H.H. (2013). Acceptance of enterprise blog for service industry, *Internet Research*, 23(3):260-297.

Wu, J.H. & Wang, S.C. (2005). What drives mobile commerce? An empirical evaluation of the revised technology acceptance model. *Information & Management 42*:719-729.

Wu, L.Y., Chen, K.Y., Chen, P.Y. & Cheng, S.L. (2014). Perceived value, transaction cost, and repurchase-intention in online shopping: A relational exchange perspective. *Journal of Business Research,* 67:2768-2776.

Xu, X. (2020). How do consumers in the sharing economy value sharing? Evidence from online reviews. *Decision Support Systems*, 128:1-13.

Yan, Z., Wang, T., Chen, Y. & Zhang, H. (2016). Knowledge sharing in online health communities: A social exchange theory perspective. *Information & Management*, 53:643-653.

Yang, K. (2010). Determinants of US consumer mobile shopping services adoption: implications for designing mobile shopping services. *Journal of Consumer Marketing*, 27(3):262-270.

Yang, Y., Liu, Y., Li, H. & Yu, B. (2015). Understanding perceived risks in mobile payment acceptance. *Industrial Management & Data Systems*, 115(2):253-269.

Yap, S.F. & Gaur, S.S. (2016). Integrating functional, social, and psychological determinants to explain online social networking usage. *Behaviour & Information Technology*, 35(3):166-183.

Yen, C., Hsu, M.H. & Chang, C.M. (2013). Exploring the online bidder's repurchase intention: A cost and benefit perspective. *Information Systems & E-Business Management*, 11:211-234.

Yong, G. & Pearce, S. (2013). A beginner's guide to factor analysis: focusing on exploratory factor analysis. *Tutorials in Quantitative Methods for Psychology*, 9(2):79-94.

Young, R. (2014). *In South Africa, more evolution than revolution*. Available from: https://www.businessoffashion.com/articles/market-gps/south-africa-more-evolution-than-revolution

YourStory.com. (2016). *Mobile retail sales worldwide will reach $220bn in 2016*. Available from: https://yourstory.com/2016/10/mobile-retail-sales-growth-worldwide/

Zafirovski, M. (2005). Social exchange theory under scrutiny: A positive critique of its economic behaviorist formulations. *Electronic Journal of Sociology*, 1-40.

Zando. (2020a). *Clothing*. Available from: https://www.zando.co.za/women/sports/clothing/

Zando. (2020b). *Who we are*. Available from: https://www.zando.co.za/about/

Zhang, L., Zhu, J. & Liu, Q. (2012). A meta-analysis of mobile commerce adoption and the moderating effect of culture. *Computers in Human Behaviour*, 28:1902-1911.

Zikmund, W.G., & Babin, B.J. (2010). *Exploring marketing research*. 10th ed. Canada: South-Western, Cengage Learning.

ANNEXURES

Annexure 1: Summarisation of foundational theories and models, and their associated constructs grounding the study

	SET	TCT	IDT	TRA	SCT	TAM	TPB	UTAUT	UTAUT2
Essence of the theory	Buyers and sellers interact with one another in order to minimise cost while exploiting reward	Individuals have a preference for conducting transactions in the most cost-effective way	Attempts to explain a user's adoption of innovative technologies and their decision-making process	Considers the relationships between a human being's beliefs system, attitudes, intentions and ultimate behaviour	Attempts to create an inclusive understanding of an individual's behavioural intention to adopt new technologies	An individual will be motivated to adopt a new technology based on three elements – perceived ease of use, perceived usefulness, and attitude	An individual's behaviour is the result of a consideration of available resources, the individual's attitude, and others' opinions	Created in an effort to consolidate the host of technology acceptance theories and models into one, singular model	Adapted the UTAUT to allow for application to consumer-use contexts
Performance expectancy (PE)			X (represented by Relative advantage)		X (represented by Outcome expectations)	X (represented by Perceived usefulness)		X	X
Effort expectancy (EE)						X (represented by Perceived ease of use)		X	X
Social influence (SI)				X (represented by Subjective norm)			X (represented by Subjective norm)	X	X
Facilitating conditions (FC)			X (represented by Compatibility)				X (represented by Perceived behavioural control)	X	X
Hedonic motivation (HM)									X
*Price value (PV_*									X
Habit (HT)									X
Perceived risk (PR)	X					X		X	X
Trust (TR)	X	X				X		X	X
Behavioural intention (BI)				X		X	X	X	X
Actual use (AU)				X		X	X	X	X

Annexure 2: Research philosophy and perspectives

Research philosophy and perspectives	**Definition**	**Application to this study**
Research philosophy: Positivism	This research philosophy has a preference for the collection of quantitative data through observable reality and searching for relationships and regularities in the collected data to create generalisations (Benzo *et al.*, 2018:96-97; Ragab & Arisha, 2018:3; Saunders *et al.*, 2016:135-136). A positivist researcher typically makes use of theory already in existence to develop and either confirm or refute hypotheses (Saunders *et al.*, 2016:137).	This study seeks to produce knowledge on the constructs that influence consumers' acceptance and use of mCommerce apps to purchase fashion apparel in South Africa, with a specific focus on athleisure apparel. Fifteen hypotheses, based on various constructs informed by the UTAUT2, have been formulated for testing in this study by means of a questionnaire. Relationships and regularities in the collected data are used to create generalisations.
Ontological perspective	Positivist researchers believe that reality is tangible and external, and independent of the researcher's interest in it. Reality can be separated into different constructs (Ragab & Arisha, 2018:4; Chilisa & Kawulich, 2012:8-9).	
Epistemological perspective	Positivist researchers consider knowledge to be a series of objective statements that can be tested through empirical research which then leads to these statements being confirmed or denied. The researchers further believe these statements to be generalisable to greater populations (Ragab & Arisha, 2018:4; Chilisa & Kawulich, 2012:8-9).	
Axiological perspective	Positivist researchers believe in objectivity and complete neutrality during the research process through the use of scientific methods to gather data. This ensures that the research remains objective and "value-free" (Ragab & Arisha, 2018:4; Chilisa & Kawulich, 2012:8-9).	

Annexure 3: Questionnaire covering letter

<u>mCommerce acceptance and use behaviour: a South African case study</u>

Dear Sir/Madam,

You are invited to participate, by completing this questionnaire, in a study being conducted to determine the factors that influence your acceptance and use of mobile commerce (commonly referred to as mCommerce or mobile shopping) apps to purchase "athleisure" apparel in South Africa. Examples of "athleisure" apparel include:

I HEREBY AGREE TO PARTICIPATE IN THE STUDY:

Yes	1	
No	2	*Please do not continue*

Further details of the study are provided below:

Research title	mCommerce acceptance and use behaviour: a South African case study
Researcher	Karen van Niekerk, University of Johannesburg, College of Business and Economics, School of Consumer Intelligence and Information Systems, Department of Marketing Management
Purpose	To elicit feedback from you regarding the constructs that influence your acceptance and use of mCommerce apps to purchase "athleisure" apparel in South Africa.
What does "athleisure" mean?	"Athleisure" is a term used to describe clothing that can be used for both exercising and general wearing. Such apps include, for example, Superbalist, Takealot.com, Zando, etc.
Procedure	For this study, you will be required to participate in a survey by completing a paper-based questionnaire which will take about 20 minutes to complete.
Risk of participation	There are no known risks associated with this research project.
Benefits	Your participation will contribute to findings that will add to the academic body of knowledge through the compilation of a journal article and a conference paper published in conference proceedings.
Confidentiality	Your response will remain anonymous and confidential, and will not be linked to any identifiable information. Please do not provide your name or personal details on any part of the questionnaire.
Participation right	Your participation in this study is completely voluntary. You have the right to withdraw from this research study at any time without any reprisal and or penalty.
Contact details	Should you have any questions or concerns regarding the completion of this questionnaire, you may contact the researcher on the following details: Researcher: Karen van Niekerk Phone no: 083 376 0258 Email address: karen-vn@hotmail.com

Source: *Researcher's own*

Annexure 4: Items and scales used in the questionnaire

Construct	No.	Items	Sources	Response format	Scale type
Screening questions					
Do you have a smartphone?	A	Yes No	Developed by the researcher	Multiple choice	Nominal
Have you used an app on your smartphone to browse and/or buy athleisure apparel (i.e. Clothing for exercise and general wearing as depicted in the pictures above)? Examples of apps include Zando, Superbalist or Takealot.com	B	Browse Buy Browse and buy	Developed by the researcher	Multiple choice	Nominal
When was the last time you used an app to browse and/or buy products from your smartphone?	C	Within the last week Within the last month Within the last year More than 12 months ago	Developed by the researcher	Multiple choice	Nominal
Section A: Demographic information					
Gender	1	Male Female	Developed by the researcher	Multiple choice	Nominal
Ethnicity	2	Black White Coloured Asian/Indian Other	Developed by the researcher	Multiple choice	Nominal
Education	3	Matric National Diploma/Certificate University degree Post-graduate degree	Developed by the researcher	Multiple choice	Nominal
Age	4	18-24 years 25-29 years 30-35 years 35-40 years Older than 40	Developed by the researcher	Multiple choice	Nominal
Home language	5	Afrikaans English Ndebele	Developed by the researcher	Multiple choice	Nominal

		Northern Sotho			
		Sotho			
		Swazi			
		Tsonga			
		Tswana			
		Venda			
		Xhosa			
		Zulu			
		Other			
Employment status	6	Self-employed	Developed by the researcher	Multiple choice	Nominal
		Full-time employed by organisation			
		Part-time employed by organisation			
		Full-time student			
		Part-time student			
		Home executive			
		Unemployed			
		Retired			
Of the athleisure apparel you purchase, what proportion is purchased online and in-store?	7	All online	Developed by the researcher	Multiple choice	Nominal
		Most online			
		About half online and half in-store			
		Most in-store			
		All in-store			
Section B: Constructs influencing behavioural intention					
Performance expectancy (PE)	PE1	I find mobile shopping useful in my daily life when browsing and/or purchasing athleisure apparel.	Adapted from Venkatesh *et al.* (2012:178) Supported by Shaw & Sergueeva (2019:53-54); Alalwan *et al.* (2018:135-136); Chopdar *et al.* (2018:123-124); Hew *et al.* (2015:1276); Martins *et al.* (2014:11); Venkatesh *et al.* (2003:460)	Scaled	Interval (Likert)
	PE2	Using mobile shopping apps helps me to do my shopping for athleisure apparel more quickly.	Adapted Venkatesh *et al.* (2012:178) Supported by Alalwan *et al.* (2018:135-136); Chopdar *et al.* (2018:123-124); Hew *et al.* (2015:1276); Martins *et al.* (2014:11); Venkatesh *et al.* (2003:460)		
	PE3	Using mobile shopping apps increases my chances of	Adapted from Venkatesh *et al.* (2012:178)		

		achieving tasks that are important to me, such as browsing and/or purchasing athleisure apparel.	Supported by Alalwan *et al.* (2018:135-136); Chopdar *et al.* (2018:123-124)		
	PE4	Using mobile shopping apps for browsing and/or purchasing athleisure apparel increases my productivity.	Adapted from Venkatesh *et al.* (2003:460) Supported by Shaw & Sergueeva (2019:53-54); Alalwan *et al.* (2018:135-136); Chopdar *et al.* (2018:123-124); Hew *et al.* (2015:1276); Martins *et al.* (2014:11); Venkatesh *et al.* (2012:178)		
Effort expectancy (EE)	EE1	Learning how to use mobile shopping apps to browse and/or purchase athleisure apparel is easy for me.	Adapted from Venkatesh *et al.* (2012:178) Supported by Shaw & Sergueeva (2019:53-54); Alalwan *et al.* (2018:135-136); Chopdar *et al.* (2018:123-124); Chaouali *et al.* (2016:213); Hew *et al.* (2015:1276); Martins *et al.* (2014:11); Yang (2010:265); Venkatesh *et al.* (2003:460)	Scaled	Interval (Likert)
	EE2	My interaction with mobile shopping apps when browsing and/or purchasing athleisure apparel is clear and understandable.	Adapted from Venkatesh *et al.* (2012:178) Supported by Shaw & Sergueeva (2019:53-54); Alalwan *et al.* (2018:135-136); Chopdar *et al.* (2018:123-124); Chaouali *et al.* (2016:213); Hew *et al.* (2015:1276); Martins *et al.* (2014:11); Yang (2010:265); Venkatesh *et al.* (2003:460)		
	EE3	I find mobile shopping apps easy to use when browsing and/or purchasing athleisure apparel.	Adapted from Venkatesh *et al.* (2012:178) Supported by Shaw & Sergueeva (2019:53-54); Alalwan *et al.* (2018:135-136); Chopdar *et al.* (2018:123-124); Chaouali *et al.* (2016:213); Hew *et al.* (2015:1276); Martins *et al.* (2014:11); Yang (2010:265); Venkatesh *et al.* (2003:460)		
	EE4	It is easy for me to become skilful at using mobile shopping apps to browse and/or purchase athleisure apparel.	Adapted from Venkatesh *et al.* (2012:178) Supported by Alalwan *et al.* (2018:135-136); Chopdar *et al.* (2018:123-124); Chaouali *et al.* (2016:213); Hew *et al.* (2015:1276); Martins *et al.* (2014:11); Yang (2010:265); Venkatesh *et al.* (2003:460)		
Social influence (SI)	SI1	People who are important to me think that I should use mobile	Adapted from Venkatesh *et al.* (2012:178)	Scaled	Interval (Likert)

		shopping apps to purchase athleisure apparel.	Supported by Shaw & Sergueeva (2019:53-54); Alalwan *et al.* (2018:135-136); Chopdar *et al.* (2018:123-124); Chaouali *et al.* (2016:213); Hew *et al.* (2015:1276); Martins *et al.* (2014:11); Yang (2010:265); Venkatesh *et al.* (2003:460)		
	SI2	People who influence my behaviour think that I should use mobile shopping apps to purchase athleisure apparel.	Adapted from Venkatesh *et al.* (2012:178) Supported by Shaw & Sergueeva (2019:53-54); Alalwan *et al.* (2018:135-136); Chopdar *et al.* (2018:123-124); Chaouali *et al.* (2016:213); Hew *et al.* (2015:1276); Martins *et al.* (2014:11); Yang (2010:265); Venkatesh *et al.* (2003:460)		
	SI3	People whose opinions I value prefer that I use mobile shopping apps to purchase athleisure apparel.	Adapted from Venkatesh *et al.* (2012:178) Supported by Shaw & Sergueeva (2019:53-54); Alalwan *et al.* (2018:135-136); Chopdar *et al.* (2018:123-124); Chaouali *et al.* (2016:213); Hew *et al.* (2015:1276)		
	SI4	People around me consider it appropriate to use mobile shopping apps to purchase athleisure apparel.	Adapted from Chopdar *et al.* (2018:123-124); Hew *et al.* (2015:1276)		
Facilitating conditions (FC)	FC1	I have the resources necessary to use mobile shopping apps to purchase athleisure apparel.	Adapted from Venkatesh *et al.* (2012:178) Supported by Alalwan *et al.* (2018:135-136); Chopdar *et al.* (2018:123-124); Hew *et al.* (2015:1276); Martins *et al.* (2014:11); Venkatesh *et al.* (2003:460)	Scaled	Interval (Likert)
	FC2	I have the knowledge necessary to use mobile shopping apps to purchase athleisure apparel.	Adapted from Venkatesh *et al.* (2012:178) Supported by Alalwan *et al.* (2018:135-136); Chopdar *et al.* (2018:123-124); Hew *et al.* (2015:1276); Martins *et al.* (2014:11); Yang (2010:265); Venkatesh *et al.* (2003:460)		
	FC3	Mobile shopping apps are compatible with other technologies I use when purchasing athleisure apparel.	Adapted from Venkatesh *et al.* (2012:178) Supported by Alalwan *et al.* (2018:135-136); Chopdar *et al.* (2018:123-124); Hew *et al.* (2015:1276); Martins *et al.* (2014:11); Venkatesh *et al.* (2003:460)		

