The Mediating Role of IT Ambidexterity in the Relationship between Artificial Intelligence Capability and Organisational Agility

Waseem Rawat and Justin Barnes

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Abstract

Artificial intelligence capabilities (AICs) are of particular interest, given the contemporary business challenges facing firms. However, their effect on organisational agility (OA) and information technology ambidexterity (ITA), two key organisational capabilities required for competitiveness, is still unknown. To address this gap, the study assesses the impact of AICs on ITA and OA. To test these relationships, a higher-order structural model was developed and tested with a sample of 173 survey respondents. The results indicate AICs can foster OA, and ITA, but that ITA does not translate an AIC into OA. Investing in complementary AI resources to harness AICs is also emphasised.

Keywords: Artificial Intelligence (AI), Artificial Intelligence Capability (AIC), Dynamic Capability View (DCV), Information Technology Ambidexterity (ITA), Organisational Agility (OA), Resource Based View (RBV)

JEL codes: C12, D22, D23, L29, L60, M15, O32

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1. Introduction

As organisations endeavour for commercial success in a dynamic business environment characterised by rapid change and disruption, many have sought to invest in advanced information systems (IS) and information technologies (IT) that have the capacity to enhance performance through informed decision-making and swifter action (Park et al. 2017; Torres et al. 2018). Amongst these technologies, the advent of big data, and the development of sophisticated algorithms and IT infrastructure, have led to the emergence of artificial intelligence (AI), which can be conceived as machines that imitate limited aspects of human intelligence, as the top technological antecedence of several contemporary organisations (Burström et al. 2021; Haenlein and Kaplan 2019; Kaplan and Haenlein 2019; Mikalef and Gupta 2021). However, despite the enthusiasm of applying AI to deliver potential business value, several organisations have experienced challenges when adopting the technology that have inhibited them from attaining performance improvements (Fountaine et al. 2019; Ransbotham et al. 2018). In one global executive study, published in a popular business journal, up to 70% of organisations reported that AI has delivered negligible to no impact on business performance thus far (Ransbotham et al. 2019). One cited reason for the failure of AI to deliver business value is that organisations find it challenging to integrate it into their traditional business models (Burström et al. 2021). Similarly, Brynjolfsson et al. (2019) argue that resource restructuring at a firm-level is one of the most compelling reasons why AI has failed to deliver value.

For organisations to successfully leverage their investments in AI, they need to invest in other complementary resources that can enhance the impact of the technology (Brynjolfsson et al. 2019; Mikalef and Gupta 2021). To understand these complementary resources, recent work has focused on the specific organisation-level AI resources that can collectively lead to an advanced AI capability (AIC) (Mikalef & Gupta 2021; Mikalef et al. 2021b). Based on the resource-based view (RBV) of the firm (Barney 1991; Wernerfelt 1984), in addition to an organisation's tangible resources, its intangible and human resources have been identified as the complementary resources required to develop an organisation's AIC (Mikalef and Gupta 2021). Such AICs can potentially lead to the improvement of an organisation's key capabilities and, ultimately, its business performance (Enholm et al. 2021; Mikalef and Gupta 2021; Mikalef et al. 2021b; Wamba-Taguimdje et al. 2020).

Organisational adaptability, ambidexterity and agility have surfaced as key capabilities required for firms to be competitive in a dynamic and complex modern business environment that is characterised by emerging digital transformation trends and new digital business models (Burström et al. 2021; Del Giudice et al. 2021; Grass et al. 2020). Given the dynamism of business, organisational agility (OA) has been positioned as a rewarding competence supporting the rapid exploitation of business opportunities (Hatzijordanou et al. 2019; Meinhardt et al. 2018; Walter 2020). OA can be conceived as an organisation's capacity to respond swiftly to market changes and is regarded as one of the key factors that increase firm competitiveness (Teece et al. 2016; Walter 2020). The realisation of an organisation's agility is enabled through, amongst others: a flexible workforce; supportive organisational structures; support from top management; and the successful development of IT capabilities (Sindhwani and Malhotra 2017; Walter 2020).

IT capabilities have been identified as a significant enabler of OA, and as an integral part of an organisation's capability-building process (Ghasemaghaei et al. 2017; Gunasekaran et al. 2018; Lee et al. 2015; Tallon et al. 2019; Walter 2020). The dynamic capability view (DCV) has gained prominence in the strategic management literature as an appropriate theoretical perspective to explain the effects of lower-order organisational capabilities, such as IT capabilities, on higher-order dynamic capabilities, such as OA (Grant 1996; Lee et al. 2015; Teece et al. 1997, 2016). Dynamic capabilities describe how an organisation senses and responds to environmental disruptions through resource reconfiguration and integration, leading it to gaining and sustaining competitive advantage (Teece 2007, 2018a, 2018b; Teece et al. 1997).

While the extant literature has focused on the effect of general IT (Lee et al. 2015) and data analytics capabilities (Côrte-Real et al. 2017; Ghasemaghaei et al. 2017; Gunasekaran et al. 2018) on OA (conceived as a dynamic capability), no prior studies appear to have explored the effect of an organisation's AIC (Mikalef and Gupta 2021; Schmidt et al. 2020; Wamba-Taguimdje et al. 2020) on its agility (Tallon et al. 2019; Teece et al. 2016). Given the rapid recent adoption of AI in the organisational context, exploring the factors that can help enable OA through the development of AICs has significant theoretical and business implications (Brynjolfsson and McAfee 2017; Ghasemaghaei et al. 2017; Mikalef and Gupta 2021).

There is evidence that IT capabilities can improve OA (Gunasekaran et al. 2018; Tallon et al. 2019), although some studies have found it has no impact (Ghasemaghaei et al. 2017; Liang et al. 2017; Liu et al., 2013). This inconsistency can possibly be explained by moderating and mediating factors (Ghasemaghaei et al. 2017; Liu et al. 2020). Amidst several organisation-level capabilities such as adaptability (Del Giudice et al. 2021) and fit (Ghasemaghaei et al. 2017), a few researchers have begun exploring the impact of ambidexterity on agility (Del Giudice et al. 2021; Lee et al. 2015; Rialti et al. 2018). Ambidexterity can be conceived as an organisation's ability to utilise a robustly balanced combination of knowledge and strategic exploration and operational exploitation (Del Giudice et al. 2021; Lee et al. 2015; O'Reilly and Tushman 2013; Raisch and Birkinshaw 2008).

Building on this definition of ambidexterity from the strategic management literature, an emerging stream of IS literature has started to focus on a particular form of ambidexterity, namely IT ambidexterity (ITA) (Benitez et al. 2018a; Chang et al. 2019; Gregory et al. 2015; Lee et al. 2015; Syed et al. 2020a, 2020b). ITA can be conceived as an organisation's simultaneous exploration of new IT resources and practices, accompanied by the exploitation of their existing IT resources and practices (Lee et al. 2015). While some authors have found that ITA is emerging as a vital capability to support the agile manoeuvres of organisations (Chang et al. 2019; Del Giudice et al. 2021; Gregory et al. 2015; Lee et al. 2015), there is scant literature examining ITA as a key enabler of OA (Lee et al. 2015; Zhen et al., 2021a, 2021b; Zhou et al. 2018). Furthermore, despite the overwhelming recent interest in AI (Brynjolfsson and McAfee 2017; Fountaine et al. 2019; Ransbotham et al. 2018, 2019), prior work has not studied the relationship between the notion and ITA.

Gaps in the extant literature have consequently been identified: No prior studies have explored the effect of an organisation's AIC (Mikalef and Gupta 2021) on its OA (Tallon et al. 2019; Teece et al. 2016) or its ITA (Lee et al. 2015; Gregory et al. 2015), whilst the influence of ITA in enabling OA (Zhen et al. 2021b) is also yet to be explored. To contribute to bridging these gaps and using the DCV as our theoretical lens, we attempted to answer the following research questions: 1) How does an AIC influence OA? 2) What is the effect of an AIC on ITA? and 3) Does ITA translate an AIC into OA? To address these questions, we theorised and developed a nomological network that links AICs, ITA and OA into one model, which we tested empirically.

This paper endeavours to enrich the emerging literature on AI deployment in the organisational context, which is a key focus of practitioners and academics who are keen to gain an in-depth understanding of how AI can improve business value (Enholm et al. 2021; Mikalef and Gupta 2021). Moreover, it contributes to advancing the IT-enabled agility and ambidexterity literature by unveiling the implications of AIC for these capabilities. The paper is arranged as follows: Section 2 provides the theoretical background to an AIC, ITA and OA, while introducing DCV as the study's theoretical lens. Section 3 deals with the research model and the study's hypotheses, before the methodology and main results are presented in Sections 4 and 5 respectively. In Section 6, the results are discussed, whilst selected implications for practice and research, supplemented by the study's limitations, are introduced. The study is concluded in Section 7.

2. Theoretical Background

2.1 Artificial Intelligence Capability (AIC)

The accelerating adoption of AI in an organisational context (Enholm et al. 2021; Mikalef and Gupta, 2021; Schmidt et al. 2020; Wamba-Taguimdje et al. 2020) has led to the relatively new notion of artificial intelligence capability (AIC), which has been introduced to explain how organisations should arrange their resources to obtain value from AI initiatives and to elucidate how this value is achieved (Enholm et al. 2021; Mikalef and Gupta 2021; Mikalef et al. 2019). The concept of an AIC builds on a tradition of IS research, which suggests that rather than merely focusing on the technical aspects of new technologies, a holistic firm-level capability to leverage them is required to deliver business value from novel technology deployments (Mikalef and Gupta 2021; Mikalef et al. 2019, 2021b). More specifically, IT capability, the concept on which an AIC is grounded, contends that technological and other complementary resources need to be leveraged for organisations to realise value from new technology deployments (Bharadwaj 2000; Irfan et al. 2019; Mikalef et al. 2021b). Following this logic, an AIC builds on the technical and organisational elements that are essential to effectively establish AI technologies in an organisational setting (Enholm et al. 2021; Mikalef and Gupta, 2021; Mikalef et al. 2019, 2021b).

Lately, AICs have been defined as "the ability of a firm to select, orchestrate, and leverage its AI-specific resources" (Mikalef and Gupta 2021: 2). This definition (see Appendix A for other definitions) signifies that harnessing an AIC promotes taking a holistic view of AI deployments in an organisational context (Enholm et al. 2021; Mikalef and Gupta, 2021; Mikalef et al. 2021b), and thus goes beyond merely selecting and deploying the technology (Mikalef et al. 2021b). Mikalef and Gupta (2021) argue that, because an AIC is theoretically underpinned by the RBV (Barney 1991; Wernerfelt 1984), it is developed through an organisation's ability to develop its complementary tangible, intangible and human resources (Grant 1996; Gupta and George 2016; Mikalef et al. 2021b). According to the RBV (Barney 1991; Wernerfelt 1984), if these resources are valuable, rare, imperfectly imitable and non-substitutable (VRIN), they can generate performance gains and competitiveness for organisations (Bharadwaj 2000; Mikalef and Gupta 2021; Mikalef and Pateli 2017; Teece 2018a).

Prior work has argued that AICs consist of tangible, intangible and human resources that are complementary and related to organisational AI initiatives (Mikalef and Gupta 2021; Mikalef et al. 2021b). Tangible complementary resources, such as the data required to realise AI algorithms, the processing power to run them, and the supporting computing, storage and network infrastructures, have been noted as fundamental to AI success (Desouza et al. 2020; Duan et al. 2019; Mikalef and Gupta 2021; Wirtz et al. 2019). Intangible complementary resources, such as an organisation's capacity to initiate and foster change, its proclivity for high-risk yet highly impactful AI initiatives, and its interdepartmental coordination (Davenport and Ronanki 2018; Ransbotham et al. 2018), have been argued to be critical facets in the effective deployment of AI. Finally, human-related resources, such as technical and business skills, have been suggested as key resources required to derive value from AI investments (Mikalef and Gupta 2021; Mikalef et al. 2020, 2021b). Specifically, it is argued that technical skills are needed to handle data and develop AI algorithms, whilst managerial skills are required to envision imperative areas for AI application and to lead and coordinate AI initiatives (Dwivedi et al. 2021; Spector and Ma 2019). Holistically, these tangible, intangible and human resources are conceptualised to constitute a robust measure of an organisation's AIC (Mikalef and Gupta 2021; Mikalef et al. 2021b).

2.2 Organisational Agility (OA)

In an ever-evolving, complex business landscape, characterised by trade wars, volatile prices and changing consumer demands, attaining and sustaining competitiveness and superior business performance comprise a major challenge for most organisations (Mikalef and Pateli 2017; Tallon et al. 2019; Walter 2020). This complexity is amplified by trends in digital transformation and incipient digital business models (Burström et al. 2021; Del Giudice et al. 2021; Grass et al. 2020). For organisations to respond appropriately and seize opportunities in this environment, OA has been positioned as a rewarding capability (Hatzijordanou et al. 2019; Meinhardt et al. 2018; Teece et al. 2016), as agile organisations are traditionally better positioned to enhance their revenue and secure higher profit margins (Chen et al. 2014; Ghasemaghaei et al. 2017; Queiroz et al. 2018; Walter 2020; Zhou et al. 2019). OA has been conceptualised as an organisation-wide capability to deal with unforeseen changes that arise in business through rapid, flexible and proactive responses that exploit changes as potential opportunities to develop and thrive. It has often been considered to consist of two dimensions (Lu and Ramamurthy 2011; Mikalef and Pateli 2017) – operational adjustment agility (OAA) and market capitalising agility (MCA). OAA is concerned with the rapid and physical adjustment of an organisation's internal business processes to cope with demand or market changes (Lu and Ramamurthy 2011; Mikalef and Pateli 2017; Sambamurthy et al. 2003). On the other hand, MCA refers to an organisation's ability to continuously monitor and exploit changes that occur in the business environment by swiftly enhancing product or service offerings in response to consumer needs (Mikalef and Pateli 2017). MCA highlights a growth-orientated, entrepreneurial strategic organisational intent concerning decision-making and judgment, which is dynamic and through which uncertain and volatile environments are perceived as fecund opportunities to enact new strategic directions (Lu and Ramamurthy 2011; Mikalef and Pateli 2017; Sambamurthy et al. 2003).

The role of IT capabilities in either enabling or hindering OA has been of significant interest to researchers for the past two decades (Bharadwaj 2000; Lee et al. 2015; Liu et al. 2013; Mikalef and Pateli 2017; Ravichandran 2018; Sambamurthy et al. 2003; Swafford et al. 2008; Tallon et al. 2019). Table 1 presents a review of selected recent IT-enabled OA studies. As indicated, both general (Lee et al. 2015, 2021; Irfan et al. 2019; Mikalef and Pateli 2017) and specialised emerging IT capabilities, such as big analytics (Côrte-Real et al. 2017; Ghasemaghaei et al. 2017; Gunasekaran et al. 2018) and cloud computing (Liu et al., 2018), have influenced OA. Furthermore, recent work has advocated a focus on complementary organisational factors, rather than merely technological ones, to foster OA from IT capabilities (Lee et al. 2021; Liu et al. 2018; Mikalef et al. 2021b). This is consistent with the holistic notion of the AIC construct (Mikalef and Gupta 2021).

While several studies have found that IT capabilities have a positive effect on OA (Côrte-Real et al. 2017; Gunasekaran et al. 2018; Mikalef and Pateli 2017; Ravichandran 2018), others have found they have a neutral or negative effect on OA (Ghasemaghaei et al. 2017; Liang et al. 2017; Liu et al. 2013; Swafford et al. 2008). Thus, as advocated by Liu et al. (2018), and illustrated in Table 1, an "IT-agility contradiction" (p. 98) exists in the literature. Considering the IT-agility contradiction, it has been argued that IT capabilities are too far away from OA in the organisational capability hierarchy (Benitez-Amado and Walczuch 2012; Liu et al. 2020). Some authors have therefore argued that certain organisational factors may be required to translate IT capabilities into OA (Ghasemaghaei et al. 2017; Lee et al. 2015, 2021; Liang et al. 2017; Liu et al. 2020; Ravichandran 2018).