	FC4	I can get help from others when I have difficulties using mobile shopping apps to purchase athleisure apparel.	Adapted from Venkatesh *et al.* (2012:178) Supported by Alalwan *et al.* (2018:135-136); Hew *et al.* (2015:1276); Venkatesh *et al.* (2003:460)		
Hedonic motivation (HM)	HM1	Using mobile shopping apps to browse and/or purchase athleisure apparel is fun.	Adapted from Venkatesh *et al.* (2012:178) Supported by Shaw & Sergueeva (2019:53-54); Alalwan *et al.* (2018:135-136); Chopdar *et al.* (2018:123-124); Hew *et al.* (2015:1276)	Scaled	Interval (Likert)
	HM2	Using mobile shopping apps to browse and/or purchase athleisure apparel is enjoyable.	Adapted from Venkatesh *et al.* (2012:178) Supported by Shaw & Sergueeva (2019:53-54); Alalwan *et al.* (2018:135-136); Chopdar *et al.* (2018:123-124); Hew *et al.* (2015:1276)		
	HM3	Using mobile shopping apps to browse and/or purchase athleisure apparel is very entertaining.	Adapted from Venkatesh *et al.* (2012:178) Supported by Alalwan *et al.* (2018:135-136); Chopdar *et al.* (2018:123-124); Hew *et al.* (2015:1276)		
	HM4	Using mobile shopping apps to browse and/or purchase athleisure apparel is very pleasurable.	Developed by the researcher		
Price value (PV)	PV1	Athleisure apparel available via mobile shopping apps is reasonably priced.	Adapted from Venkatesh *et al.* (2012:178) Supported by Alalwan *et al.* (2018:135-136); Chopdar *et al.* (2018:123-124); Hew *et al.* (2015:1276)	Scaled	Interval (Likert)
	PV2	Athleisure apparel on mobile shopping apps offers good value for money.	Adapted from Venkatesh *et al.* (2012:178) Supported by Alalwan *et al.* (2018:135-136); Chopdar *et al.* (2018:123-124); Hew *et al.* (2015:1276)		
	PV3	At current prices, mobile shopping apps provide good value for athleisure apparel.	Adapted from Venkatesh *et al.* (2012:178) Supported by Alalwan *et al.* (2018:135-136); Chopdar *et al.* (2018:123-124); Hew *et al.* (2015:1276)		
	PV4	Athleisure apparel available via mobile shopping apps is affordable.	Developed by the researcher		
Habit (HT)	HT1	The use of mobile shopping apps to browse and/or purchase	Adapted from Venkatesh *et al.* (2012:178)	Scaled	Interval (Likert)

		athleisure apparel has become a habit for me.	Supported by Alalwan *et al.* (2018:135-136); Chopdar *et al.* (2018:123-124); Hew *et al.* (2015:1276)		
	HT2	I am addicted to using mobile shopping apps to browse and/or purchase athleisure apparel.	Adapted from Venkatesh *et al.* (2012:178) Supported by Alalwan *et al.* (2018:135-136); Chopdar *et al.* (2018:123-124); Hew *et al.* (2015:1276)		
	HT3	I must use mobile shopping apps to browse and/or purchase athleisure apparel.	Adapted from Venkatesh *et al.* (2012:178) Supported by Alalwan *et al.* (2018:135-136); Chopdar *et al.* (2018:123-124); Hew *et al.* (2015:1276)		
	HT4	Using mobile shopping apps to browse and/or purchase athleisure apparel has become natural to me.	Adapted from Venkatesh *et al.* (2012:178) Supported by Alalwan *et al.* (2018:135-136); Chopdar *et al.* (2018:123-124); Hew *et al.* (2015:1276)		
Perceived risk (PR)	FR1	(Financial risk): The chance of me losing money is high when using mobile shopping apps to purchase athleisure apparel.	Adapted from Marriott & Williams (2018:143-144); Martins *et al.* (2014:11); Featherman & Pavlou (2003:470-471)	Scaled	Interval (Likert)
	FR2	(Financial risk): My credit card number may not be secure when using mobile shopping apps to purchase athleisure apparel.	Adapted from Dai *et al.* (2014:19); Forsythe *et al.* (2006:61); McKnight *et al.* (2002:319)		
	FR3	(Financial risk): The use of mobile shopping apps to purchase athleisure apparel is a financial risk.	Adapted from Alalwan *et al.* (2018:135-136); Yang *et al.* (2015:268); Martins *et al.* (2014:11); Featherman & Pavlou (2003:470-471);		
	PPR1	(Product performance risk): The probability of receiving the wrong item is high when using mobile shopping apps to purchase athleisure apparel.	Adapted from Marriott & Williams (2018:143-144); Martins *et al.* (2014:11); Featherman & Pavlou (2003:470-471)		
	PPR2	(Product performance risk): Using a mobile shopping app to purchase athleisure apparel is risky because I can't examine the product before making the payment.	Adapted from Dai *et al.* (2014:19); Forsythe *et al.* (2006:61)		

	PPR3	(Product performance risk): The athleisure apparel product purchased may not be suitable in size, style or colour.	Adapted from Marriott & Williams (2018:143-144); Yang *et al.* (2015:268); Dai *et al.* (2014:19)		
Trust (TR)	TR1	I trust that my mobile device will be reliable when I shop for athleisure apparel via mobile apps.	Adapted from Alalwan *et al.* (2018:135-136)	Scaled	Interval (Likert)
	TR2	I trust the shopping systems available on mobile apps to browse and/or purchase athleisure apparel.	Adapted from Alalwan *et al.* (2018:135-136)		
	TR3	Mobile app retailers selling athleisure apparel are trustworthy.	Adapted from Marriott & Williams (2018:143-144); Martins *et al.* (2014:11)		
	TR4	Mobile app retailers selling athleisure apparel have high integrity.	Adapted from Marriott & Williams (2018:143-144); Forsythe *et al.* (2006:61)		
	TR5	Mobile app retailers selling athleisure apparel have my best interests in mind.	Adapted from Marriott & Williams (2018:143-144); Martins *et al.* (2014:11)		
	TR6	When shopping online for athleisure apparel, I feel that my mobile device is just as reliable as my computer.	Adapted from Alalwan *et al.* (2018:135-136)		
Behavioural intention (BI)	BI1	I intend to use mobile shopping apps to purchase athleisure apparel in the future.	Adapted from Venkatesh *et al.* (2012:178) Supported by Shaw & Sergueeva (2019:53-54); Alalwan *et al.* (2018:135-136); Chopdar *et al.* (2018:123-124); Marriott & Williams (2018:143-144); Chaouali *et al.* (2016:213); Hew *et al.* (2015:1276); Yang *et al.* (2015:269); Martins *et al.* (2014:11); Yang (2010:265); Venkatesh *et al.* (2003:460)	Scaled	Interval (Likert)
	BI2	I will use mobile shopping apps to purchase athleisure apparel where feasible.	Adapted from Shaw & Sergueeva (2019:53-54)		

	BI3	I plan to use mobile shopping apps to purchase athleisure apparel in the future.	Adapted from Alalwan *et al.* (2018:135-136); Chopdar *et al.* (2018:123-124); Chaouali *et al.* (2016:213); Martins *et al.* (2014:11); Venkatesh *et al.* (2003:460)		
	BI4	I predict I will use mobile shopping apps to purchase athleisure apparel in the future.	Adapted from Alalwan *et al.* (2018:135-136); Chopdar *et al.* (2018:123-124); Chaouali *et al.* (2016:213); Hew *et al.* (2015:1276); Martins *et al.* (2014:11); Venkatesh *et al.* (2003:460)		
	BI5	I will use mobile shopping apps to purchase athleisure apparel in my daily life.	Adapted from Venkatesh *et al.* (2012:178) Supported by Alalwan *et al.* (2018:135-136); Marriott & Williams (2018:143-144); Hew *et al.* (2015:1276)		
Actual use (AU)	AU1	When did you last use a mobile shopping app to purchase athleisure apparel (choose only one)? • Last week • Last month • Within the last 3 months • Within the last 6 months • Within the last year	Adapted from Chopdar *et al.* (2018:123-124)	Multiple choice	Nominal
	AU2	How many athleisure apparel items did you purchase during this time (choose only one)? • 1 item • 2-3 items • 4-5 items • 6 or more items	Developed by the researcher	Multiple choice	Nominal
	AU3	In general, how much time do you spend shopping for athleisure apparel via mobile shopping apps per week (choose only one)? • 0-5 minutes • 6-15 minutes • 16-60 minutes • Over 60 minutes	Adapted from Klopping & McKinney (2004:48)	Multiple choice	Nominal

	AU4	On average, how many different mobile shopping apps do you visit in a given month (choose only one)? • 1-2 • 3-4 • 5-6 • 7 or more	Adapted from Klopping & McKinney (2004:48)	Multiple choice	Nominal
	AU5	What was the approximate Rand value of your most recent purchase of athleisure apparel (choose only one)? • R250 or less • R250-R500 • R500-R800 • R800-R1000 • R1000 or more	Developed by the researcher	Multiple choice	Nominal

Annexure 5: Secondary objectives of the study and sections in the questionnaire that represent each secondary objective

Secondary objective	**Items in the questionnaire**
1. To determine whether performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, habit and trust have a positive influence on the behavioural intention of consumers to use mCommerce apps to purchase athleisure apparel.	Section B **PE1-PE4** EE1-EE4 SI1-SI4 FC1-FC4 HM1-HM4 PV1-PV4 HT1-HT4 TR1-TR6
2. To establish whether facilitating conditions and habit have a positive influence on consumers' actual use of mCommerce apps to purchase athleisure apparel.	Section B **FC1-FC4** HT1-HT4
3. To investigate whether perceived risk has a negative influence on the behavioural intention of consumers to use mCommerce apps to purchase athleisure apparel.	Section B FR1-FR3 PPR1-PPR3
4. To determine whether perceived risk has a negative influence on consumers' actual use of mCommerce apps to purchase athleisure apparel.	Section B FR1-FR3 PPR1-PPR3
5. To establish whether trust mediates the influence of perceived risk on the behavioural intention of consumers, and consumers' actual use of mCommerce apps to purchase athleisure apparel.	Section B FR1-FR3 PPR1-PPR3 TR1-TR6
6. To determine whether behavioural intention has a positive influence on consumers' actual use of mCommerce apps to purchase athleisure apparel.	Section C BI1-BI5 AU1-AU5
7. To determine which of the independent variables has the greatest influence on the behavioural intention of consumers to use mCommerce apps to purchase athleisure apparel.	Section B PE1-PE4 EE1-EE4 SI1-SI4 FC1-FC4 HM1-HM4 PV1-PV4 HT1-HT4 FR1-FR3 PPR1-PPR3 TR1-TR6
8. To determine which of the independent variables has the greatest influence on consumers' actual use of mCommerce apps to purchase athleisure apparel.	Section B FC1-FC4 HT1-HT4 FR1-FR3 PPR1-PPR3 BI1-BI5 AU1-AU5

Annexure 6: Development of measurement scales

Constructs	Origin	Scales
Performance expectancy (PE)	Adapted from previously-validated items and scales	Adapted from Venkatesh *et al.* (2012:178) Supported by Shaw & Sergueeva (2019:53-54); Alalwan *et al.* (2018:135-136); Chopdar *et al.* (2018:123-124); Hew *et al.* (2015:1276); Martins *et al.* (2014:11); Venkatesh *et al.* (2003:460)
Effort expectancy (EE)		Adapted from Venkatesh *et al.* (2012:178) Supported by Shaw & Sergueeva (2019:53-54); Alalwan *et al.* (2018:135-136); Chopdar *et al.* (2018:123-124); Chaouali *et al.* (2016:213); Hew *et al.* (2015:1276); Martins *et al.* (2014:11); Yang (2010:265); Venkatesh *et al.* (2003:460)
Social influence (SI)		Adapted from Venkatesh *et al.* (2012:178) Supported by Shaw & Sergueeva (2019:53-54); Alalwan *et al.* (2018:135-136); Chopdar *et al.* (2018:123-124); Chaouali *et al.* (2016:213); Hew *et al.* (2015:1276); Martins *et al.* (2014:11); Yang (2010:265); Venkatesh *et al.* (2003:460)
Facilitating conditions (FC)		Adapted from Venkatesh *et al.* (2012:178) Supported by Alalwan *et al.* (2018:135-136); Chopdar *et al.* (2018:123-124); Hew *et al.* (2015:1276); Martins *et al.* (2014:11); Yang (2010:265); Venkatesh *et al.* (2003:460)
Hedonic motivation (HM)		Adapted from Venkatesh *et al.* (2012:178) Supported by Shaw & Sergueeva (2019:53-54); Alalwan *et al.* (2018:135-136); Chopdar *et al.* (2018:123-124); Hew *et al.* (2015:1276)
Price value (PV)		Adapted from Venkatesh *et al.* (2012:178) Supported by Alalwan *et al.* (2018:135-136); Chopdar *et al.* (2018:123-124); Hew *et al.* (2015:1276)
Habit (HT)		Adapted from Venkatesh *et al.* (2012:178) Supported by Alalwan *et al.* (2018:135-136); Chopdar *et al.* (2018:123-124); Hew *et al.* (2015:1276)
Perceived risk (PR)		Adapted from Alalwan *et al.* (2018:135-136); Marriott & Williams (2018:143-144); Yang *et al.* (2015:268); Dai *et al.* (2014:19); Martins *et al.* (2014:11); Forsythe *et al.* (2006:99); Featherman & Pavlou (2003:470-471); McKnight (2002:319)
Trust (TR)		Adapted from Alalwan *et al.* (2018:135-136); Marriott & Williams (2018:143-144); Martins *et al.* (2014:11); Forsythe *et al.* (2006:99)
Behavioural intention (BI)		Adapted from Venkatesh *et al.* (2012:178) Supported by Shaw & Sergueeva (2019:53-54); Alalwan *et al.* (2018:135-136); Chopdar *et al.* (2018:123-124); Marriott & Williams (2018:143-144); Chaouali *et al.* (2016:213); Hew *et al.* (2015:1276); Yang *et al.* (2015:269); Yang (2010:265); Venkatesh *et al.* (2003:460); Martins *et al.* (2014:11)
Actual use (AU)		Adapted from Chopdar *et al.* (2018:123-124); Klopping & McKinney (2004:48)

Annexure 7: Final questionnaire

mCommerce acceptance and use behaviour: A South African case study

Dear Sir/Madam,

You are invited to participate, by completing this questionnaire, in a study being conducted to determine the factors that influence your acceptance and use of mobile commerce (commonly referred to as mCommerce or mobile shopping) apps to purchase "athleisure" apparel in South Africa. Examples of "athleisure" apparel include:




I HEREBY AGREE TO PARTICIPATE IN THE STUDY:

Yes	1	
No	2	*Please do not continue*

Further details of the study are provided below:

Research title	mCommerce acceptance and use behaviour: A South African case study
Researcher	Karen van Niekerk, University of Johannesburg, College of Business and Economics, School of Consumer Intelligence and Information Systems, Department of Marketing Management
Purpose	To elicit feedback from you regarding the constructs that influence your acceptance and use of mCommerce apps to purchase "athleisure" apparel in South Africa. Such apps include, for example, Superbalist, Takealot.com, Zando, etc.
What does "athleisure" mean?	"Athleisure" is a term used to describe clothing that can be used for both exercising and general wearing.
Procedure	For this study, you will be required to participate in a survey by completing a paper-based questionnaire which will take about 20 minutes to complete.
Risk of participation	There are no known risks associated with this research project.
Benefits	Your participation will contribute to findings that will add to the academic body of knowledge through the compilation of a journal article and a conference paper published in conference proceedings.
Confidentiality	Your response will remain anonymous and confidential, and will not be linked to any identifiable information. Please do not provide your name or personal details on any part of the questionnaire.
Participation right	Your participation in this study is completely voluntary. You have the right to withdraw from this study at any time without any reprisal and / or penalty.
Contact details	Should you have any questions or concerns regarding the completion of this questionnaire, you may contact the researcher on the following details: Researcher: Karen van Niekerk Phone no: 083 376 0258 Email address: karen-vz@hotmail.com

SCREENING QUESTIONS

Indicate your answer by placing an X in the appropriate box or complete where required.

1. DO YOU HAVE A SMARTPHONE?

Yes	1	
No	2	*Please do not continue*

2. HAVE YOU USED AN APP ON YOUR SMARTPHONE TO BROWSE AND/OR BUY "ATHLEISURE" APPAREL (I.E. CLOTHING FOR EXERCISE AND GENERAL WEARING AS DEPICTED IN THE PICTURES ABOVE)? EXAMPLES OF APPS INCLUDE ZANDO, SUPERBALIST OR TAKEALOT.COM

Browse	1	*Please continue to Q3, then complete sections A and B*
Buy	2	*Please continue to Q3, then complete sections A, B and C*
Browse and buy	3	*Please continue to Q3, then complete sections A, B and C*

3. WHEN WAS THE LAST TIME YOU USED AN APP TO BROWSE AND/OR BUY PRODUCTS FROM YOUR SMARTPHONE?

Within the last week	1	Within the last month	2	Within the last year	3
More than 12 months ago	4				

SECTION A: DEMOGRAPHICS

A1. GENDER:

Male	1
Female	2

A2. ETHNICITY:

Black	1	Coloured	3	Other	5
White	2	Asian/Indian	4		

A3. EDUCATION: your *highest level*

Matric/Grade 12	3
National Diploma/Certificate	4
University degree	5
Post-graduate degree	6

A4. HOW OLD ARE YOU?

18 – 24 years old	1
25 – 29 years old	2
30 – 35 years old	3
35 – 40 years	4
Older than 40*	5
*Please write down your age	

A5. HOME LANGUAGE:

Afrikaans	1	English	2	Ndebele	3
Northern Sotho	4	Sotho	5	Swazi	6
Tsonga	7	Tswana	8	Venda	9
Xhosa	10	Zulu	11	Other (specify)______________	12

A6. EMPLOYMENT STATUS:

Self-employed	1
Full-time employed by organisation	2
Part-time employed by organisation	3
Full-time student	4
Part-time student	5
Home executive	6
Unemployed	7
Retired	8

A7: OF THE "ATHLEISURE" APPAREL YOU PURCHASE, WHAT PROPORTION IS PURCHASED ONLINE AND IN-STORE?