Table 1: Selected recent studies on the effect of IT capabilities on agility

Authors	Theoretical lens	Type of IT capability	Effect on OA	Key findings
Lee et al. (2015)	Ambidexterity theory, dynamic capability view	ITA	Positive	ITA facilitates OA through operational ambidexterity, which in turn is dependent on the level of environmental dynamism
Liu et al. (2018)	IT infrastructure theory	Cloud computing	Positive	Cloud computing sub-constructs of cloud flexibility and integration are critical to improving OA
Irfan et al. (2019)	Dynamic capability view	IT infrastructure and IT integration	Positive	IT infrastructure and IT integration affect OA through the specific supply chain capabilities of operational coordination and information integration
Ravichandran (2018)	Dynamic capability view	IS, digital platform capabilities	Positive	IS capabilities, supplemented by aggressive IT investments, contribute to OA through digital platform capabilities
Lee et al. (2021)	Agile process capabilities, environmental contingency	Knowledge management, process integration	Positive	IT capabilities contribute in different degrees towards OA measured through sensing and responding processes
Mikalef and Pateli (2017)	Dynamic capability view	General IT capabilities	Positive	IT-enabled capabilities facilitate market capitalising and operational adjustment agility
Ghasemaghaei et al. (2017)	Dynamic capability view	Data analytics	Negative	Data analytics capabilities do not lead to agility; at low levels of fit, a negative relationship exists
Liang et al. (2017)	Organisational inertia theory, coordination theory	Intellectual and social alignment	Positive/ Negative	Social IT alignment facilitates OA by improving emergent business-IT coordination, whilst intellectual IT agility impedes agility by increasing organisational inertia

2.3 Ambidexterity

Considering the IT-agility contradiction (Ghasemaghaei et al. 2017; Liu et al. 2018), a nascent area of research has focused on moderating or mediating factors that govern the translation of an organisation’s IT capabilities into OA (Ghasemaghaei et al. 2017; Lee et al. 2015; Queiroz et al. 2018; Ravichandran 2018). In this literature, several organisational capabilities, such as adaptability (Del Giudice et al. 2021), fit (Ghasemaghaei et al. 2017), strategic orientation (Queiroz et al. 2018), innovation capacity (Ravichandran 2018; Zhou et al. 2019), and ambidexterity (Del Giudice et al. 2021; Lee et al. 2015; Rialti et al. 2018), have been identified as important capabilities that can potentially influence OA. Organisational ambidexterity, conceived as “an organisation's ability to be aligned and efficient in its management of today's business demands while simultaneously being adaptive to changes in the environment” (Raisch and Birkinshaw 2008:375), has consequently attracted “burgeoning academic emphasis” in the last two decades (Snehvrat et al. 2018:344).

An organisation’s ability to both exploit existing capabilities and explore new opportunities lies at the core of the overall notion of ambidexterity (Benitez et al. 2018a; Del Giudice et al. 2021; Gibson and Birkinshaw 2004; Im and Rai 2008; Lee et al. 2015; O’Reilly and Tushman 2013; Rialti et al. 2018; Snehvrat et al. 2018; Wirtz 2020), with this identified as a key capability required for competitiveness and the long-term favourable performance of an organisation (O’Reilly & Tushman 2013; Snehvrat et al. 2018).

2.4 Dynamic Capability View (DCV)

The enabling role of IT capabilities as an antecedent of OA has been studied through several theoretical lenses (see Tallon et al. 2019 for a review), including the capability-building perspective (Ayabakan et al. 2017; Grant 1996; Sambamurthy et al. 2003), the RBV (Barney 1991; Wernerfelt 1984), and the DCV (Teece, 2007; Teece et al. 1997, 2016). However, the DCV has received the most attention recently (Ayabakan et al. 2017; Lee et al. 2015; Mikalef and Pateli 2017; Park et al. 2017; Queiroz et al. 2018; Steininger et al. 2022; Tallon et al. 2019; Walter 2020; Zhou et al. 2019). The DCV is widely considered an extension of the RBV (Mikalef and Pateli 2017; Schilke et al. 2018; Steininger et al. 2022; Teece 2018b). However, whilst the RBV posits that organisations can achieve competitiveness based on the rarity and inimitability of their resources, the notion of resource rarity and inimitability is confined to the boundaries of the organisation, and to a specific timeframe (Mikalef and Pateli 2017; Steininger et al. 2022).

Table 2: Summary of selected recent studies on the emerging construct of ITA

Source	Definition of ITA	Theoretical lens	Role of ITA	Key findings
Gregory et al. (2015:58)	"IT management's capability to resolve paradoxical tensions associated with IT transformation programs"	Ambidexterity theory; dynamic capabilities	Facilitator of IT transformation programmes	Identification of theoretical paradoxes that require ambidextrous resolution strategies
Lee et al. (2015: 398)	"the ability of firms to simultaneously explore new IT resources and practices (IT exploration) as well as exploit their current IT resources and practices (IT exploitation)"	Dynamic capabilities	Lower-order functional IT capability	ITA facilities OA through operational agility, which in turn is dependent on the level of environmental dynamism
Mithas and Rust (2016: 224)	"firms pursuing an IS innovator and an IS conservative strategy at the same time"	Resource-based view; IT strategic orientation	Moderator	ITA moderates the relationship between IT investments and performance, especially at higher levels of investment
Chi et al. (2017:44)	"the focal firm's simultaneous pursuit of IT flexibility and IT standardization"	Ambidexterity theory; resource-based view	Moderator	ITA positively moderates the relationship between governance strategy and relational performance
Syed et al. (2020a: 656)	"ITA refers to a firm's ability to refine its existing technologies (IT exploitation) and search for new technological solutions (IT exploration) simultaneously"	IT-enabled capabilities, ambidexterity theory	IT capability	ITA capabilities improve IT success, uncertain environments significantly moderate this relationship
Syed et al. (2020b:3)	"the ability of a firm to exploit its existing IT resources (IT exploitation) and, at the same time, explore new IT solutions (IT exploration)"	IT-enabled capabilities, ambidexterity theory	IT capability	ITA improves new product development speed by facilitating operational agility

The DCV argues that, for sustained competitive advantage, organisations need to continuously evolve their resources and capabilities (Peteraf et al. 2013; Steininger et al. 2022; Teece 2018b). The core notion of the DCV is that dynamic capabilities govern the change of other organisational capabilities such as ordinary (or functional) capabilities, which are required for short-term survival (Teece 2018a, 2018b; Teece et al. 2016). Dynamic capabilities can therefore promote the strategic renewal of existing organisational capabilities in response to environmental changes, leading to the sustained competitive survival of the organisation (Mikalef et al. 2020; Steininger et al. 2022). Organisations with dynamic capabilities sense and respond to threats or opportunities they face in their environment (Teece 2007) by integrating, building and reconfiguring their internal and external capabilities (Teece et al. 1997), thus improving their evolutionary fitness and averting rigidities (Girod and Whittington 2017; Mikalef and Pateli 2017).

Despite the potential competitive gains that can arise from harnessing dynamic capabilities (Steininger et al. 2022; Teece 2018a, 2018b; Teece et al. 2016), previous studies have predominately explored the outcomes of dynamic capabilities, with limited research on the underlying processes that cause dynamic capabilities to emerge (Conboy et al. 2020; Drnevich and Kriauciunas 2011; Mikalef et al. 2021a; Protogerou et al. 2012). It is argued in this literature that dynamic capabilities are developed through a hierarchical organisational capability-building process (Ayabakan et al. 2017; Grant 1996; Irfan et al. 2019; Sambamurthy et al. 2003), in which lower-order ordinary (or functional) capabilities, required for organisational survival, can lead to the development of higher-order dynamic capabilities, required for sustained competitiveness (Lee et al. 2015; Teece et al. 1997). According to this perspective, the development and leveraging of IT capabilities, conceptualised as lower-order functional capabilities (Ayabakan et al. 2017; Ghasemaghaei et al. 2017; Irfan et al. 2019; Lee et al. 2015; Mikalef and Pateli 2017; Steininger et al. 2021; Tallon et al. 2019), lead to OA, conceptualised as a higher-order dynamic capability (Ghasemaghaei et al. 2017; Lee et al. 2015; Queiroz et al. 2018; Roberts and Grover 2012; Teece et al. 2016). Inspired by this hierarchal perspective, and the emerging AIC (Mikalef and Gupta 2021; Mikalef et al. 2019, 2021b) and ITA (Gregory et al. 2015; Lee et al. 2015; Syed et al. 2020a, 2020b) literature, both AIC and ITA are conceptualised as lower-order functional capabilities in this study.

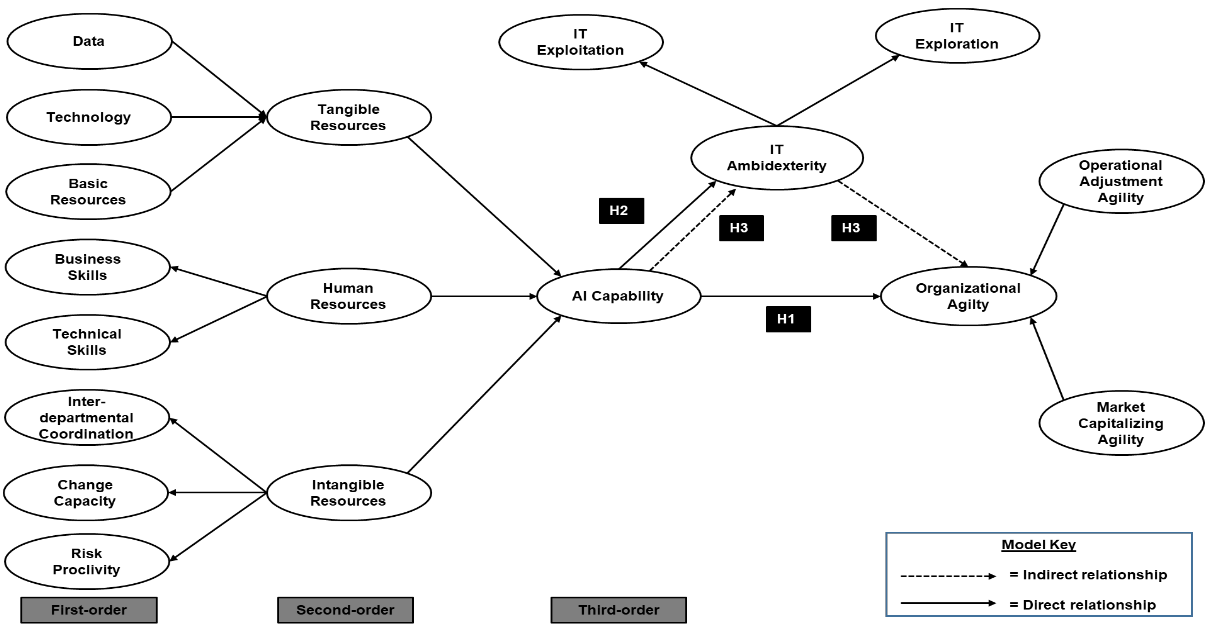
While it can be argued that AI (Mikalef and Gupta 2021; Mikalef et al. 2021b) and ITA (Lee et al. 2015; Mithas and Rust 2016) capabilities, as conceptualised through the RBV (Barney 1991; Wernerfelt 1984), are VRIN and can provide some degree of competitive advantage (Mikalef and Gupta 2021; Lee et al. 2015; Teece 2018a), being lower-order functional capabilities means they cannot ensure that the organisation would be able to change when faced with a new threat or opportunity in the business environment (O'Reilly and Tushman 2008; Teece 2018a, 2018b). Conversely, OA has been positioned as an appropriate organisational capability that encompasses the higher-order dynamic-capability entrepreneurial activities (Teece 2018b) of sensing and swiftly responding to environmental changes (Park et al. 2017; Roberts and Grover 2012; Teece et al. 2016). Furthermore, it has been argued that lower-order IT capabilities are key enablers of OA (Ghasemaghaei et al. 2017; Lee et al. 2015; Queiroz et al. 2018; Roberts and Grover 2012; Teece et al. 2016). As such, building on prior work (Ghasemaghaei et al. 2017; Irfan et al. 2019; Lee et al. 2015; Mikalef and Pateli 2017; Park et al. 2017; Queiroz et al. 2018; Ravichandran 2018; Roberts and Grover 2012; Steininger et al. 2022; Teece et al. 2016), OA is conceptualised as a specific higher-order dynamic capability in this study. Based on the conceptualisation of AI and ITA capabilities as lower-order functional capabilities, and OA as a high-order dynamic capability, the DCV is deemed an appropriate theoretical lens for this study.

3. Research Model

3.1 Impact of AIC on OA and ITA

Drawing on the RBV and DCV of the firm, this study proposes the research model shown in Figure 1. Building on prior work (Mikalef and Gupta 2021; Mikalef et al. 2020, 2021b), we maintain that a combination of different resources is required to build an AIC within an organisation. Specifically, an AIC is conceptualised as a higher-order construct that comprises of tangible, intangible and human resources, which in turn comprise of the sub-dimensions illustrated in Figure 1. Individually, these dimensions cannot by themselves form an AIC, hence its conceptualisation as a higher-order construct. Resource classification into the tangible, intangible and human resource categories has a long history in the IT capability literature (Bharadwaj 2000; Chae et al. 2014; Gupta and George 2016; Mikalef et al. 2020) and is consistent with the seminal resource classification view proposed by Grant (1991). Theoretically underpinned by the RBV (Barney 1991; Wernerfelt 1984), harnessing such tangible, intangible and human resources, especially if they are VRIN, can foster improvements in organisational performance (Bharadwaj 2000; Mikalef and Gupta 2021; Mikalef and Pateli 2017; Teece 2018a). If these resources are evolved and rearranged appropriately, they can lead to long-term competitiveness, which is consistent with the DCV argument (Peteraf et al. 2013; Steininger et al. 2022; Teece 2018b). As such, building on the RBV, DCV, and the emerging literature on AICs (Mikalef and Gupta 2021) and ITA (Lee et al. 2015; Syed et al. 2020a, 2020b), this study proposes an evolutionary fitness view (Helfat et al. 2007; Mikalef et al. 2020; Steininger et al. 2022) by which an AIC enables an organisation to reposition itself in a dynamic business environment (Mikalef and Gupta 2021; Mikalef et al. 2021a; Schilke et al. 2018). Specifically, if AICs, conceptualised as lower-order capabilities, are reconfigured appropriately, they can lead to ITA, and the high-order dynamic capability of OA.

Figure 1: Research model



3.1.1 AICs and process efficiency

At a process level, AI can be used to enhance several key performance metrics within an organisation, including efficiency, productivity, capacity, quality and, ultimately, profitability and competitiveness (Enholm et al. 2021; Mikalef and Gupta 2021; Wamba-Taguimdje et al. 2020). In manufacturing, organisations are increasingly using AI technologies to optimise the efficiency of product development cycles and manufacturing processes, and to improve predictive maintenance capabilities (Björkdahl 2020; Dubey et al. 2020; Enholm et al. 2021). AI technologies are also being integrated into the broader manufacturing value chain to improve logistics and transportation efficiencies (Björkdahl 2020; Dwivedi et al. 2021; Enholm et al. 2021). This means that tasks can be performed in shorter cycle times and throughput can be improved (Enholm et al. 2021). Organisations that leverage AI can therefore improve the speed and responsiveness of their operations, which are key attributes of OAA (Lu and Ramamurthy 2011; Mikalef and Pateli 2017). When combined with using AI to improve marketing decisions and tasks, identify customer preferences or anticipate consumer buying habits and trends, organisations that leverage the technology can respond faster to market demand (Enholm et al. 2021), which is a key attribute of MCA (Lu and Ramamurthy 2011; Mikalef and Pateli 2017). Consequently, AIC could be an enabler of OA (i.e., OAA and MCA).

3.1.2 AICs and insight generation

AIC can be used to uncover patterns and reveal insights that are otherwise hidden in large volumes of data (Collins et al. 2021; Duan et al. 2019; Mikalef and Gupta 2021; Enholm et al. 2021). By leveraging AI appropriately, organisations can gain insights their competitors lack (Enholm et al. 2021; Lichtenthaler 2019). The insights revealed and patterns unlocked by AI can facilitate the partial automation of organisational tasks, allowing organisations "to make better-informed decisions" (Enholm et al. 2021:14). By having access to more comprehensive knowledge, superior and timely decisions can be made (Enholm et al. 2021; Keding 2021; Wamba-Taguimdje et al. 2020). AI can thus promote faster and better decision-making (Enholm et al. 2021). Organisations that can exploit the informational effects of AI will be able to promptly sense and respond to changes in the market and environment of business (Wamba-Taguimdje et al. 2020).

The strategic organisational tasks of sensing and responding are encompassed in the delineation of OA (Lee et al. 2021; Park et al. 2017; Ravichandran 2018; Roberts and Grover 2012). In addition to the sensing and responding tasks inherent in OA, it has also been argued that strategic decision-making is a key characteristic of OA (Lee et al. 2021; Park et al. 2017), whilst this study argues that MCA and OAA (Lu and Ramamurthy 2011; Mikalef and Pateli 2017) encompass the characteristics of strategic decision-making. It therefore is plausible that an AIC can promote the strategic-event management tasks of sensing, decision-making and responding, thereby enabling OA.