All online	1
Most online	2
About half online and half in-store	3
Most in-store	4
All in-store	5

SECTION B: CONSTRUCTS INFLUENCING BEHAVIOURAL INTENTION (ACCEPTANCE)

INDICATE YOUR ANSWER BY PLACING AN X IN THE APPROPRIATE BOX, WHERE 1 INDICATES "STRONGLY DISAGREE" AND 5 INDICATES "STRONGLY AGREE"

NOTE: "ATHLEISURE" APPAREL REFERS TO CLOTHING FOR EXERCISE AND GENERAL WEARING AS DEPICTED IN THE PICTURES ABOVE.

Performance Expectancy (PE)	Strongly disagree				Strongly agree
I find mobile shopping useful in my daily life when browsing and/or purchasing **"athleisure"** apparel.	1	2	3	4	5
Using mobile shopping apps helps me to do my shopping for **"athleisure"** apparel more quickly.	1	2	3	4	5
Using mobile shopping apps increases my chances of achieving tasks that are important to me, such as browsing and/or purchasing **"athleisure"** apparel.	1	2	3	4	5
Using mobile shopping apps for browsing and/or purchasing **"athleisure"** apparel increases my productivity.	1	2	3	4	5
Effort Expectancy (EE)	Strongly disagree				Strongly agree
Learning how to use mobile shopping apps to browse and/or purchase **"athleisure"** apparel is easy for me.	1	2	3	4	5
My interaction with mobile shopping apps when browsing and/or purchasing **"athleisure"** apparel is clear and understandable.	1	2	3	4	5
I find mobile shopping apps easy to use when browsing and/or purchasing **"athleisure"** apparel.	1	2	3	4	5
It is easy for me to become skilful at using mobile shopping apps to browse and/or purchase **"athleisure"** apparel.	1	2	3	4	5
Social Influence (SI)	Strongly disagree				Strongly agree
People who are important to me think that I should use mobile shopping apps to browse and/or purchase **"athleisure"** apparel.	1	2	3	4	5
People who influence my behaviour think that I should use mobile shopping apps to browse and/or purchase **"athleisure"** apparel.	1	2	3	4	5
People whose opinions I value prefer that I use mobile shopping apps to browse and/or purchase **"athleisure"** apparel.	1	2	3	4	5
People around me consider it appropriate to use mobile shopping apps to browse and/or purchase **"athleisure"** apparel.	1	2	3	4	5
Facilitating Conditions (FC)	Strongly disagree				Strongly agree
I have the resources necessary to use mobile shopping apps to browse and/or purchase **"athleisure"** apparel.	1	2	3	4	5
I have the knowledge necessary to use mobile shopping apps to browse and/or purchase **"athleisure"** apparel.	1	2	3	4	5
Mobile shopping apps are compatible with other technologies I use when browsing and/or purchasing **"athleisure"** apparel.	1	2	3	4	5
I can get help from others when I have difficulties using mobile shopping apps to browse and/or purchase **"athleisure"** apparel.	1	2	3	4	5
Hedonic Motivation (HM)	Strongly disagree				Strongly agree
Using mobile shopping apps to browse and/or purchase **"athleisure"** apparel is fun.	1	2	3	4	5
Using mobile shopping apps to browse and/or purchase **"athleisure"** apparel is enjoyable.	1	2	3	4	5
Using mobile shopping apps to browse and/or purchase **"athleisure"** apparel is very entertaining.	1	2	3	4	5
Using mobile shopping apps to browse and/or purchase **"athleisure"** apparel is very pleasurable.	1	2	3	4	5
Price Value (PV)	Strongly disagree				Strongly agree

“Athleisure” apparel available via mobile shopping apps is reasonably priced.	1	2	3	4	5
“Athleisure” apparel on mobile shopping apps offers good value for money.	1	2	3	4	5
At current prices, mobile shopping apps provide good value for **“athleisure”** apparel.	1	2	3	4	5
“Athleisure” apparel available via mobile shopping apps is affordable.	1	2	3	4	5

Habit (HT)	Strongly disagree				Strongly agree
The use of mobile shopping apps to browse and/or purchase **“athleisure”** apparel has become a habit for me.	1	2	3	4	5
I am addicted to using mobile shopping apps to browse and/or purchase **“athleisure”** apparel.	1	2	3	4	5
I must use mobile shopping apps to browse and/or purchase **“athleisure”** apparel.	1	2	3	4	5
Using mobile shopping apps to browse and/or purchase **“athleisure”** apparel has become natural to me.	1	2	3	4	5
Perceived Risk (PR)	Strongly disagree				Strongly agree
The chance of me losing money is high when using mobile shopping apps to purchase **“athleisure”** apparel.	1	2	3	4	5
My credit card number may not be secure when using mobile shopping apps to purchase **“athleisure”** apparel.	1	2	3	4	5
The use of mobile shopping apps to purchase **“athleisure”** apparel is a financial risk.	1	2	3	4	5
The probability of receiving the wrong item is high when using mobile shopping apps to purchase **“athleisure”** apparel.	1	2	3	4	5
Using a mobile shopping app to purchase **“athleisure”** apparel is risky because I can’t examine the product before making the payment.	1	2	3	4	5
The **“athleisure”** apparel product purchased may not be suitable in size, style or colour.	1	2	3	4	5
Trust (TR)	Strongly disagree				Strongly agree
I trust that my mobile device will be reliable when I shop for **“athleisure”** apparel via mobile apps.	1	2	3	4	5
I trust the shopping systems available on mobile apps to browse and/or purchase **“athleisure”** apparel.	1	2	3	4	5
Mobile app retailers selling **“athleisure”** apparel are trustworthy.	1	2	3	4	5
Mobile app retailers selling **“athleisure”** apparel have high integrity.	1	2	3	4	5
Mobile app retailers selling **“athleisure”** apparel have my best interests in mind.	1	2	3	4	5
When shopping online for **“athleisure”** apparel, I feel that my mobile device is just as reliable as my computer.	1	2	3	4	5
Behavioural Intention (BI)	Strongly disagree				Strongly agree
I intend to use mobile shopping apps to purchase **“athleisure”** apparel in the future.	1	2	3	4	5
I will use mobile shopping apps to purchase **“athleisure”** apparel where feasible.	1	2	3	4	5
I plan to use mobile shopping apps to purchase **“athleisure”** apparel in the future.	1	2	3	4	5
I predict I will use mobile shopping apps to purchase **“athleisure”** apparel in the future.	1	2	3	4	5
I will use mobile shopping apps to purchase **"athleisure"** apparel in my daily life.	1	2	3	4	5

Please only continue to the next section if you answered “Buy” or “Browse or buy” under question 2 of the screening questions.

SECTION C: USE OF MOBILE SHOPPING APPS (USE BEHAVIOUR)

INDICATE YOUR ANSWER BY PLACING AN X IN THE APPROPRIATE BOX OR COMPLETE WHERE REQUIRED.

NOTE: "ATHLEISURE" APPAREL REFERS TO CLOTHING FOR EXERCISE AND GENERAL WEARING AS DEPICTED IN THE PICTURES ABOVE.

Actual Use (AU)	
When last did you use a mobile shopping app to purchase **"athleisure"** apparel (choose only one)?	
1	Last week
2	Last month
3	Within the last 3 months
4	Within the last 6 months
5	Within the last year
How many **"athleisure"** apparel items did you purchase during this time (choose only one)?	
1	1 item
2	2-3 items
3	4-5 items
4	6 or more items
In general, how much time do you spend shopping for **"athleisure"** apparel via mobile shopping apps per week (choose only one)?	
1	0-5 minutes
2	6-15 minutes
3	16-60 minutes
4	Over 60 minutes
On average, how many different mobile shopping apps do you visit in a given month (choose only one)?	
1	1-2
2	3-4
3	5-6
4	7 or more
What was the approximate Rand value of your most recent purchase of **"athleisure"** apparel (choose only one)?	
1	R250 or less
2	R250-R500
3	R500-R800
4	R800-R1000
5	R1000 or more

Thank you again for taking the time to complete this questionnaire.

Annexure 8: Pilot test results: Reliability statistics

Construct	**No of items**	**Cronbach's alpha**	**Cronbach's alpha based on standardised items**
Performance expectancy (PE)	4	0.808	0.813
Effort expectancy (EE)	4	0.913	0.913
Social influence (SI)	4	0.846	0.849
Facilitating conditions (FC)	4	0.865	0.882
Hedonic motivation (HM)	4	0.896	0.895
Price value (PV)	4	0.661	0.659
Habit (HT)	4	0.845	0.846
Perceived risk (PR)	6	0.838	0.839
Trust (TR)	6	0.855	0.858
Behavioural intention (BI)	5	0.908	0.914

Annexure 9: Pilot test results: Item-Total statistics

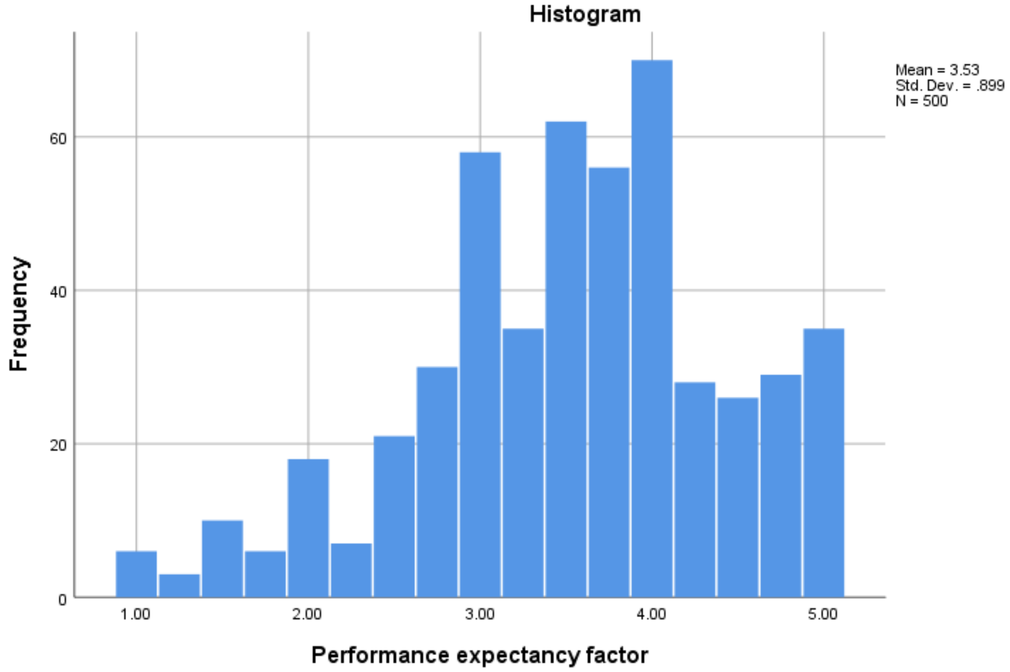
Code	Item	Scale mean if item deleted	Scale variance if item deleted	Corrected item - total correlation	Squared multiple correlation	Cronbach's alpha if item deleted
Performance expectancy (PE)						
PE1	I find mobile shopping useful in my daily life when browsing and/or purchasing athleisure apparel.	10.95	8.213	0.619	0.414	0.763
PE2	Using mobile shopping apps helps me to do my shopping for athleisure apparel more quickly.	11.18	7.668	0.639	0.438	0.752
PE3	Using mobile shopping apps increases my chances of achieving tasks that are important to me, such as browsing and/or purchasing athleisure apparel.	11.32	7.681	0.701	0.492	0.724
PE4	Using mobile shopping apps for browsing and/or purchasing athleisure apparel increases my productivity.	11.55	7.497	0.558	0.344	0.798
Effort expectancy (EE)						
EE1	Learning how to use mobile shopping apps to browse and/or purchase athleisure apparel is easy for me.	12.44	9.989	0.768	0.619	0.898
EE2	My interaction with mobile shopping apps when browsing and/or purchasing athleisure apparel is clear and understandable.	12.64	9.657	0.817	0.692	0.881
EE3	I find mobile shopping apps easy to use when browsing and/or purchasing athleisure apparel.	12.74	9.301	0.821	0.711	0.880
EE4	It is easy for me to become skilful at using mobile shopping apps to browse and/or purchase athleisure apparel.	12.72	9.629	0.799	0.665	0.888
Social influence (SI)						
SI1	People who are important to me think that I should use mobile shopping apps to purchase athleisure apparel.	9.51	10.572	0.559	0.512	0.856
SI2	People who influence my behaviour think that I should use mobile shopping apps to purchase athleisure apparel.	9.18	9.730	0.797	0.691	0.760
SI3	People whose opinions I value prefer that I use mobile shopping apps to purchase athleisure apparel.	9.46	9.571	0.695	0.653	0.799
SI4	People around me consider it appropriate to use mobile shopping apps to purchase athleisure apparel.	9.00	9.421	0.698	0.554	0.798

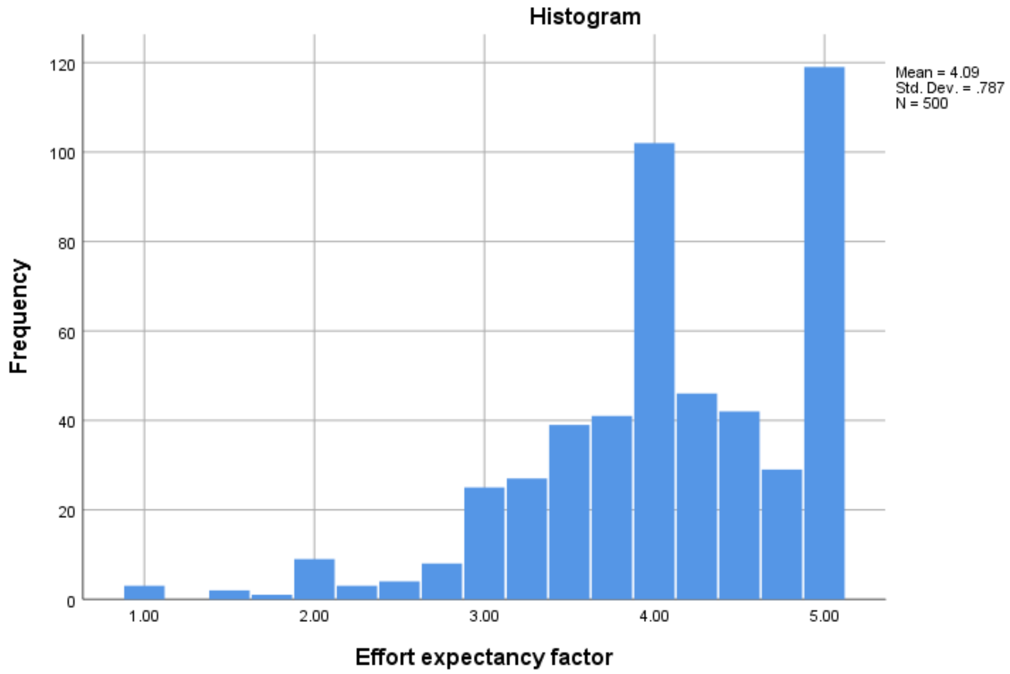
Facilitating conditions (FC)						
FC1	I have the resources necessary to use mobile shopping apps to purchase athleisure apparel.	12.28	9.945	0.807	0.794	0.800
FC2	I have the knowledge necessary to use mobile shopping apps to purchase athleisure apparel.	12.26	9.985	0.826	0.831	0.796
FC3	Mobile shopping apps are compatible with other technologies I use when purchasing athleisure apparel.	12.67	8.439	0.755	0.630	0.813
FC4	I can get help from others when I have difficulties using mobile shopping apps to purchase athleisure apparel.	12.87	9.641	0.557	0.330	0.902
Hedonic motivation (HM)						
HM1	Using mobile shopping apps to browse and/or purchase athleisure apparel is fun.	11.03	10.499	0.776	0.735	0.864
HM2	Using mobile shopping apps to browse and/or purchase athleisure apparel is enjoyable.	11.03	9.605	0.886	0.873	0.821
HM3	Using mobile shopping apps to browse and/or purchase athleisure apparel is very entertaining.	11.28	11.787	0.582	0.374	0.929
HM4	Using mobile shopping apps to browse and/or purchase athleisure apparel is very pleasurable.	11.36	9.499	0.847	0.798	0.835
Price value (PV)						
PV1	Athleisure apparel available via mobile shopping apps is reasonably priced.	10.15	4.765	0.538	0.363	0.524
PV2	Athleisure apparel on mobile shopping apps offers good value for money.	10.28	4.787	0.589	0.705	0.491
PV3	At current prices, mobile shopping apps provide good value for athleisure apparel.	10.13	4.588	0.641	0.759	0.451
PV4	Athleisure apparel available via mobile shopping apps is expensive.	10.44	6.989	0.079	0.108	0.807
Habit (HT)						
HT1	The use of mobile shopping apps to browse and/or purchase athleisure apparel has become a habit for me.	7.39	10.408	0.651	0.521	0.817
HT2	I am addicted to using mobile shopping apps to browse and/or purchase athleisure apparel.	7.95	10.105	0.738	0.611	0.777
HT3	I must use mobile shopping apps to browse and/or purchase athleisure apparel.	8.00	11.297	0.673	0.562	0.807

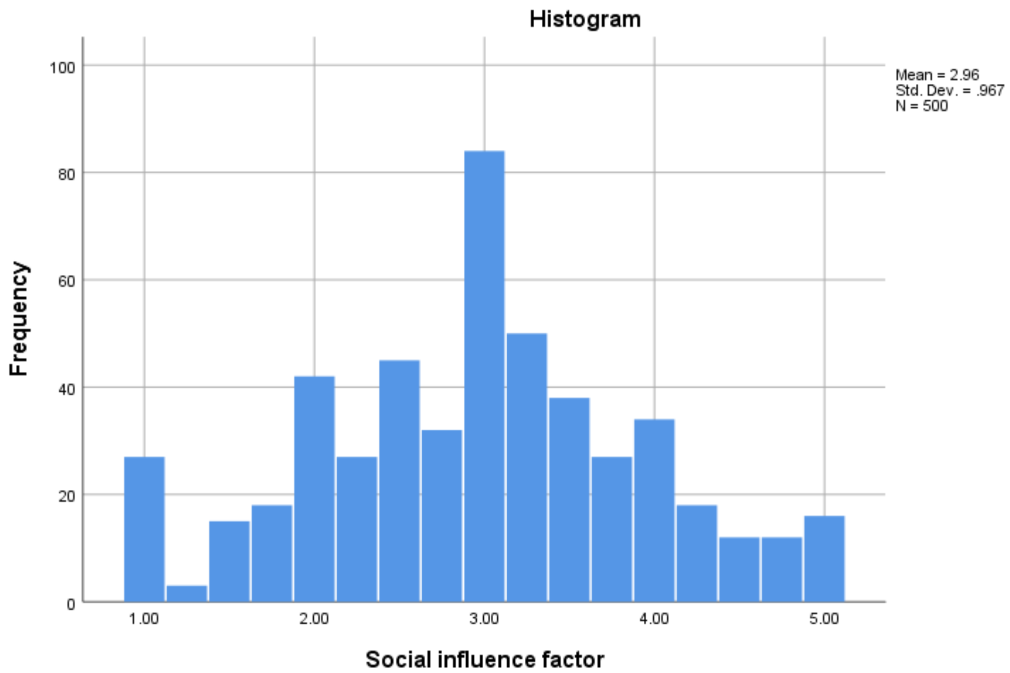
HT4	Using mobile shopping apps to browse and/or purchase athleisure apparel has become natural to me.	7.53	10.905	0.667	0.499	0.809
Perceived risk (PR)						
FR1	(Financial risk): The chance of me losing money is high when using mobile shopping apps to purchase athleisure apparel.	17.54	19.590	0.597	0.467	0.816
FR2	(Financial risk): My credit card number may not be secure when using mobile shopping apps to purchase athleisure apparel.	17.29	19.570	0.633	0.540	0.808
FR3	(Financial risk): The use of mobile shopping apps to purchase athleisure apparel is a financial risk.	17.35	19.443	0.680	0.518	0.799
PPR1	(Product performance risk): The probability of receiving the wrong item is high when using mobile shopping apps to purchase athleisure apparel.	17.16	19.821	0.674	0.482	0.800
PPR2	(Product performance risk): Using a mobile shopping app to purchase athleisure apparel is risky because I can't examine the product before making the payment.	16.86	20.821	0.575	0.518	0.820
PPR3	(Product performance risk): The athleisure apparel product purchased may not be suitable in size, style or colour.	16.87	21.494	0.531	0.450	0.828
Trust (TR)						
TR1	I trust that my mobile device will be reliable when I shop for athleisure apparel via mobile apps.	17.92	18.183	0.673	0.588	0.825
TR2	I trust the shopping systems available on mobile apps to browse and/or purchase athleisure apparel.	18.11	17.502	0.617	0.596	0.838
TR3	Mobile app retailers selling athleisure apparel are trustworthy.	18.34	17.420	0.779	0.793	0.805
TR4	Mobile app retailers selling athleisure apparel have high integrity.	18.26	19.280	0.649	0.748	0.831
TR5	Mobile app retailers selling athleisure apparel have my best interests in mind.	18.26	18.199	0.633	0.512	0.832
TR6	When shopping online for athleisure apparel, I feel that my mobile device is just as reliable as my computer.	17.79	19.198	0.529	0.365	0.851
Behavioural intention (BI)						

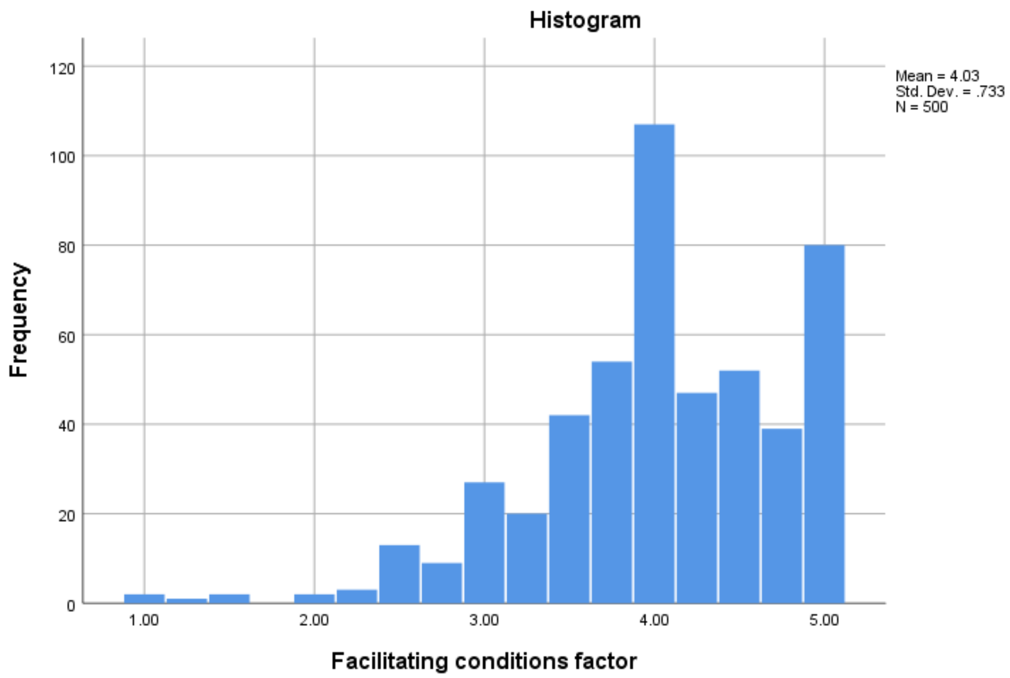
BI1	I intend to use mobile shopping apps to purchase athleisure apparel in the future.	15.67	16.807	0.873	0.828	0.864
BI2	I will use mobile shopping apps to purchase athleisure apparel where feasible.	15.79	18.799	0.733	0.602	0.895
BI3	I plan to use mobile shopping apps to purchase athleisure apparel in the future.	15.67	17.544	0.845	0.806	0.872
BI4	I predict I will use mobile shopping apps to purchase athleisure apparel in the future.	15.64	17.289	0.826	0.687	0.875
BI5	I will use mobile shopping apps to purchase athleisure apparel in my daily life.	16.41	17.301	0.617	0.429	0.928

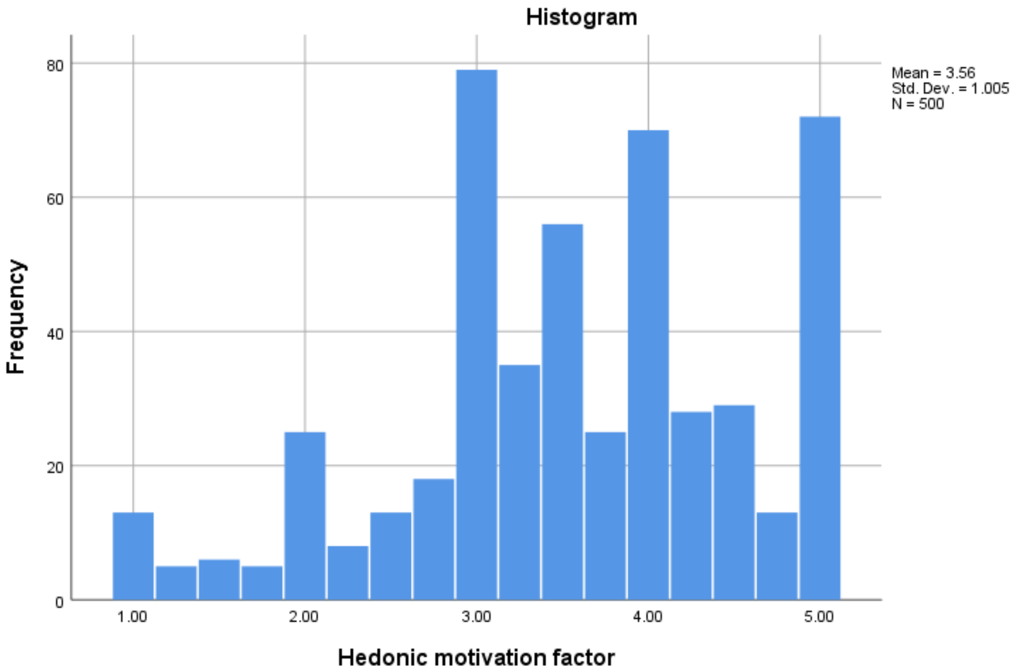
Annexure 10: Histograms for each Model A construct

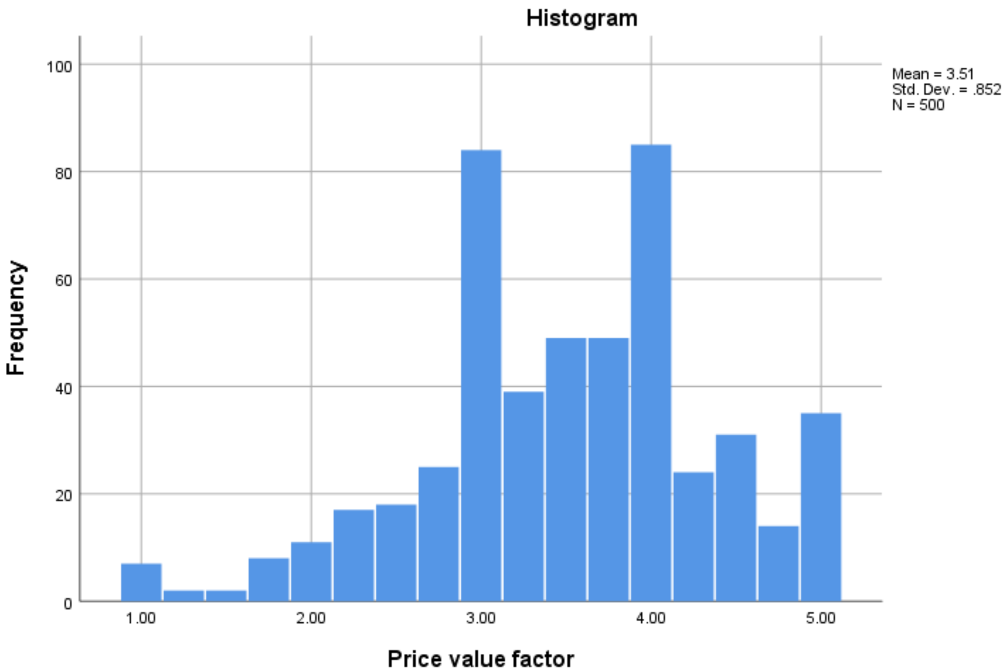


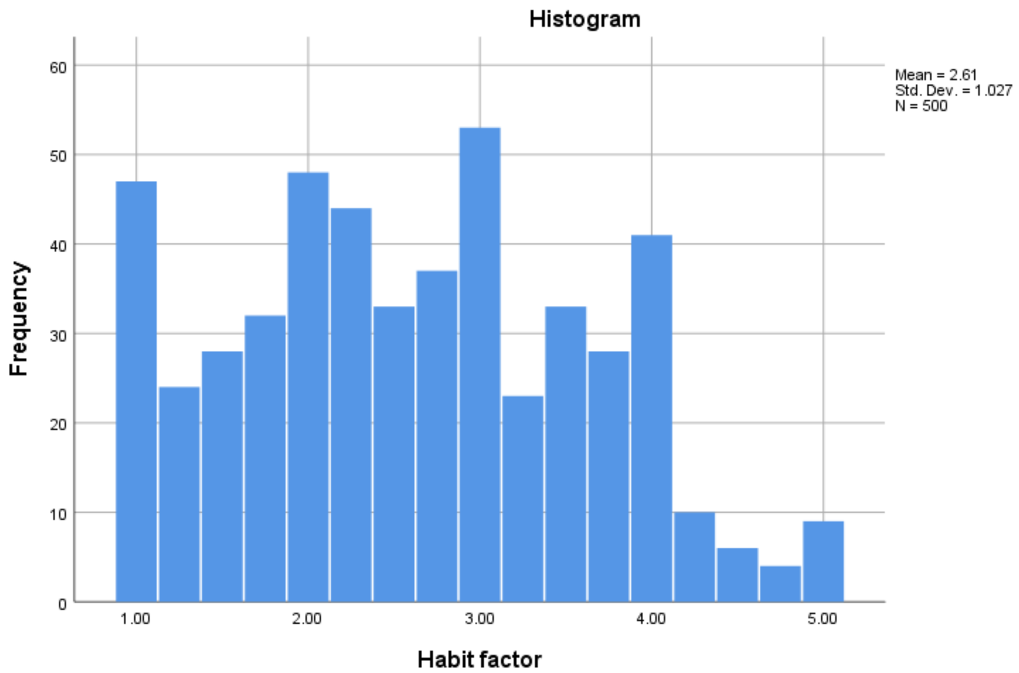


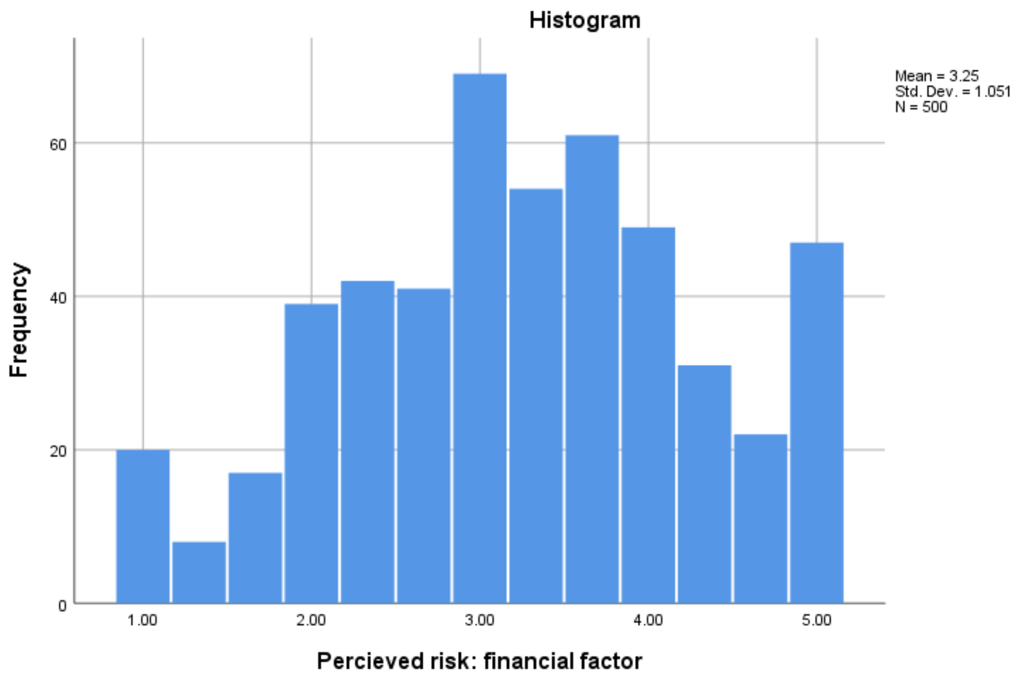

Histogram
Mean = 2.96
Std. Dev. = .967
N = 500
Frequency
0
20
40
60
80
100
1.00
2.00
3.00
4.00
5.00
Social influence factor