The arguments presented here consider the potential impact of tangible AI resources on OA; taking a more holistic stance, however, Mikalef and Gupta (2021) suggest that intangible AI resources such as interdepartmental coordination, enhanced risk proclivity and an organisational change capacity, can also promote agility. For example, by fostering interdepartmental coordination, a common understanding between employees of different departments can be nurtured, which could improve responsiveness and “is likely to make organizations more agile” (Mikalef and Gupta 2021:6). Similarly, departing from a risk-averse strategic orientation can promote agility (Fountaine et al. 2019; Mikalef and Gupta 2021), whilst fostering an organisational capacity to change can allow organisations to “agilely adapt to evolving conditions” (Mikalef and Gupta 2021:6). Consequently, the underlying dimensions encompassed in an AIC can potentially lead to OA.

Building on these arguments and the extant dynamic capability literature advocating for IT capabilities as enablers of OA (for example Ghasemaghaei et al. 2017; Lee et al. 2015, 2021; Tallon et al. 2019), it is conceivable that possessing an AIC (i.e., a lower-order functional capability) can enable OA (i.e., a higher-order dynamic capability). Based on this dynamic capability viewpoint, it is hypothesised that:

H_1: An AIC will have a positive effect on OA

3.2 The Relationship between AICs and ITA

To cope with the complexity and dynamism of the current business landscape, amplified by emerging trends in digital innovation (Nwankpa and Datta, 2017), organisations need to explore new technologies and resources to adjust organisational processes, create new opportunities, and continuously innovate their business models (Burström et al. 2021; Nwankpa and Datta 2017; Zhen et al. 2021b). Through IT exploration, organisations can scan for various digital opportunities (Nwankpa and Datta 2017) requiring different levels of IT investment (Mithas and Rust 2016; Ravichandran 2018). By adopting an explorative approach to future investments in IT assets and resources, they can develop organisational competencies, which can contribute to “better organizational performance” (Nwankpa and Datta 2017:482). Having an AIC can enhance organisational creativity, promote risk proclivity, and improve innovation capacities (Ågerfalk 2020; Mikalef and Gupta 2021; Mikalef et al. 2021b; Wamba-Taguimdje et al. 2020). It therefore is conceivable that AICs can foster such exploration (Dubey et al. 2020; Wamba-Taguimdje et al. 2020). AI can facilitate the exploration of large volumes of data (i.e., big data) to uncover patterns and trends, such as consumer buying patterns, which can enhance the quality and timeliness of decision-making (Collins et al. 2021; Duan et al. 2019; Enholm et al. 2021; Mikalef and Gupta 2021).

On the other hand, IT exploitation initiatives can allow organisations to determine and rapidly respond to changes in consumer and market demand, thus promoting external environment adaption (Tallon et al. 2019; Zhen et al. 2021b). By leveraging and refining existing technologies and resources (i.e., IT exploitation), organisations can enhance their efficiencies and augment their effectiveness (Gregory et al. 2015; Lee et al. 2015; Nwankpa and Datta 2017; Zhen et al. 2021b). Organisations with AICs can exploit prevailing opportunities in an array of manufacturing settings and service environments to enhance product and service quality, productivity, and consumer experience (Björkdahl 2020; Enholm et al. 2021; Wirtz

2020). Thus, it is plausible that having an AIC can foster both IT exploration and exploitation (Gregory et al. 2015; Lee et al. 2015; Nwankpa and Datta 2017), suggesting that an AIC can foster ITA. It is therefore hypothesised that:

H_2: An AIC will have a positive effect on ITA

3.3 The Translating Role of ITA

In light of the IT-agility contradiction (Ghasemaghaei et al. 2017; Liu et al. 2018) and the theoretical argument that IT capabilities are too far away from OA in the organisational capability hierarchy (Benitez-Amado and Walczuch 2012; Liu et al. 2020), there is emerging interest in the role that ITA can play in transforming IT capabilities into agility (Chi et al. 2017; Lee et al. 2015; Mithas and Rust 2016; Syed et al. 2020a, 2020b; Zhen et al. 2021b; Zhou et al. 2018). For instance, Mithas and Rust (2016) explored the role of strategic ITA and found that it strongly moderated the relationship between an organisation's IT investments and performance, especially at higher levels of IT investment. Leonhardt et al. (2017) also showed empirically that ITA moderates the relationship between the digitisation support and agility of an organisation's IT functions, whilst Chi et al. (2017) found that ITA moderated the relationship between complementing IT governance strategies and performance.

With a few notable exceptions (Zhen et al. 2021a, 2021b; Zhou et al. 2018), the prevailing literature has not focused much on exploring the translation characteristics of ITA. Zhen et al. (2021b) studied the relationship between IT governance and OA and found that the relationship between these constructs was significantly mediated by ITA, whilst Zhen et al. (2021a) found that ITA mediated the relationship between organisational inertia and OA. Similarly, Zhou et al. (2018) found that business and IT competence positively influenced ITA, which they conceived through the lens of IS alignment. Subsequently, they found that ITA positively affected OA, illustrating early support for ITA as a potential mediator between IT capabilities and OA (Zhen et al. 2021a, 2021b; Zhou et al. 2018).

It has already been postulated that having an AIC can foster ITA. In turn, ITA is deemed to foster timely and appropriate responses to market demand and environmental dynamism (Lee et al. 2015; Syed et al. 2020a; Zhen et al. 2021b), akin to the sensing and seizing characteristics of OA (Park et al. 2017; Teece 2007; Teece et al. 2016). Hence, it is conceivable that ITA can translate an organisation's AIC into OA. As such, it is hypothesised that:

H_3: ITA mediates the relationship between an AIC and OA

4. Empirical Study

4.1 Survey, Administration and Data

In this study, a mono-method questionnaire-based survey was adopted to facilitate easy replication whilst promoting the generalisation of the research findings (Pinsonneault and Kraemer 1993). The selected approach was further substantiated owing to its congruence with other information systems research focused on IT capabilities, which have been dominated by quantitative methods to evaluate the broader business value from such capabilities (Abbasi et al. 2016). The AIC, ITA and OA constructs and their respective items were operationalised on a seven-point Likert scale used across all measures, which allowed for equivalence across the measures and consistency during the analysis of the data obtained with the instrument (Agresti and Franklin 2013; Lee et al. 2015; Tabachnick and Fidell 2013). It has been suggested that the seven-point scale reaches the "upper limit of the scale's reliability" (Allen and Seaman 2007:64), further substantiating its selection. A small-scale pilot study was conducted with ten senior technology officials (Hill 1998; Perneger et al. 2015) who were known to the researchers and whose organisations were known to have AICs. The pilot study verified the face and content validity, and the clarity of the instrument (Hair et al. 2020; Köhler et al. 2017; Yim 2019).

To operationalise the survey and test the research model, an electronic survey was distributed to just under 4 000 technology officials in the South African manufacturing ecosystem. Data was collected primarily from South Africa in response to recent calls advocating for the need to empirically explore the development of AI capabilities in emerging economies, where AI adoption rates lag behind those observed in more advanced economies (Ayentimi and Burgess 2019; Bag et al. 2021; Mikalef and Gupta 2021; Sutherland 2020).

The contact details of senior technology officials were obtained from numerous sources, including personal contacts, university databases, business directories, and a third-party service provider who used a business-to-business database to support the data collection process. Participation by each of the listed sources was requested at different points in time, from early October 2021 until the middle of January 2022. In all cases, an initial email requesting participation was sent to the available email addresses, followed by two follow-up emails, spaced three weeks apart (Chidlow et al. 2015). Potential respondents were also contacted on professional forums, specifically LinkedIn, and requested to participate in the survey. The data collection lasted for approximately three and half months and it took 17.76 minutes on average for the survey to be completed. The raw sample size attracted by the survey was 390 responses; however, only 173 were congruent with the targeted population and were thus retained for further analysis. The response rate was well below the 5% benchmark for online surveys introduced in Wegner (2016). The poor response could potentially be attributed to low AI adoption rates in the South African context (Ayentimi and

Burgess 2019; Bag et al. 2021; Sutherland 2020). Furthermore, it has been argued that online surveys have seen a decline in response rates for some time owing to deterrent organisational policies (Baruch and Holtom 2008), and a general "lack of willingness to take the time to complete questionnaires" (Hair et al. 2017:78). Since the obtained sample (n = 173) exceeded the threshold for conducting PLS-SEM (Hair et al. 2019a, 2020), and was higher than other, similar studies that empirically validated the AIC construct (Mikalef and Gupta 2021; Mikalef et al. 2021b), it was deemed appropriate to proceed with the statistical testing.