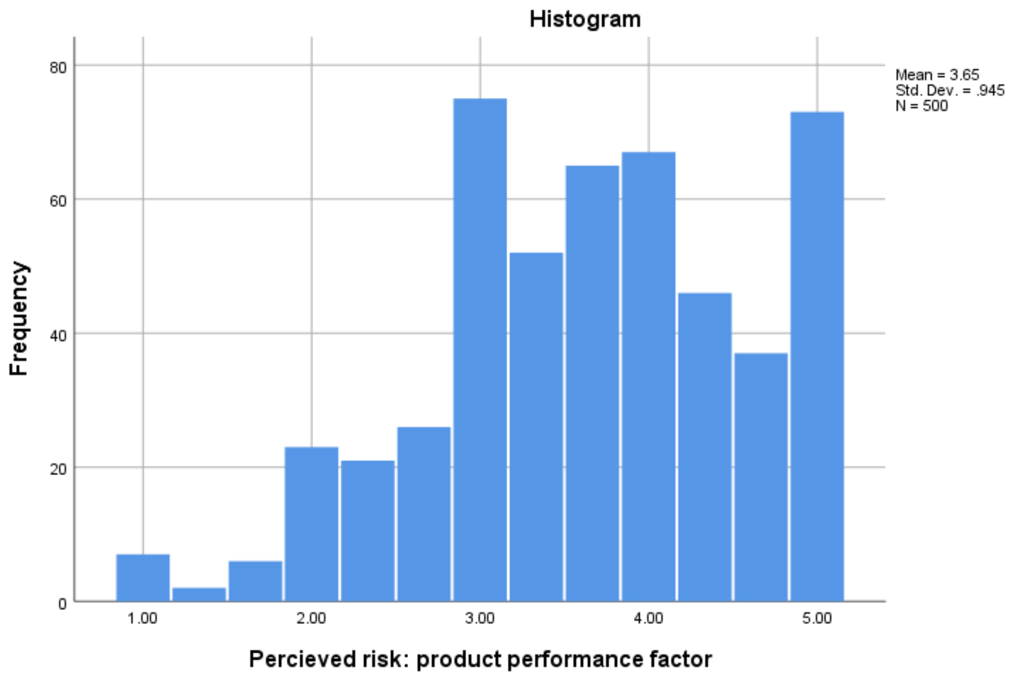

Histogram
Mean = 4.03
Std. Dev. = .733
N = 500
Frequency
0
20
40
60
80
100
120
1.00
2.00
3.00
4.00
5.00
Facilitating conditions factor

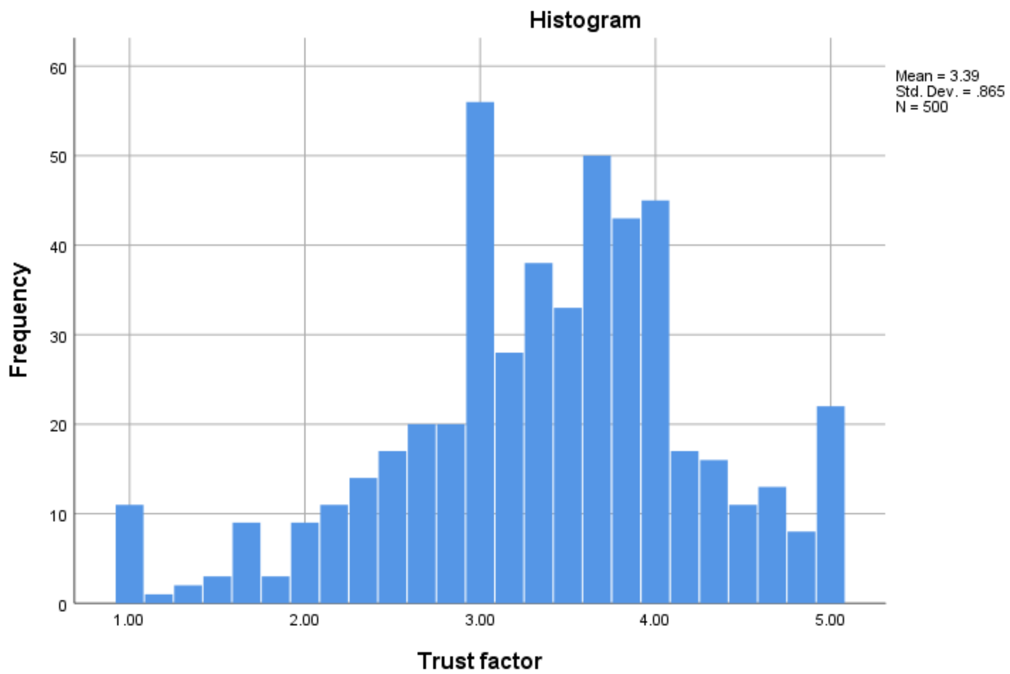

Histogram
Mean = 3.56
Std. Dev. = 1.005
N = 500
Frequency
0
20
40
60
80
1.00
2.00
3.00
4.00
5.00
Hedonic motivation factor

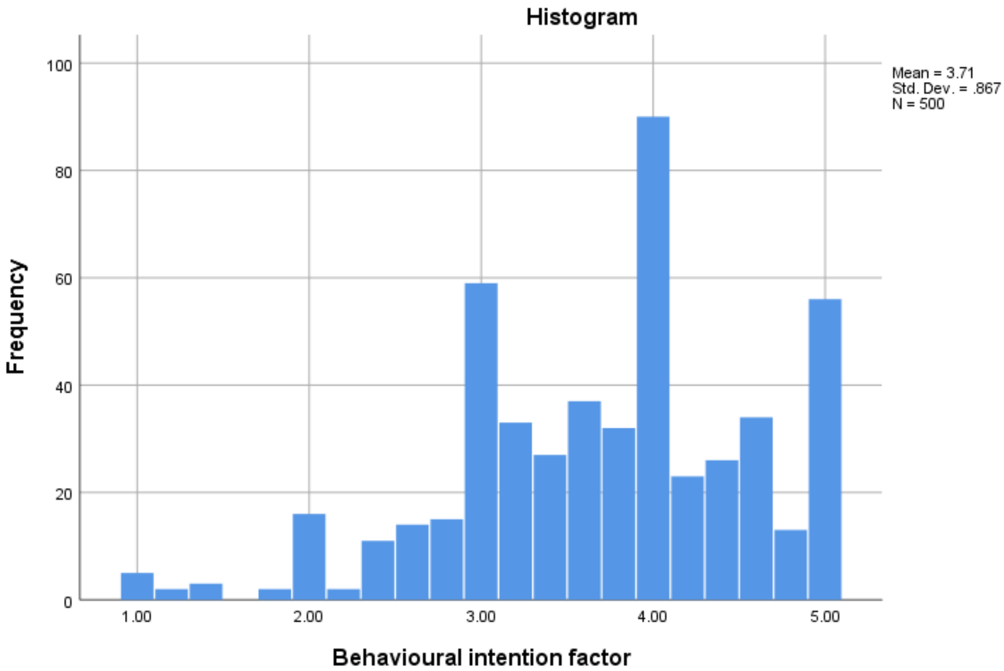

Histogram
Mean = 3.51
Std. Dev. = .852
N = 500
Frequency
0
20
40
60
80
100
1.00
2.00
3.00
4.00
5.00
Price value factor


Histogram
Mean = 2.61
Std. Dev. = 1.027
N = 500
Frequency
0
10
20
30
40
50
60
1.00
2.00
3.00
4.00
5.00
Habit factor

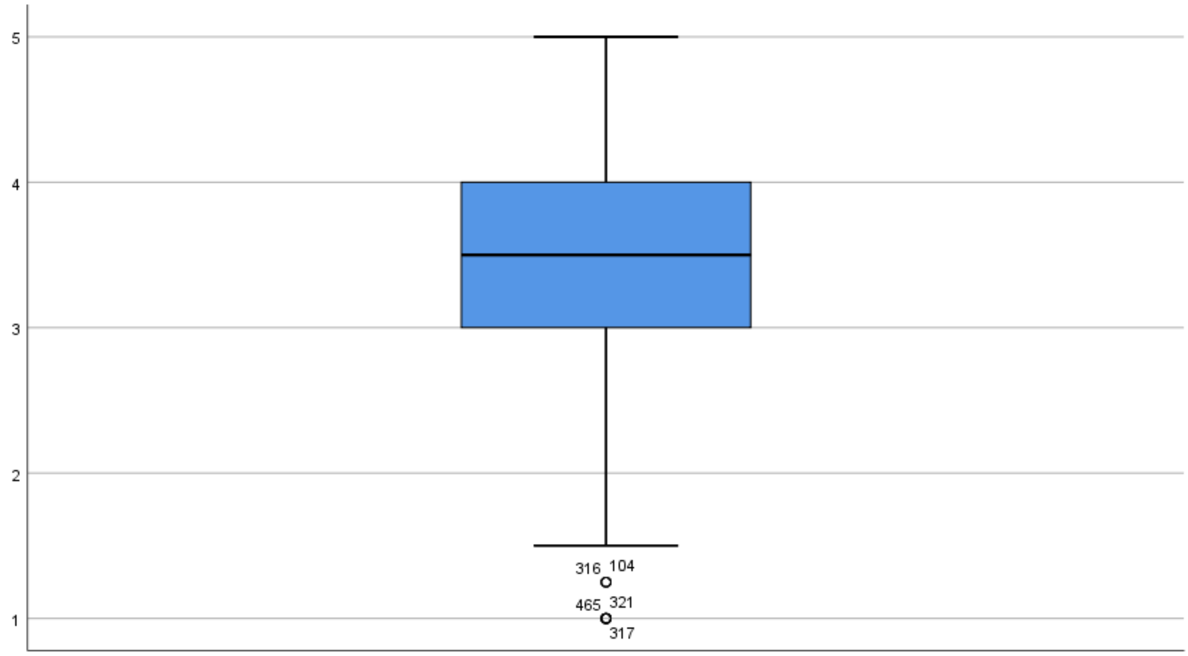

Histogram
Mean = 3.25
Std. Dev. = 1.051
N = 500
Frequency
0
20
40
60
1.00
2.00
3.00
4.00
5.00
Percieved risk: financial factor


Histogram
80
60
40
20
0
Frequency
1.00
2.00
3.00
4.00
5.00
Percieved risk: product performance factor
Mean = 3.65
Std. Dev. = .945
N = 500

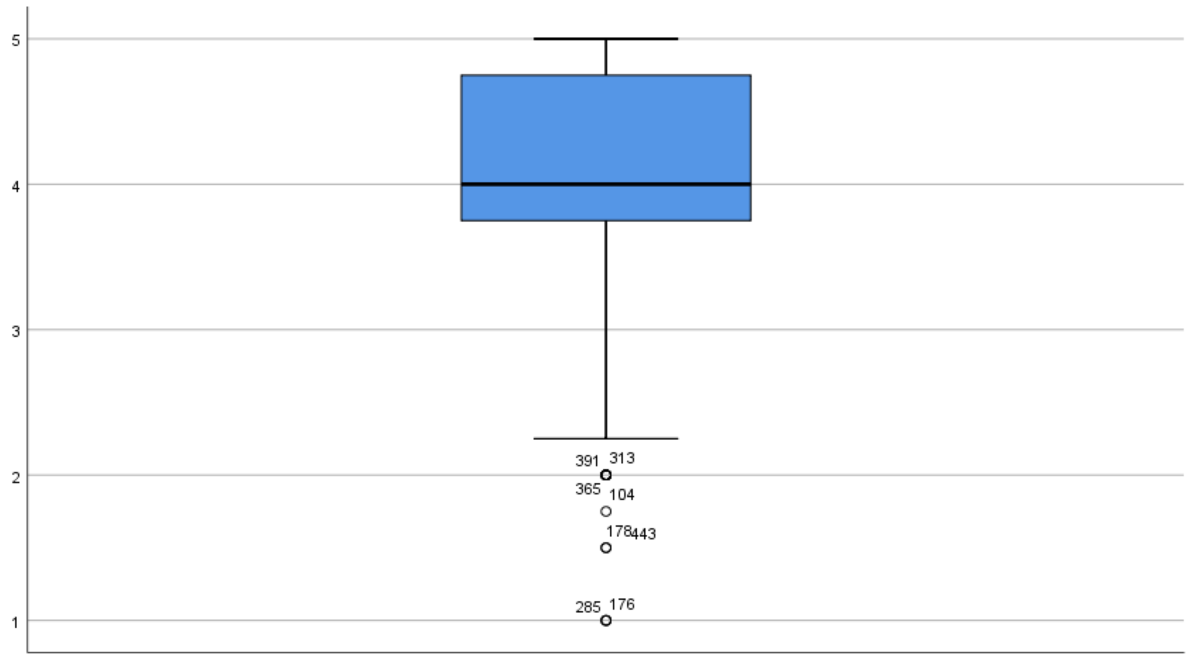

Histogram
60
50
40
30
20
10
0
Frequency
1.00
2.00
3.00
4.00
5.00
Trust factor
Mean = 3.39
Std. Dev. = .865
N = 500


Histogram
Mean = 3.71
Std. Dev. = .867
N = 500
Frequency
0
20
40
60
80
100
1.00
2.00
3.00
4.00
5.00
Behavioural intention factor

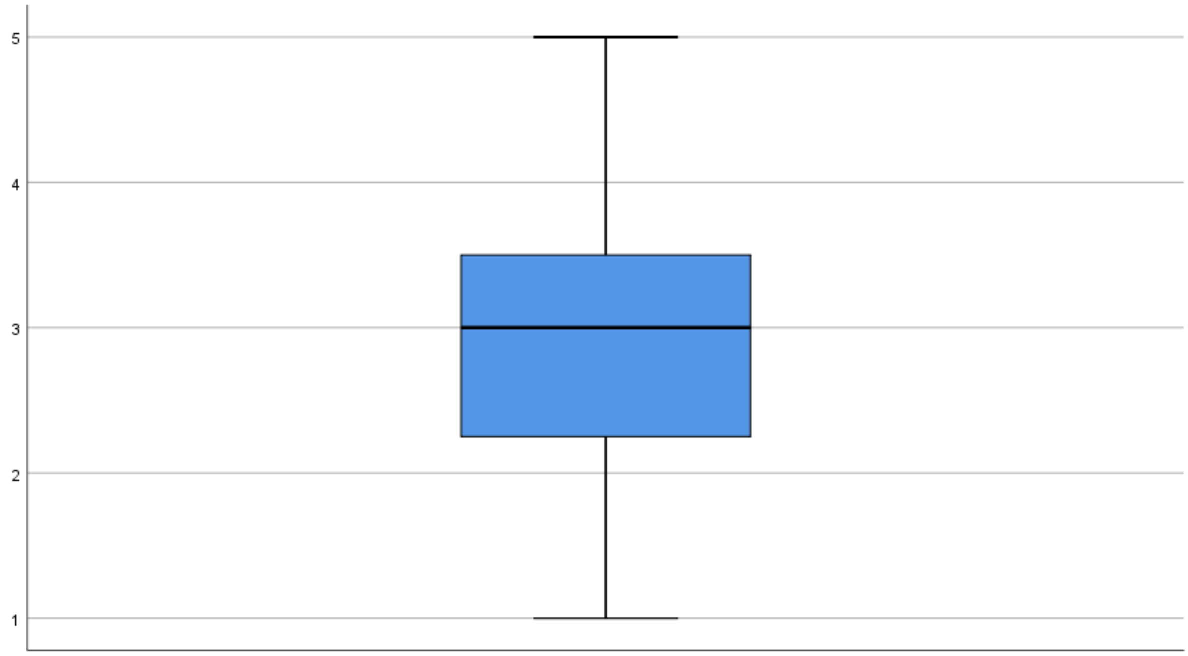
Annexure 11: Box and whisker plots for each Model A construct