Although the responses of the qualified sample came from a diverse range of manufacturing, manufacturing support and telecommunications, technology, internet and electronics (TTIE) industries, all of which form part of the broader manufacturing ecosystem, the sample was biased towards manufacturing, and specifically the automotive industry (Appendix C). To test if the biased sample distribution affected the results, a series of statistical tests were conducted – the results of which are introduced in Section 5.2. Most of the participants were from large firms (51.4% of the qualified sample). Aligned with the sampling strategy, most responses were also from South Africa (93.64%) and from middle management to C-level seniority levels (86.71%). This was expected due to the qualifying question targeting 'senior technology officials' and the purposive sampling strategy to target these individuals, since they are likely to be the most knowledgeable about the constructs under investigation (Ghasemaghaei et al. 2017; Mikalef et al. 2020).

Since this study used a single instrument, at a single point in time, there was a need to statistically test for common method bias (CMB) (Chang et al. 2010; Podsakoff and Organ 1986; Podsakoff et al. 2003). Recent work validating the AIC construct conducted a Harman's one-factor test to test for CMB, whilst in a similar AI-related study, Bag et al. (2021) used the test for multicollinearity to verify if CMB was an issue (Kock 2015; Kock and Lynn 2012). In particular, the latter method has been suggested as an appropriate means to test for CMB in the context of PLS-SEM (Kock 2015). Since testing for multicollinearity was required to assess the formative and structural model, this approach was adopted to test for CMB in this study (Bag et al. 2021; Kock 2015; Kock and Lynn 2012). The results reveal that CMB was not an issue.

Table 3: Demographic characteristics of respondents – Individual level

Demographic	Frequency sample (n=173)	Percentage
[redacted]		
Male	140	80.92%
Female	29	16.76%
Prefer not to answer	4	2.31%
[redacted]		
Entry level	5	2.89%
Intermediate	18	10.40%
Middle management	54	31.21%
Senior management	58	33.53%
Owner/executive/C level	38	21.97%

Country		
South Africa	162	93.64%
Belgium	2	1.16%
Ghana	1	0.58%
India	1	0.58%
Japan	1	0.58%
Netherlands	1	0.58%
Saudi Arabia	1	0.58%
United Kingdom	2	1.16%
Unknown	2	1.16%
Respondent tenure in AI or advanced IT (years)		
0-2	49	28.32%
2-5	45	26.01%
5-10	38	21.97%
10-15	17	9.83%
15+	24	13.87%
Organisation's AI tenure (years)		
0-2	70	40.46%
2-4	41	23.70%
4-6	29	16.76%
6-8	4	2.31%
8+	29	16.76%
Firm size (number of employees)		
1-99	30	17.34%
100-499	23	13.29%
500-999	28	16.18%
1 000 or more	89	51.45%
Don’t know	3	1.73%
Industrial sector (initial grouping)		
Manufacturing	124	71.68%
Manufacturing support	10	5.78%
TTIE	39	22.54%
Industrial sector (final grouping)		
Manufacturing automotive	50	28.90%
Manufacturing other	74	42.77%
Manufacturing support	10	5.78%
TTIE	39	22.54%

4.2 Measurements

The measures for the AIC, ITA and OA constructs were adopted from prior work and have all been tested in previous empirical research. The measures, their associated items, and the supporting literature are shown in Appendix B.

AIC was conceptualised in accordance with the study of Mikalef and Gupta (2021) as an organisation’s capability to select, arrange and deploy its AI-specific resources. This definition extricates the process of arranging AI-related resources from any performance implications (Mikalef et al. 2018, 2020, 2021b),; allowing AIC to be conceptualised as a third-order formative construct. The AIC construct was conceptualised to comprise of AI-related tangible, intangible and human resources, formulated as second-order formative constructs, which in turn consisted of eight first-order constructs. Specifically, the tangible resources of an AIC were conceptualised to include data, technology (e.g., hardware and network infrastructures) and basic resources, such as funding, represented as formative first-order constructs (Desouza et al. 2020; Duan et al. 2019; Mikalef and Gupta 2021; Wirtz et al. 2019). Intangible resources were conceptualised to consist of first-order reflective constructs, with the underlying dimensions being organisational risk proclivity, capacity to change, and interdepartmental coordination (Davenport and Ronanki 2018; Mikalef and Gupta 2021; Ransbotham et al. 2018). Finally, human resources were conceptualised to comprise the reflective underlying first-order dimensions of business and technical skills (Dwivedi et al. 2021; Mikalef and Gupta 2021; Mikalef et al. 2021b; Spector and Ma 2019). In total, this part of the survey consisted of 35 items that were used to obtain a holistic measure of an organisation's AIC. The development of the AIC construct and its sub-dimensions and measures are shown in Appendix B.

Measured through the dimensions of MCA and OAA, **OA** represents a firm-wide capability to deal with unexpected changes that arise in the business environment through swift and innovative responses (Lu and Ramamurthy 2011; Park et al. 2017; Teece et al. 2016). OAA postulates flexible and swiftly responding business operations as being crucial to facilitating the efficient and seamless translation of innovative initiatives in circumstances that necessitate change (Lu and Ramamurthy 2011; Mikalef and Pateli 2017). MCA highlights a growth-oriented, entrepreneurial strategic organisational intent concerning decision-making and judgment, which is dynamic, and through which uncertain and volatile environments are perceived as fecund opportunities to enact new strategic directions (Lu and Ramamurthy 2011; Mikalef and Pateli 2017; Sambamurthy et al. 2003). To operationalise these sub-dimensions of OA, the questions for MCA, and OAA, were adopted from Lu and Ramamurthy (2011), and followed recent work that also studied IT-enabled OA (Ghasemaghaei et al. 2017; Mikalef and Pateli 2017; Zhou et al. 2018). Whilst MCA and OAA are formative in nature (Ghasemaghaei et al. 2017), in total they consist of six reflective items, as shown in Appendix B.

ITA was developed conceptually to evaluate the ability of organisations to exploit their current IT resources and practices, while simultaneously exploring new IT resources and practices (Lee et al. 2015; Syed et al. 2020a, 2020b). As such, it was measured through the dimensions of IT exploitation and IT exploration, which is consistent with previous IT-related studies that also explored the emerging construct of ITA (Lee et al. 2015; Syed et al. 2020a, 2020b; Zhen et al. 2021b). Informed by prior work (Lee et al. 2015), and operationalised through a total of six items, both the sub-dimensions and items for the ITA construct were reflective in nature.

All the study constructs (AIC, OA and ITA) were tested by more than five items, which has been recommend as the minimum number of questions to test a construct (Zikmund et al. 2012). Excluding the qualifying and demographic questions, the survey consists of 47 items, tested on a seven-point Likert scale. The language of the adopted items facilitates the use of a single scale, ranging from “strongly disagree” to “strongly agree”, and hence did not require the incorporation of any other Likert scale category (Allen and Seaman 2007).

Two control variables were used in the study: firm size and industry sector (Mikalef and Gupta 2021; Mikalef et al. 2020), as both variables could influence an organisation’s development of AICs and their responsiveness in fostering OA and ITA (Lee et al., 2015; Lu and Ramamurthy 2011; Mikalef and Gupta 2021). Firm size was measured as an ordinal value in accordance with several studies that measured the variable through the number of employees within a firm (Benitez et al. 2018b; Liang et al. 2017; Mikalef and Gupta 2021; Ravichandran 2018). The industrial sector was also measured ordinally.

5. Empirical Analysis

The reliability and validity of the hierarchical research model shown in Figure 1 was assessed using partial least squares structural equation modelling (PLS-SEM). All analyses were conducted using the SmartPLS (version 3.3.7) software package (Ringle et al. 2015). PLS-SEM was considered appropriate for this study as it enables the simultaneous estimation of complex models with multiple relationships (indirect and total effects) between constructs, indicator variables, and structural paths (Hair et al. 2019a). It has a high predictive accuracy, making it appropriate when suggesting academic and managerial implications (Hair et al. 2019b, 2020, 2021). There has also been a proliferation in the use of PLS-SEM techniques in the IS literature (Akter et al. 2017; Benitez et al. 2020; Mikalef et al. 2021b), whilst the method was also used in recent AIC studies that inspired the current work (Mikalef and Gupta 2021; Mikalef et al. 2021b).

5.1 Measurement Model Evaluation

Since the research model contains both formative and reflective constructs, following Benitez et al. (2020) and Hair et al. (2020) different assessment criteria were used for each construct type. For the reflective constructs, reliability tests at both item (i.e. indicator) and construct level were conducted, whilst tests to confirm convergent and discriminant validity were also conducted. Indicator reliability was computed by squaring the individual item loadings and examining if the squared loadings exceeded 0.5 (Hair et al. 2017, 2019a, 2020). Per the values in Appendix D, the lowest squared loading was 0.549; hence, indicator reliability was confirmed. Cronbach’s alpha (α) and composite reliability (CR) tests were used to confirm the reliability of the reflective constructs. All values for both tests exceeded the minimum threshold of 0.7 and were below the maximum threshold of 0.95; hence, construct reliability was established, whilst redundancy, in which items measuring the same construct limit construct diversity, was not an issue (Hair et al. 2017, 2019a, 2020).

Convergent validity was confirmed by evaluating the average variance extracted (AVE) values, as shown in Table 4. It was found that AVE values ranged from 0.643 to 0.895; thus, all AVE values exceeded the minimum threshold of 0.5. Since the variance shared between each construct and its individual indicators exceeded 50%, the convergent validity of the reflective model was confirmed (Hair et al. 2020). Discriminant validity was established by evaluating the heterotrait-monotrait (HTMT) ratio of correlations, an approach recently proposed to overcome some of the performance shortcomings of other traditional approaches, such as the Fornell–Larcker criterion (Hair et al. 2019a; Henseler et al. 2015). The HTMT ratio measures “the mean value of the item correlations across constructs relative to the (geometric) mean of the average correlations for the items measuring the same construct” (Hair et al. 2019a:9); thus providing a robust means of evaluating discriminant validity (Hair et al. 2020). As shown in Table 5, all values were below the cut-off range of 0.85 to 0.90 (Hair et al. 2020); thus, discriminant validity of the reflective measurement model was confirmed. The reliability and validity of the measures and the associated indicators of the reflective measurement model were therefore established.

Table 4: Summary of reliability (α, CR) and convergent validity (AVE) results

Construct	Cronbach's alpha (α)	Composite reliability (CR)	Average variance extracted (AVE)
First-order constructs			
BS	0.916	0.937	0.750
TS	0.926	0.948	0.821
IDC	0.902	0.931	0.773
OCC	0.862	0.900	0.643
RP	0.903	0.939	0.838
MAA	0.874	0.923	0.800
OAA	0.895	0.934	0.826
ITEI	0.864	0.917	0.786
ITER	0.866	0.918	0.789
Second-order constructs			
H_RES	0.884	0.945	0.895
I_RES	0.812	0.889	0.727
ITA	0.804	0.911	0.836

Table 5: Summary of HTMT results for the first-order reflective constructs

Construct	BS	ITEI	ITER	IDC	MAA	OAA	OCC	RP	H_RES	ITA
ITEI	0.656									
ITER	0.634	0.772								
IDC	0.653	0.569	0.544							
MAA	0.689	0.635	0.600	0.627						
OAA	0.539	0.487	0.492	0.532	**0.856**					
OCC	0.636	0.618	0.570	0.761	0.726	0.647				
RP	0.596	0.517	0.601	0.547	0.721	0.596	0.663			
TS	**0.855**	0.619	0.648	0.545	0.558	0.471	0.570	0.492		
ITA									0.787	
I_RES									0.779	0.799

For the formative indicators, indicator multicollinearity was assessed first. Whilst reflective indicators are usually interchangeable, and thus often highly correlated, highly correlated formative constructs create problems with multicollinearity (Hair et al. 2020). To test for multicollinearity, the variance inflation factor (VIF) of the formative indicators was computed. VIF values ranged from 1.359 (item one of the data construct – D1) to 4.428 (item two of the basic resource construct – BR2). All values did not exceed the cut-off value (i.e., VIF < 5); thus, indicator multicollinearity was not an issue in this study (Hair et al. 2019a).

The significance and size of the indicator weights were then assessed against the guidelines suggested by Hair et al. (2019a). As shown in Table 6**,** it was found that nine out of 22 p-values for the indicator weights were statistically non-significant, with a 95% confidence level, whilst most of the weights (i.e., 16 out of 22) were less than the recommended 0.5 (Hair et al. 2020). Similarly, when evaluating the outer weights of the formative AIC construct, Mikalef and Gupta (2021) also found similar results, specifically where items D2, D4, T1, T5 and BR2, which were adopted in this study, were non-significant. When this is the case, Hair et al. (2017:168) advise that non-significant indicator weights "should not automatically be interpreted as indicative of poor measurement model quality". However, it has been suggested that researchers should evaluate the formative indicator loadings, as they provide information on the indicator, irrespective of the contributions of the other indicators (Hair et al. 2021). Specifically, if the outer weight is non-significant, but the outer loading exceeds a minimum threshold of 0.5, the indicator should be retained. As illustrated in Table 6, this was the case for all the indicators except D1, where the indicator loading was below (0.475) the threshold. To ensure that content validity was not compromised, caution was exercised and the formative indicator was not deleted, as the "theory-driven conceptualization of the construct" (Hair et al. 2017:168) strongly supported its retention (Cenfetelli and Bassellier 2009; Hair et al. 2020, 2021). Explicitly, the item in question (D1) was deemed by an expert panel to be an 'important facet' of the data construct (Hair et al. 2020; Mikalef and Gupta 2021), and its inclusion was supported by several studies documenting its importance to an AIC (Mikalef and Gupta 2021; Mikalef et al. 2021b).

Table 6: Indicator weights, loadings and VIF values for the formative indicators

Items	Indicator weights		Indicator loadings		VIF
	Original sample (O)	P-values	Original sample (O)	P-values	
D1	0.128	0.255*	0.475	0.000	1.359
D2	-0.056	0.653*	0.556	0.000	1.934
D3	0.149	0.286*	0.671	0.000	1.976
D4	0.058	0.698*	0.677	0.000	1.759
D5	0.761	0.000	0.975	0.000	2.530
D6	0.114	0.464*	0.775	0.000	2.204
T1	0.293	0.007	0.782	0.000	1.857
T2	-0.072	0.569*	0.746	0.000	2.667
T3	0.431	0.007	0.833	0.000	1.991
T4	0.063	0.653*	0.771	0.000	2.541
T5	0.473	0.000	0.882	0.000	2.349
B_RES1	0.277	0.143*	0.916	0.000	3.563
B_RES2	0.639	0.001	0.982	0.000	4.428
B_RES3	0.138	0.446*	0.861	0.000	3.016
First-order items					
B_RES	0.218	0.043	0.843	0.000	2.395
D	0.363	0.003	0.891	0.000	2.478

T	0.527	0.000	0.935	0.000	2.341
Second-order items					
T_RES	0.313	0.005	0.886	0.004	3.287
I_RES	0.570	0.000	0.933	0.000	
H_RES	0.223	0.045	0.854	0.044	
MAA	0.819	0.000	0.989	0.000	
OAA	0.223	0.042	0.847	0.043	

Note. Items marked with an * were statistically non-significant at the adopted 95% confidence level ($p > 0.05$)

5.2 Evaluation of Structural Model

Once the validity and reliability of the measurement model was established, the following steps were conducted to evaluate the structural model. First, the multicollinearity of the structural model was evaluated, before the standardised path coefficients (β) and the variance of the endogenous variables (R^2) were explained. The effect sizes of the path coefficients (f^2), and the predictive relevance of the endogenous variables measured through the Stone-Geisser (Q^2), were also modelled before the test for mediation was conducted.

To ascertain if multicollinearity was present in the inner model, the VIF values for the inner model were computed. As illustrated in Table 7, all VIF values were below the threshold (VIF < 5) suggested by Hair et al. (2017), whilst 60% of the obtained VIF values were below the conservative lower bound (V < 3) proposed by Hair et al. (2020); hence, multicollinearity in the structural model was not an issue in this study. It was also concluded that CMB was not an issue in the context of this work (Bag et al. 2021; Chang et al. 2010; Kock 2015; Kock and Lynn 2012; Podsakoff et al. 2003).