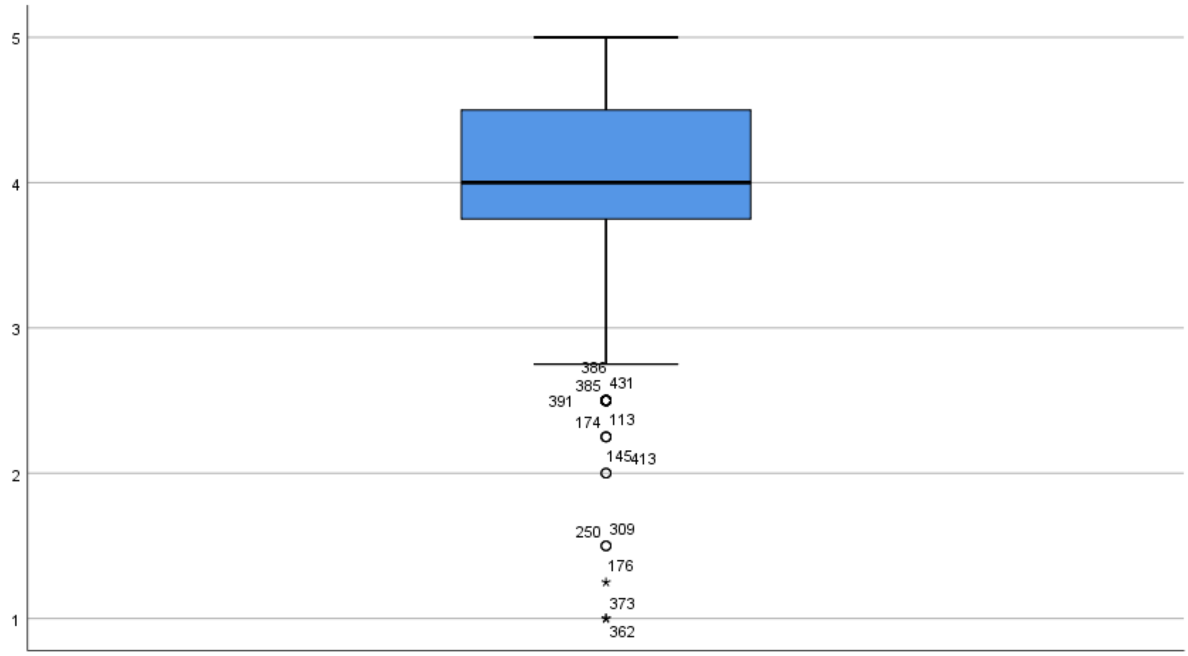


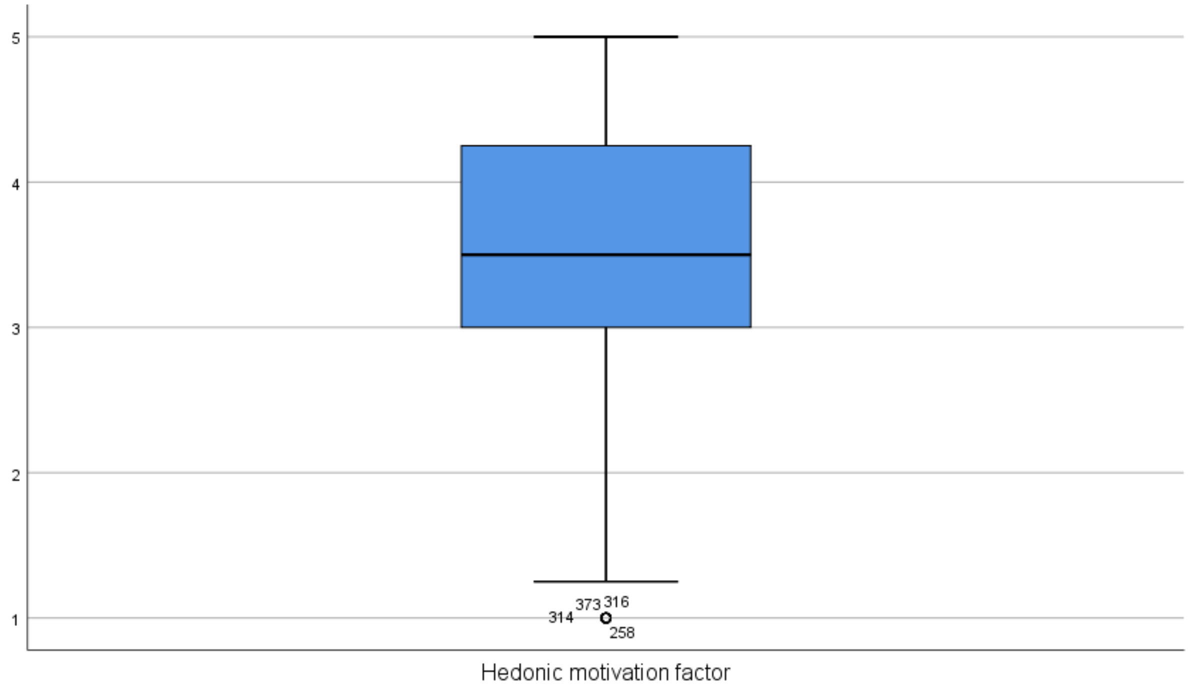
Performance expectancy factor

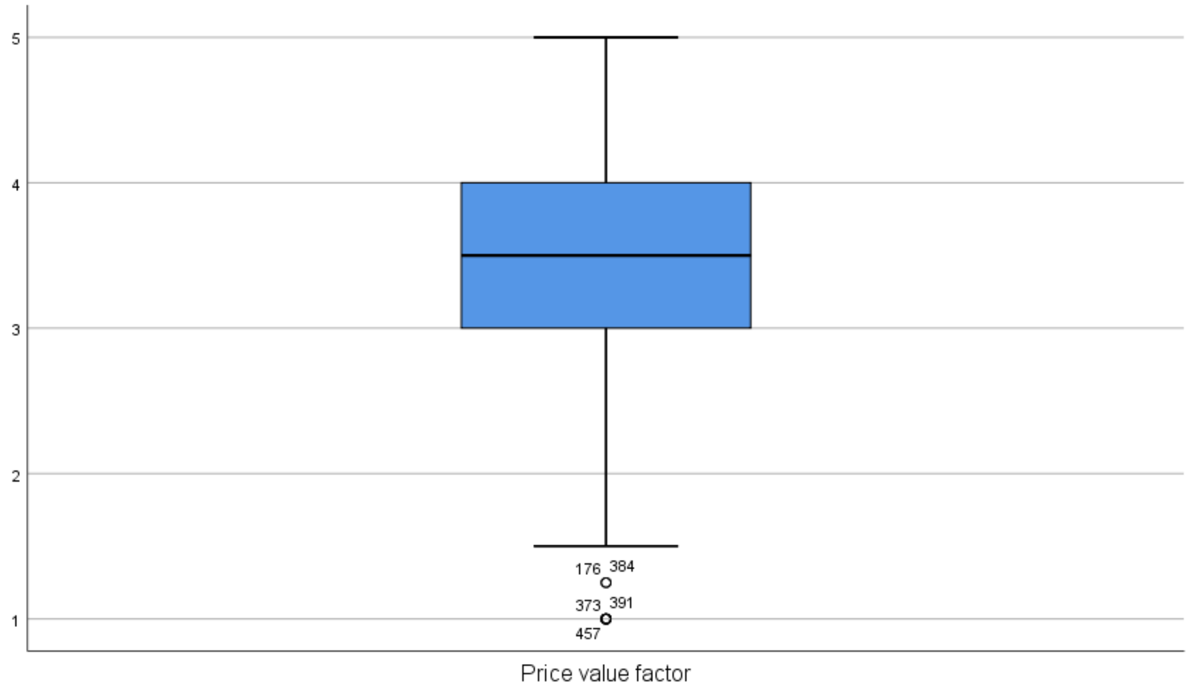


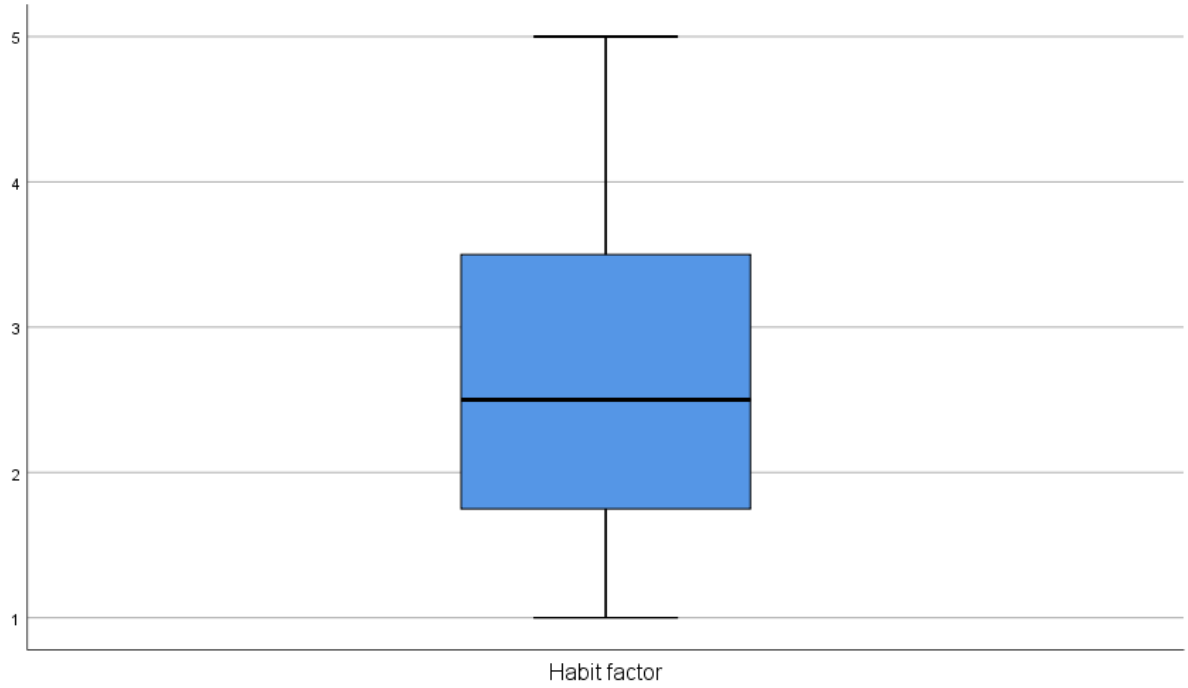
Effort expectancy factor

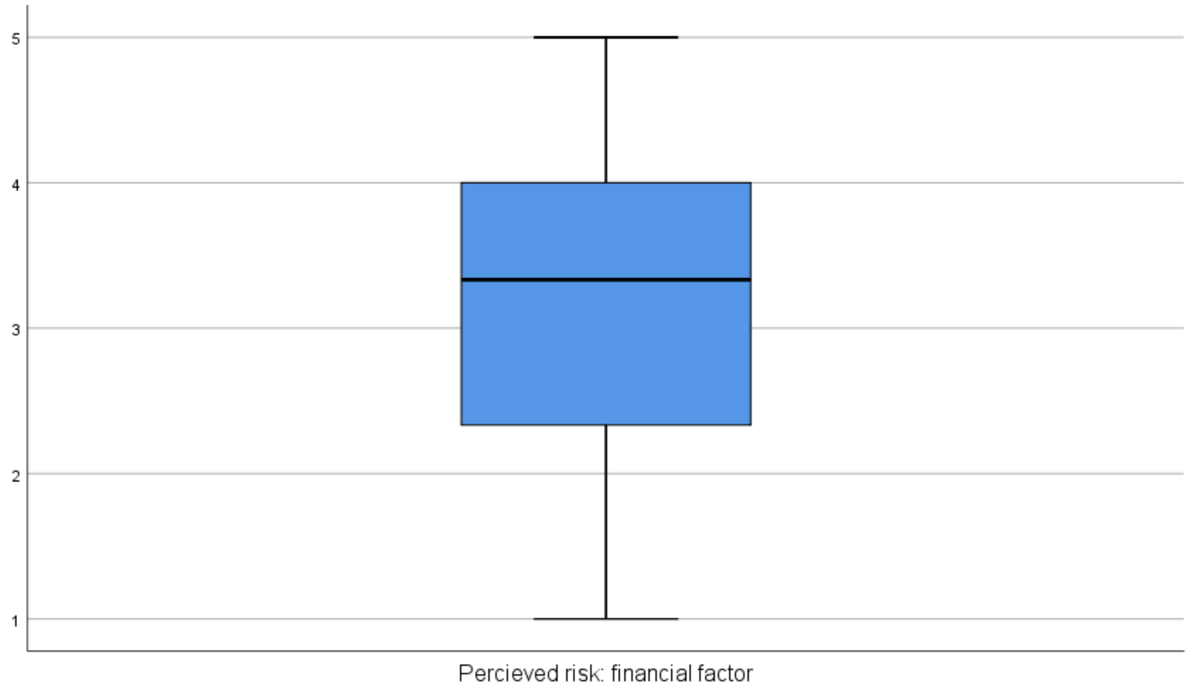

5
4
3
2
1
Social influence factor

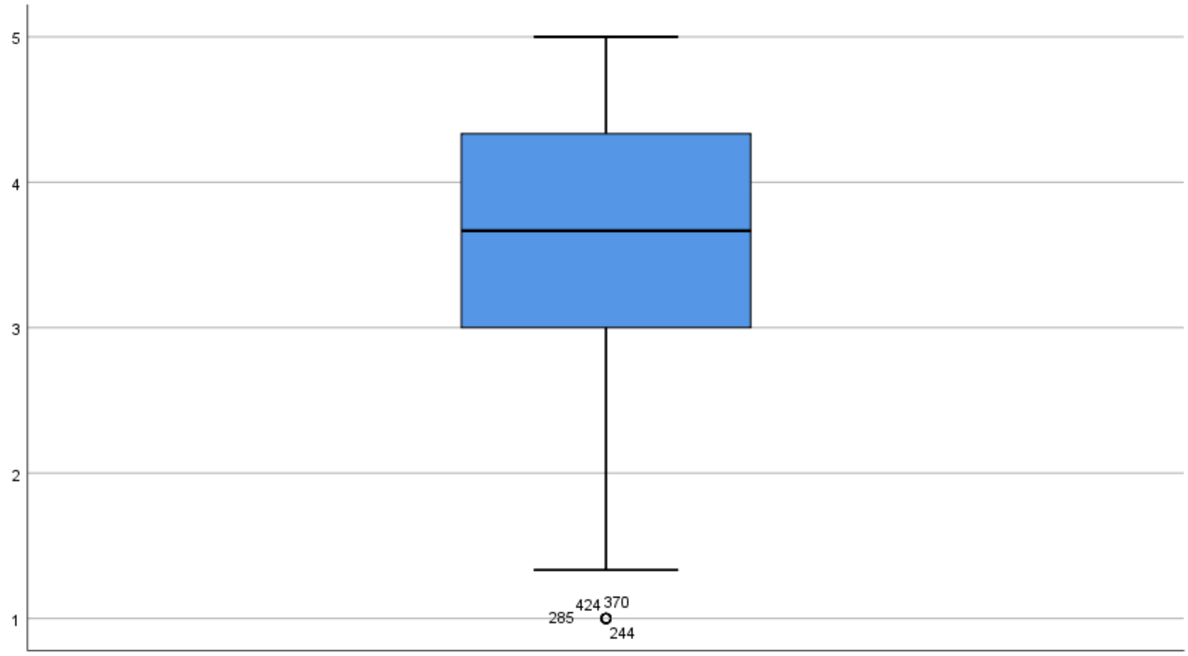

5
4
3
2
1
386
385
431
391
174
113
145
413
250
309
176
373
362
Facilitating conditions factor


5
4
3
2
1
373 316
314
258
Hedonic motivation factor

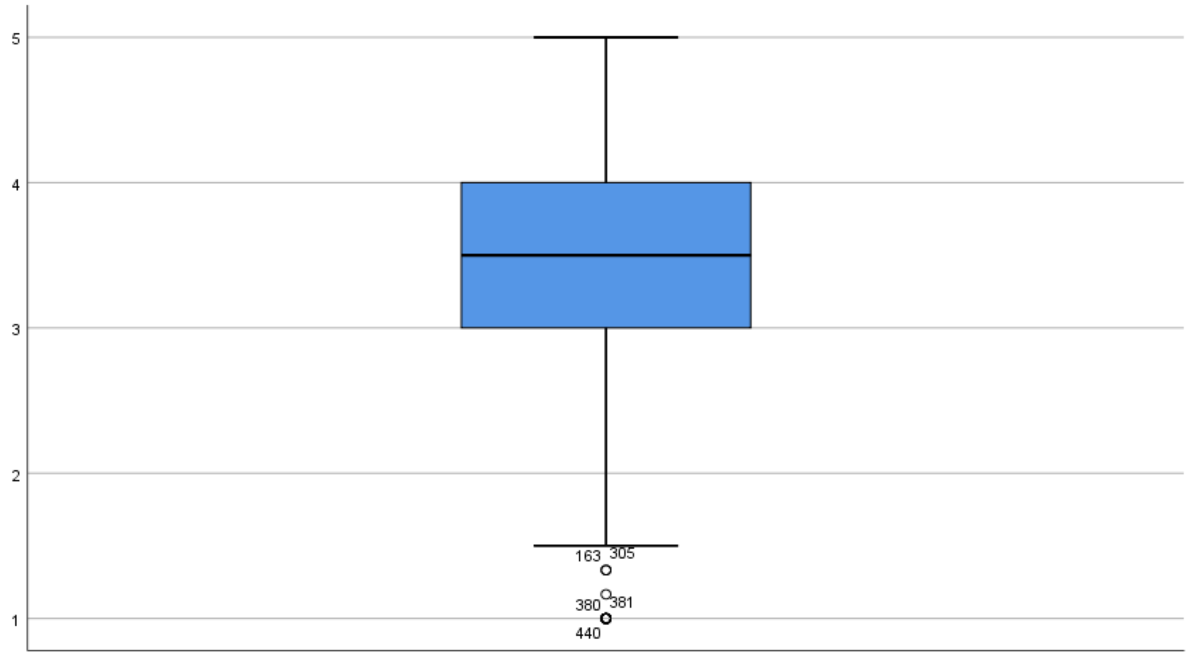

5
4
3
2
1
176 384
373 391
457
Price value factor


5
4
3
2
1
Habit factor

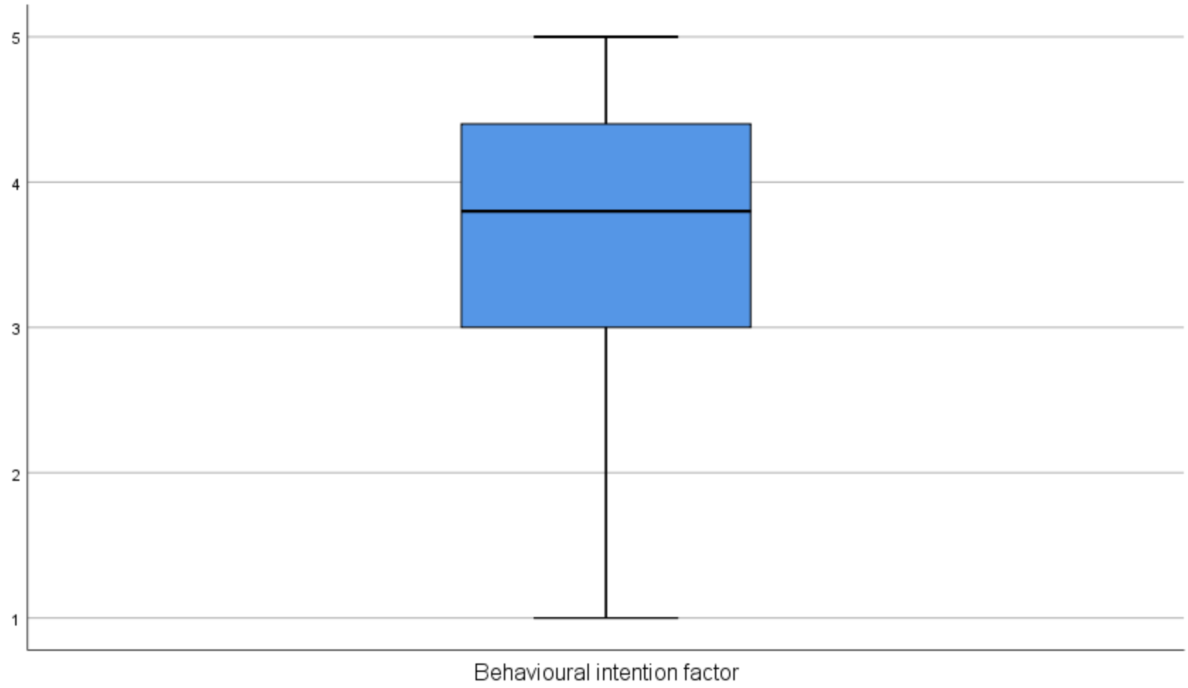

5
4
3
2
1
Percieved risk: financial factor



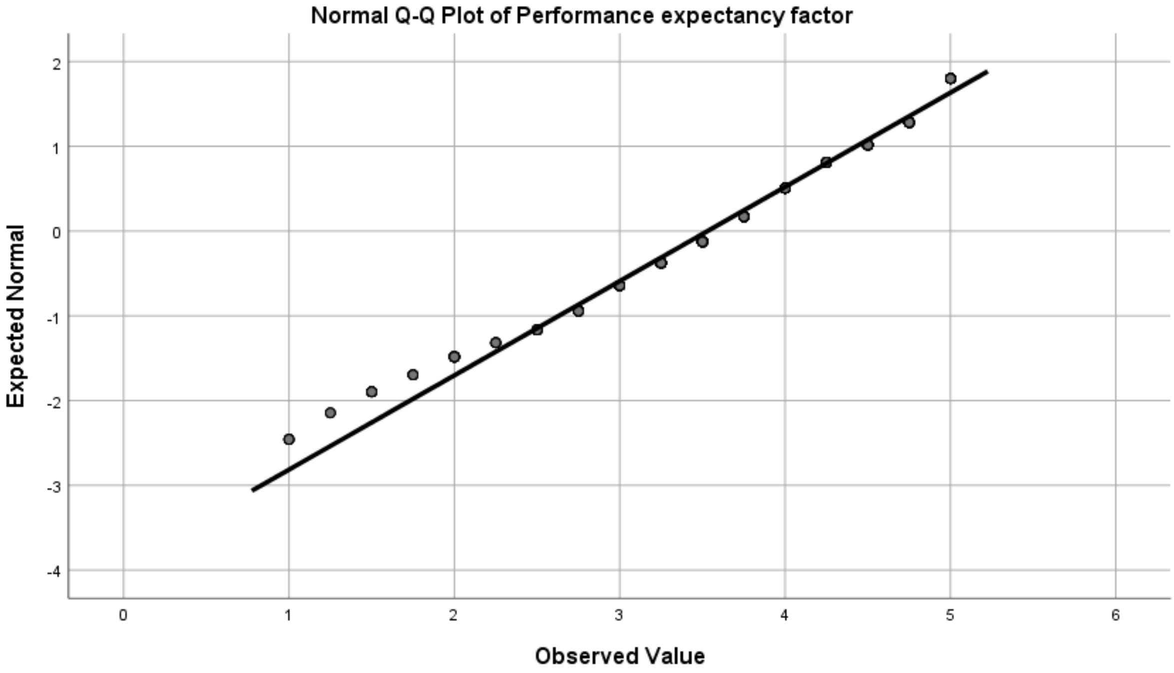
Percieved risk: product performance factor

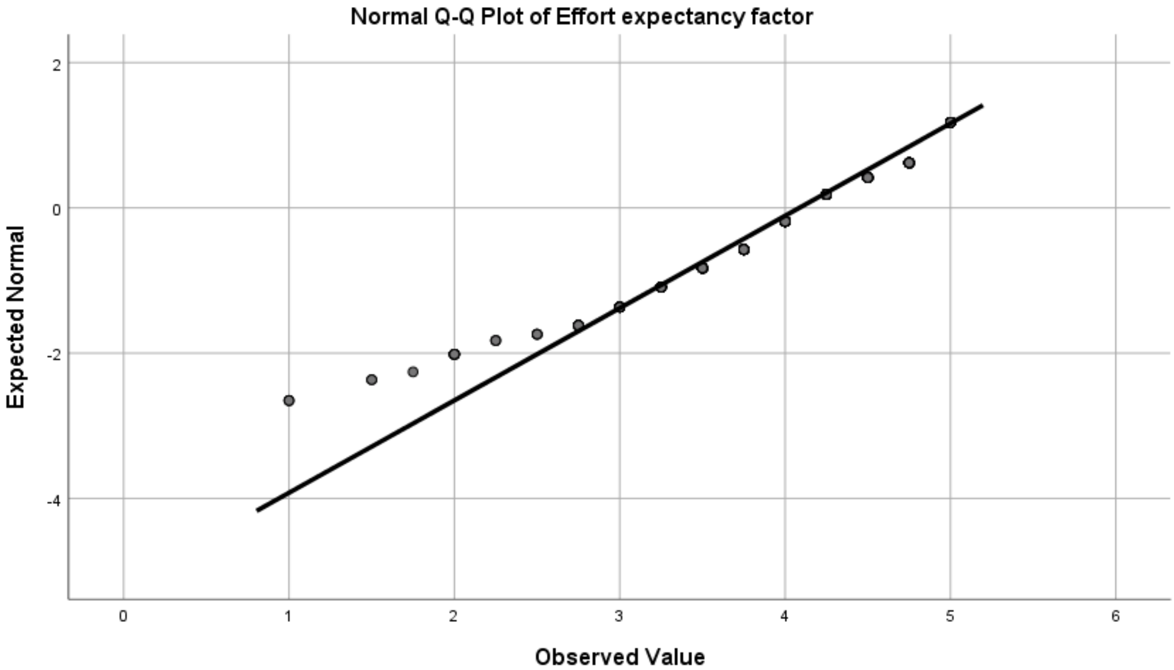


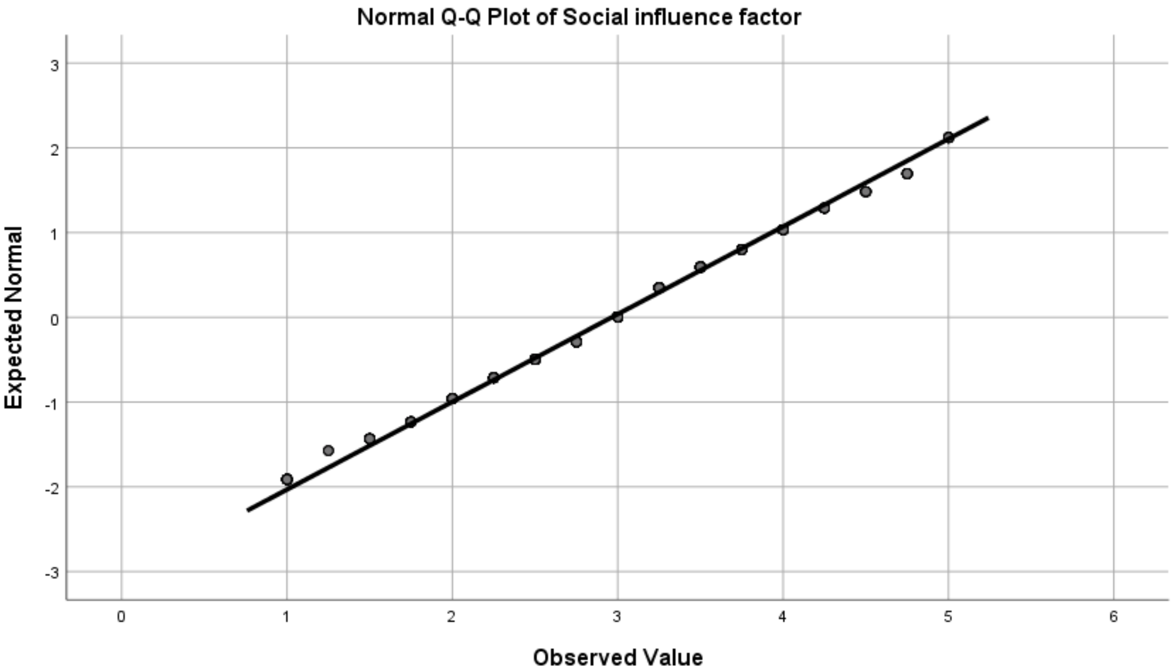
Trust factor

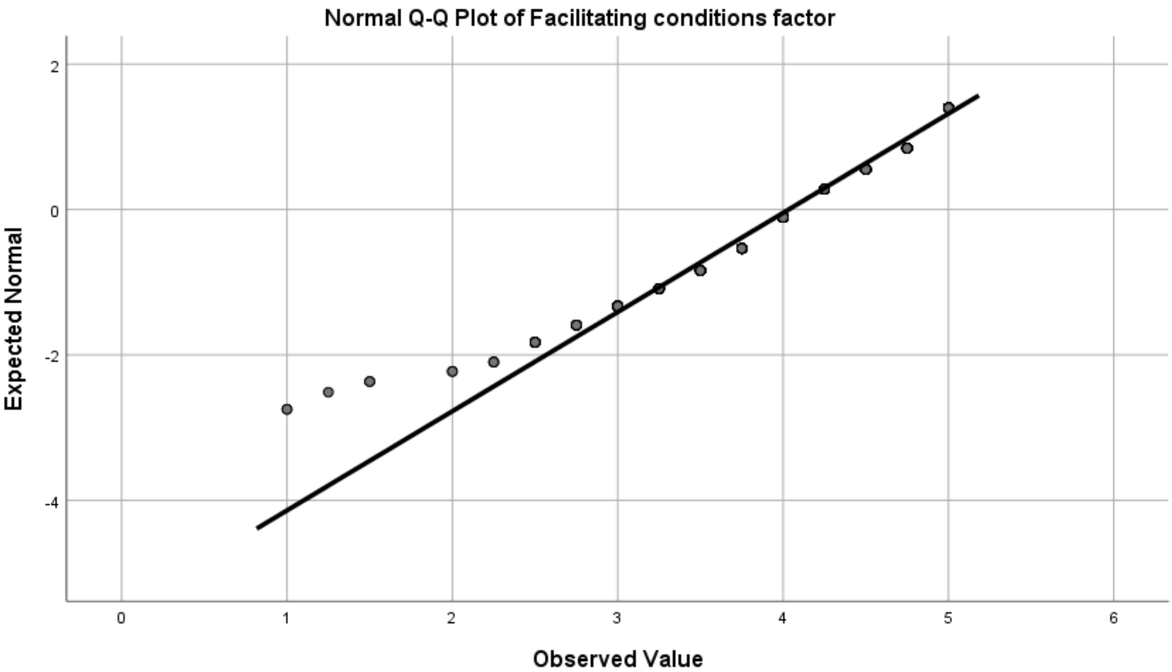

5
4
3
2
1
Behavioural intention factor

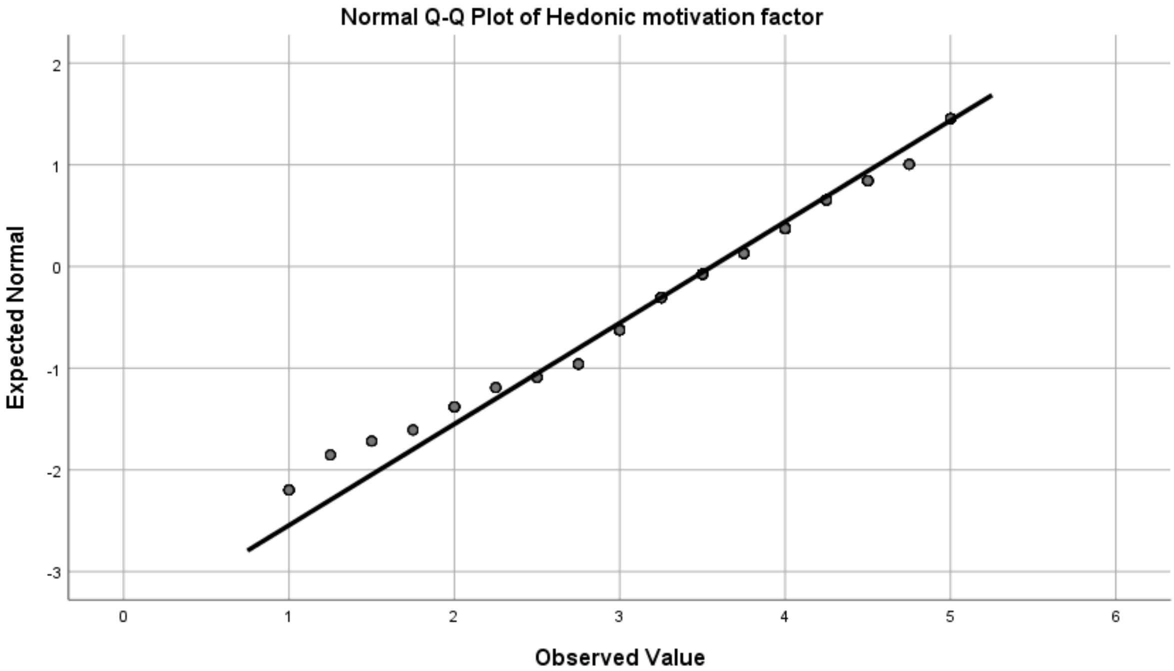
Annexure 12: Scatter plots for each Model A construct

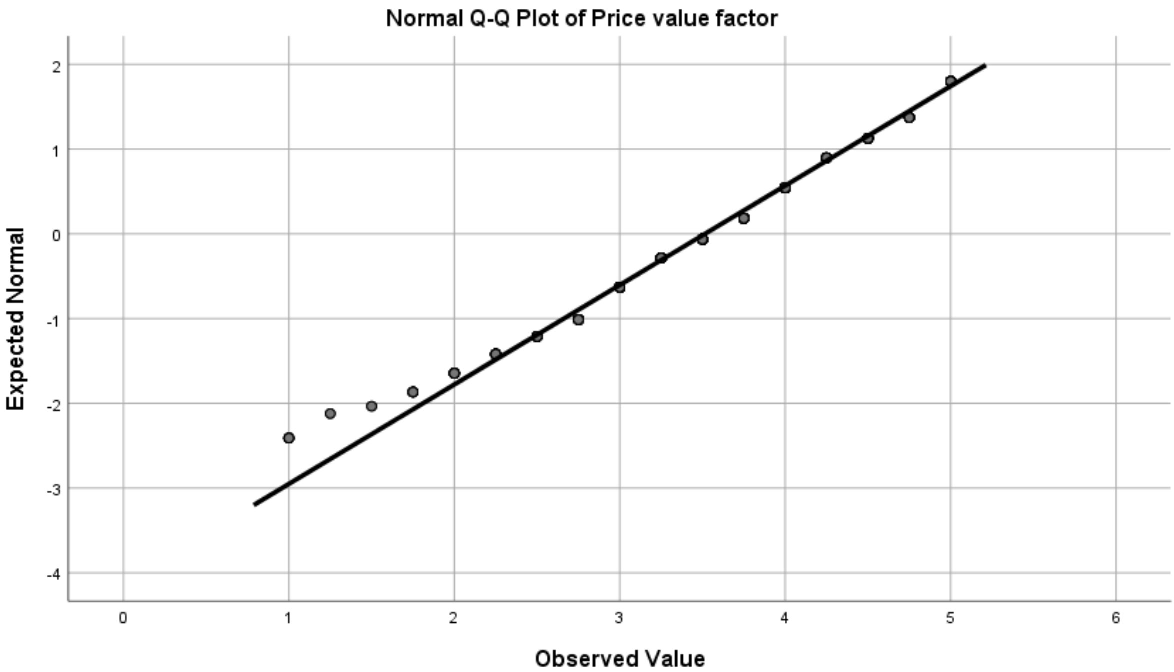


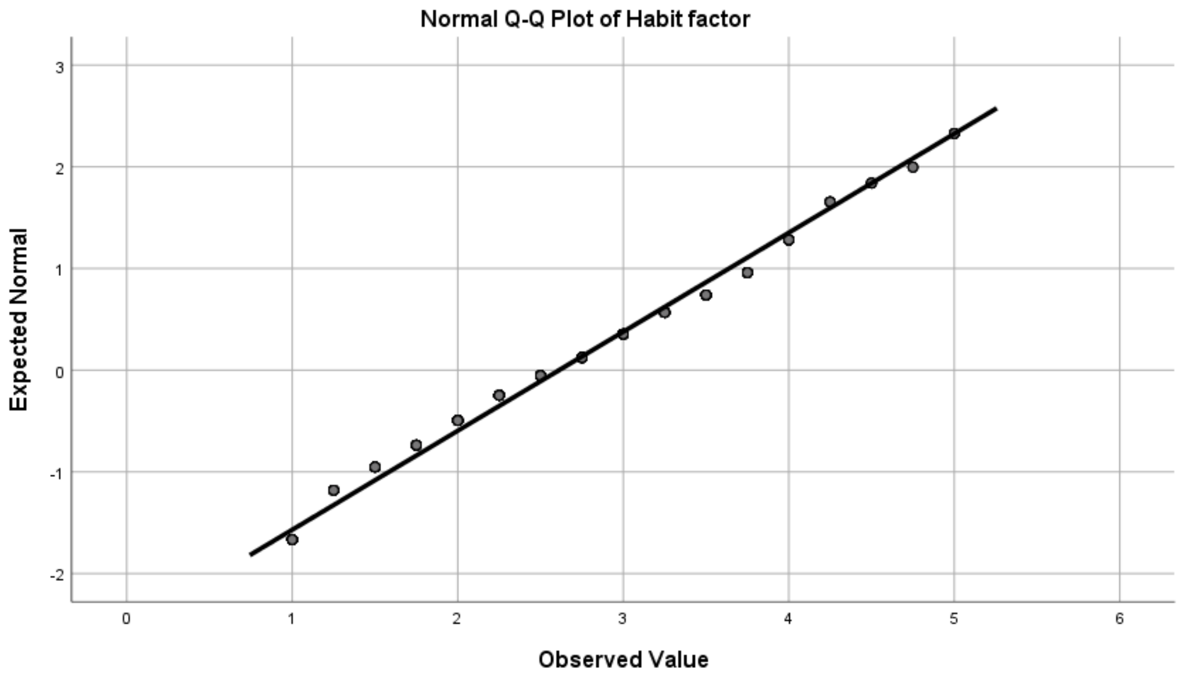


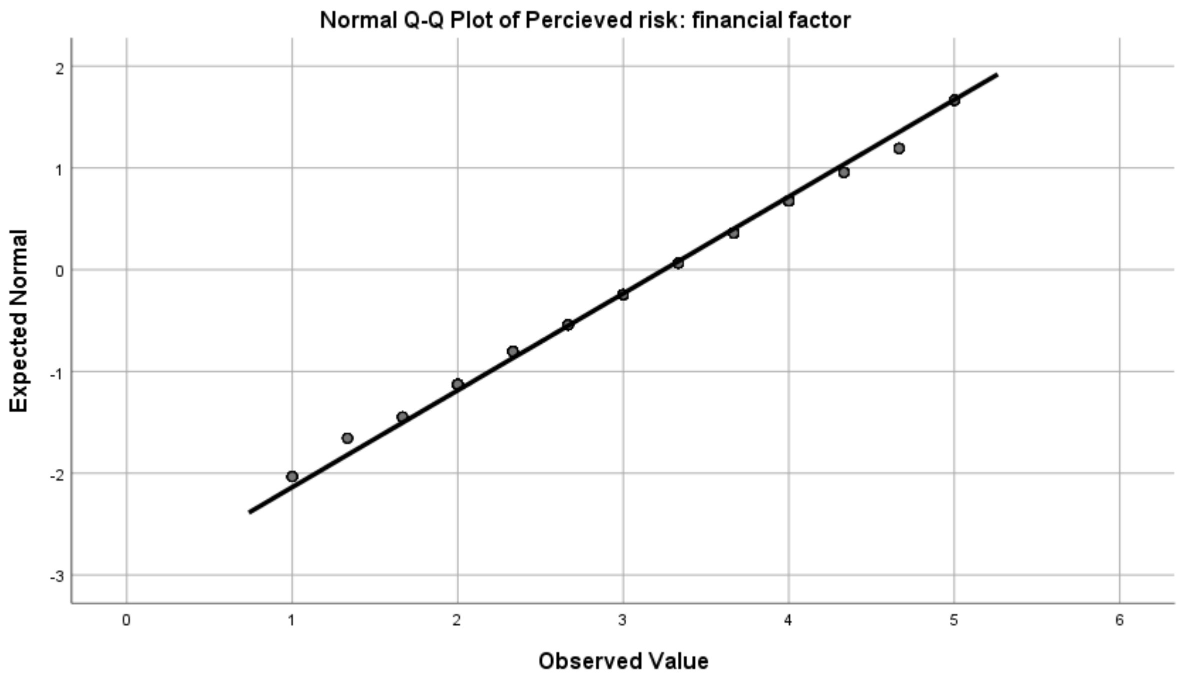

Normal Q-Q Plot of Social influence factor
Expected Normal
Observed Value
3
2
1
0
-1
-2
-3
0
1
2
3
4
5
6

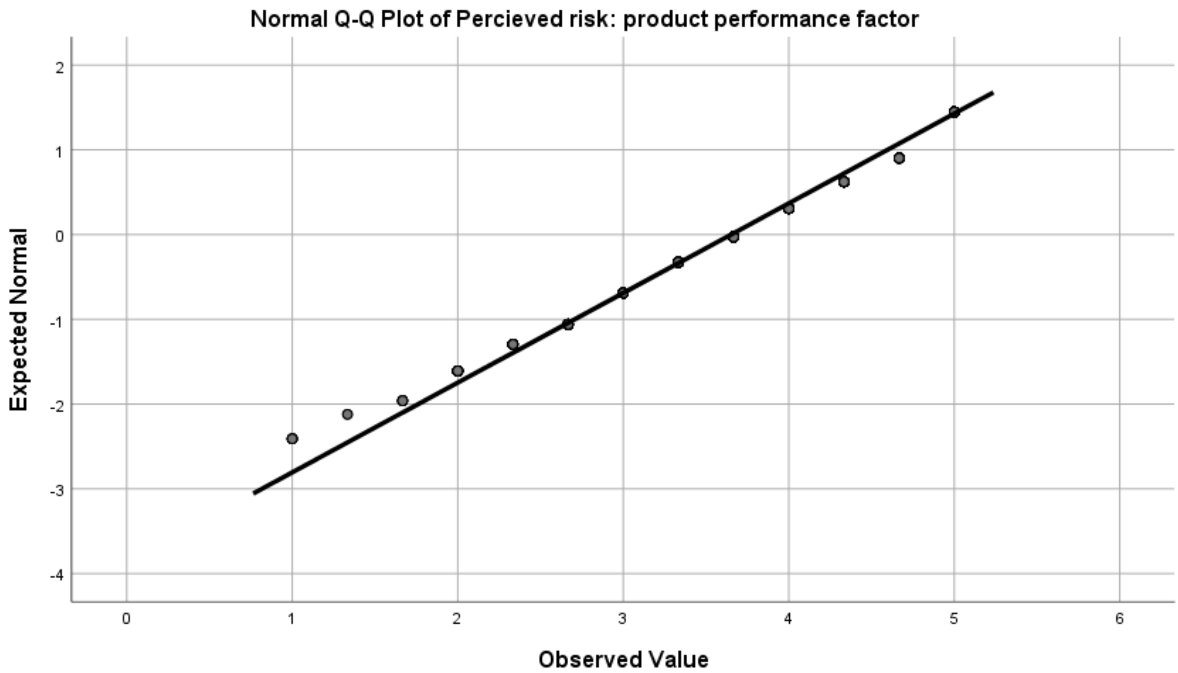

Normal Q-Q Plot of Facilitating conditions factor
Expected Normal
Observed Value
2
0
-2
-4
0
1
2
3
4
5
6


Normal Q-Q Plot of Hedonic motivation factor
Expected Normal
Observed Value
2
1
0
-1
-2
-3
0
1
2
3
4
5
6

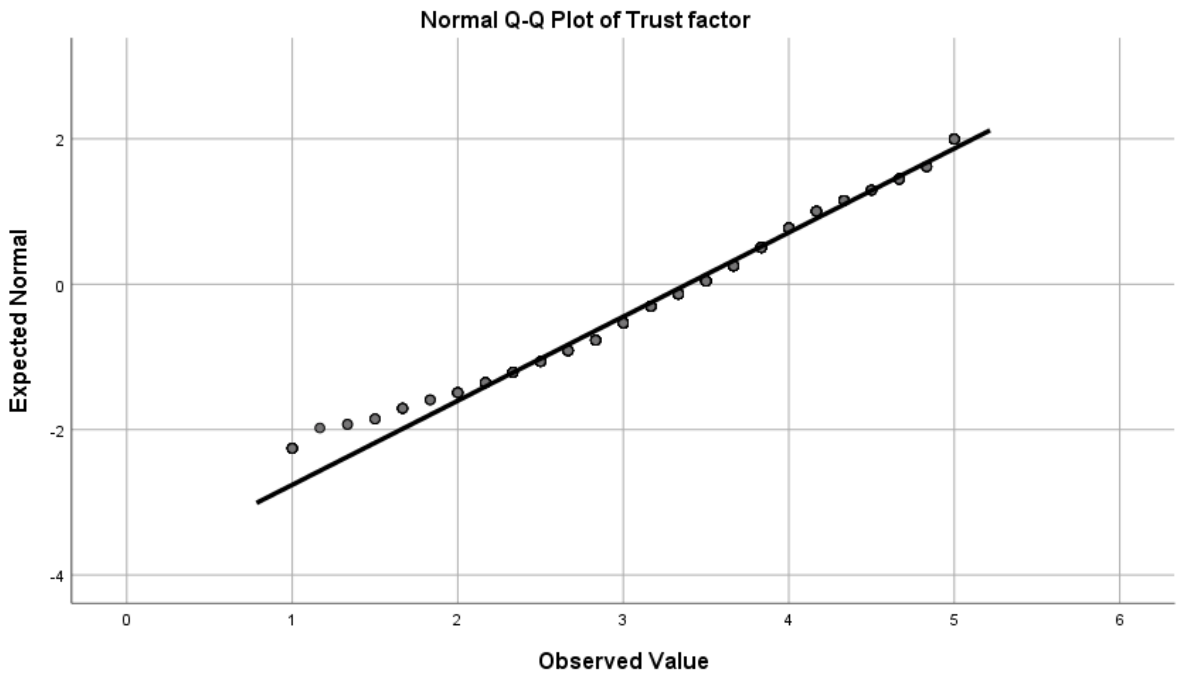

Normal Q-Q Plot of Price value factor
Expected Normal
Observed Value
2
1
0
-1
-2
-3
-4
0
1
2
3
4
5
6


Normal Q-Q Plot of Habit factor
Expected Normal
Observed Value
3
2
1
0
-1
-2
0
1
2
3
4
5
6

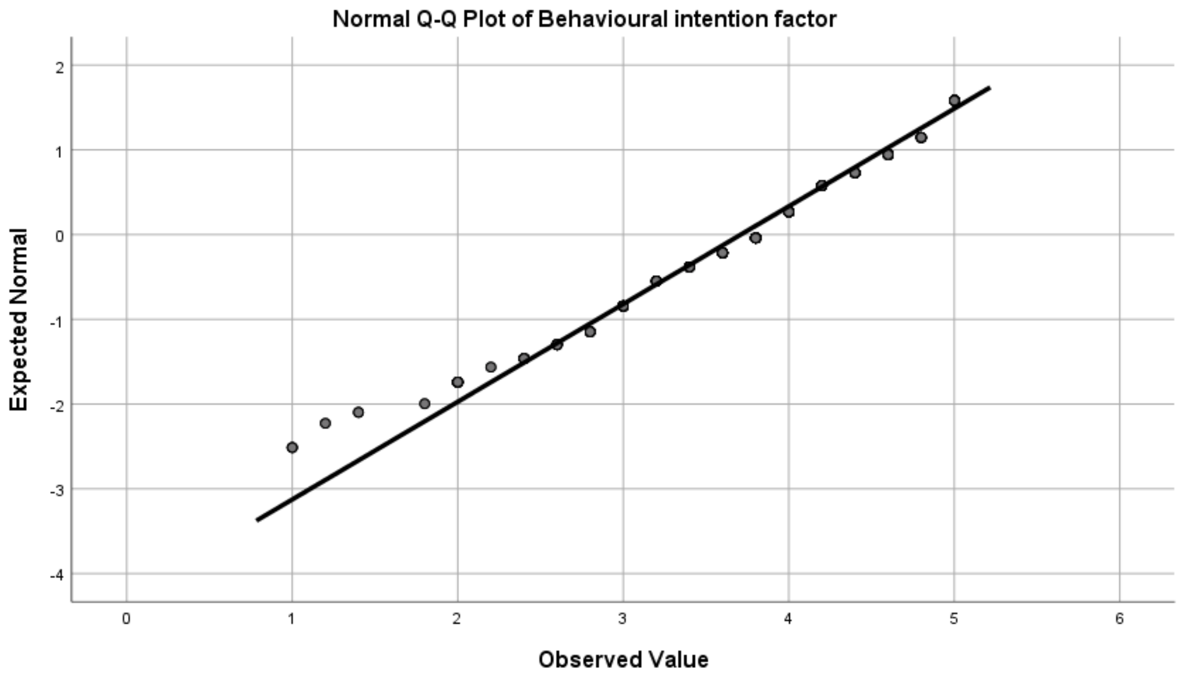

Normal Q-Q Plot of Percieved risk: financial factor
Expected Normal
Observed Value
2
1
0
-1
-2
-3
0
1
2
3
4
5
6



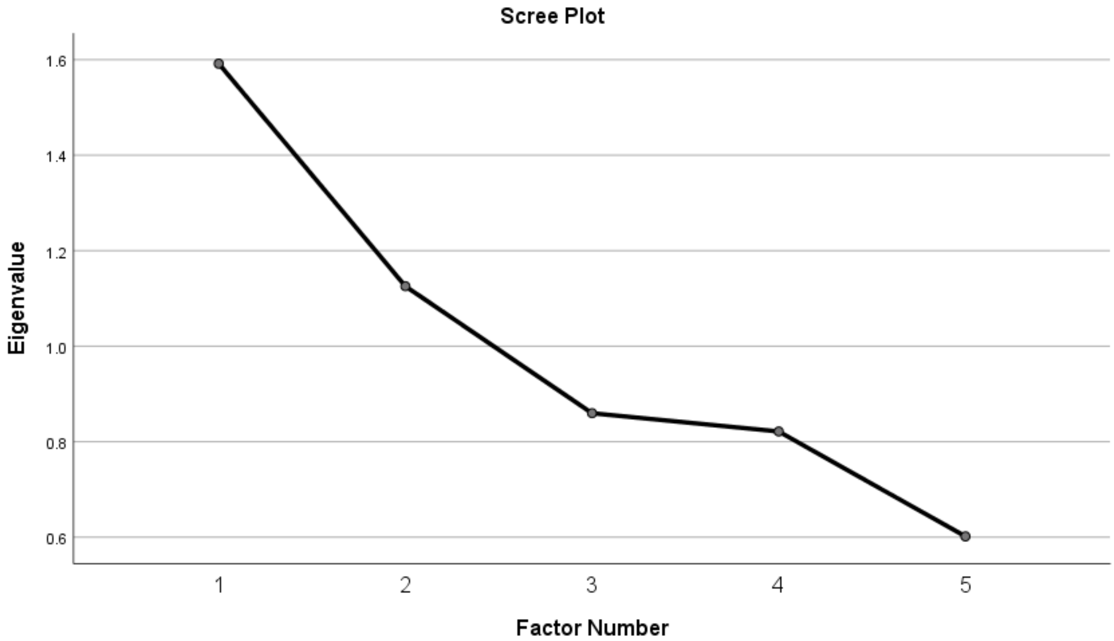
Normal Q-Q Plot of Percieved risk: product performance factor
Expected Normal
Observed Value
2
1
0
-1
-2
-3
-4
0
1
2
3
4
5
6



Normal Q-Q Plot of Trust factor
Expected Normal
Observed Value
2
0
-2
-4
0
1
2
3
4
5
6


Normal Q-Q Plot of Behavioural intention factor
Expected Normal
2
1
0
-1
-2
-3
-4
0
1
2
3
4
5
6
Observed Value

Annexure 13: Scree plot for Model B



Annexure 14: Proof of language editing

GRAMMAR GIRL

LANGUAGE & TECHNICAL EDITING

Camilla Smolicz
+27 84 9999 327
camilla.smolicz@gmail.com
linkedin.com/in/camilla-smolicz/

12 April 2020

TO WHOM IT MAY CONCERN

I would like to confirm that I edited the Master's dissertation of Ms Karen van Niekerk entitled **Factors that Influence the Adoption of mCommerce Applications for Purchasing Athleisure Fashion Apparel.**

Camilla Smolicz

Member, Professional Editors' Guild

Camilla Smolicz
Maîtrise, Sorbonne IV (Paris, France) & BA Honours, University of Adelaide (Australia)
203 Melrose Court, Melrose 2196
Johannesburg, RSA