Table 7: Multicollinearity assessment (VIF values) of higher-order constructs

Higher-order constructs	ITEI	ITER	MAA	OAA	ITA	OA
D	2.865	2.865	2.884	2.879		
T	2.518	2.518	3.204	3.186		
B_RES	3.367	3.367	3.451	3.441		
BS	3.638	3.638	3.68	3.669		
TS	3.503	3.503	3.577	3.577		
IS	2.238	2.238	2.245	2.24		
RP	1.766	1.766	1.944	1.854		
OCC	2.364	2.364	2.595	2.473		
OAA			1.725			
ITEI			2.437	2.431		
ITER			2.392	2.385		
H_RES					3.086	3.109
I_RES					2.018	2.148
T_RES					3.287	3.933
ITA						2.472
AIC					1.000	2.289

The standardised path coefficients (β) were then modelled in SmartPLS (Ringle et al. 2015) to test the study's hypotheses. T-statistics were obtained through bootstrapping with 5 000 resamples (Hair et al. 2020). As hypothesised, an organisation's AIC was found to have a positive, direct impact on OA ($\beta = 0.646$, $t = 10.546$, $p < 0.001$) and on ITA ($\beta = 0.750$, $t = 20.579$, $p < 0.001$). Compared to the AIC→OA relationship, the path coefficient for the AIC→ITA relationship was higher, indicating that an AIC has a relatively stronger effect on ITA than OA. Although not a separate hypothesis, the direct link between ITA and OA was also tested (see mediation analysis in Section 5.3), and it was noted that this relationship was statistically non-significant at the 95% confidence level ($p > 0.05$).

After evaluating the path coefficients, the coefficient of determination (R^2) values were evaluated to understand the in-sample predictive ability of the endogenous constructs (ITA and OA). As shown in Figure 2, the final model accounted for 56.3% of the variance with regard to ITA ($R^2 = 0.563$), and 53.1% of the variance for OA ($R^2 = 0.531$). Both obtained R^2 values falling within the moderate range (Hair et al. 2017), inferring that the model presents a moderate in-sample predictive ability. This predictive ability was further evaluated by measuring the effect size, f^2, which allowed us to estimate the predictive ability of each independent construct in the model (Hair et al. 2020). This facilitated assessing the contribution of the exogenous constructs to the endogenous latent variable's R^2 (Mikalef and Gupta 2021; Mikalef et al. 2020). Although the f^2 value for the structural link between AIC and ITA is approximately 3.3 times larger than the f^2 for the link between AIC and OA, both the effect sizes fall into the large effect category ($f^2 > 0.35$), as suggested by Benitez et al. (2020) and Hair et al. (2020).

Consistent with prior IS research, the effect of the study's control variables on the results was tested by adding the firm size and industry to the structural path of the model and executing the bootstrapping procedure (Benitez et al. 2018b; Mikalef and Gupta 2021). Specifically, two different models – one that tested the manufacturing sector holistically, and the other that tested the automotive industry as a separate category in the manufacturing ecosystem (see Appendix C) – were computed. For all cases, the influence of the CVs on OA, the main endogenous construct in this study, was found to be nonsignificant.

5.3 Test for Mediation

A mediation analysis was conducted to examine the indirect effects involved in the research model. This was per the approach of Zhao et al. (2010), which has been employed in several studies (Benitez et al. 2018b; Hair et al., 2017; Rueda et al., 2017). To examine if the impact of AIC on OA was direct or was mediated by ITA, the bootstrap method (Preacher and Hayes, 2008), was used. As a nonparametric resampling procedure, bootstrapping is congruent with PLS-SEM, since it does not impose any assumptions on the normality of the sampling distribution (Benitez et al. 2018b; Hair et al. 2019b; Preacher and Hayes 2008). It is particularly relevant when testing for mediation, as it facilitates interpreting the indirect effect of target constructs through one or more intervening constructs (Hair et al. 2019a).

Specifically, 5 000 bootstrap samples were used to ascertain the level of significance for the indirect effects involved in the structural model (Hair et al. 2020). We first tested the indirect relationship between the AIC and OA constructs (AIC→ITA→OA) and, as per the results in Table 8 and Figure 2, the indirect relationship between the mentioned constructs was statistically non-significant at the 95% level of confidence ($p > 0.05$). Next, we analysed the significance of the direct relationship between the AIC and OA constructs, which was already done during the testing of H_1. This relationship (AIC→OA) was deemed statistically significant at the 99% confidence level ($p < 0.001$). It therefore was concluded that a direct-only relationship existed between the AIC and OA constructs, with no mediation taking place (Zhao et al. 2010). Thus, for H_3, we failed to reject the null hypothesis; a potential theoretical argument to explain this result is suggested in Section 6.1. The mediation analysis was consequently aborted, as the remaining steps suggested by Zhao et al. (2010) were only required in the presence of mediation.

Table 8: Summary of hypothesis tests and results

Structural model path	Relationship	Path coefficient	t-statistics	P-values	Conclusion
AIC → ITA	Direct	0.750	20.579	0.000	Supported
AIC → OA	Direct	0.646	7.707	0.000	Supported
ITA → OA	Direct	0.106	1.001	0.320*	
AIC → ITA → OA	Indirect	0.079	0.999	0.318*	Not supported

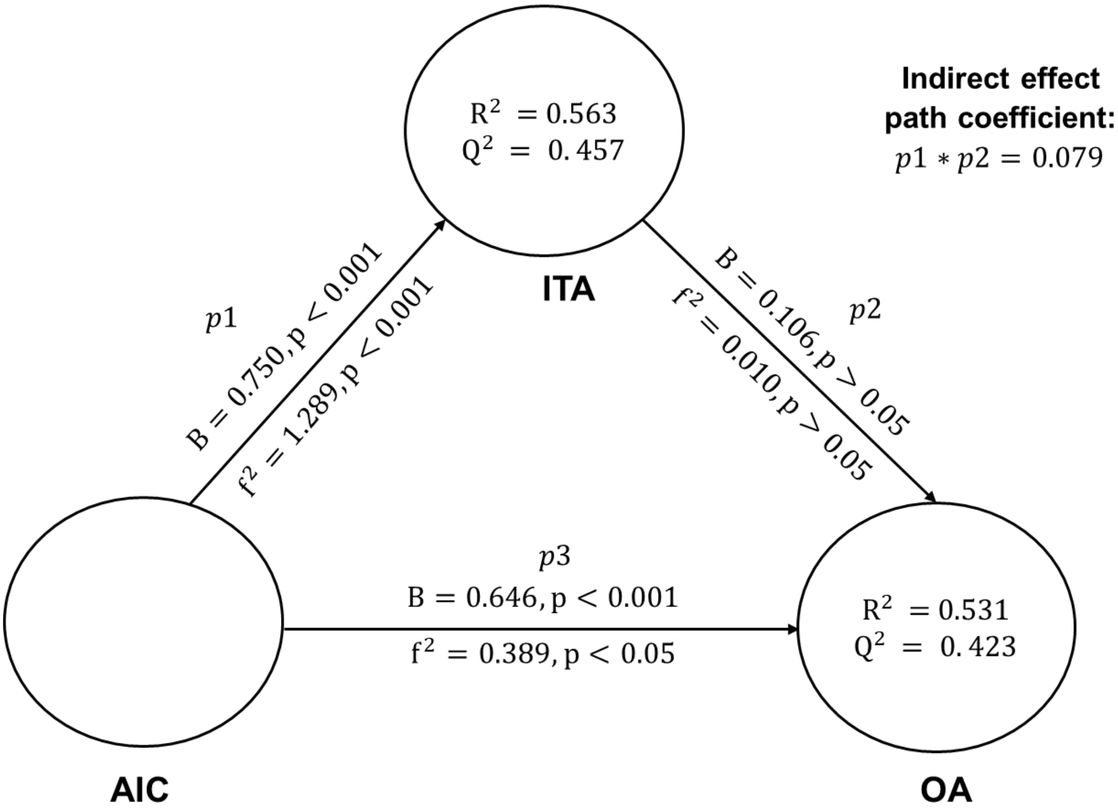
Note. * denotes statistically non-significant relationship at the 95% confidence level ($p > 0.05$)

5.4 Predictive Validity

In addition to evaluating the coefficient of determination (R^2) and effect sizes (f^2), the predictive capability of the structural model was further assessed through the examination of the Stone-Geisser Q^2 metric, which is computed through the blindfolding technique (Hair et al. 2017, 2020). This metric is computed by imputing the mean and estimates of the model's parameters into single deleted points in the data matrix (Sarstedt and Mooi 2014). Considering this, the Q^2 metric combines elements of a model's in-sample explanatory capabilities, and certain characteristics of its out-of-sample predictive capabilities (Hair et al. 2019a, 2020). Stone-Geisser Q^2 values greater than 0 infer that the model has predictive relevance (Hair et al. 2017), whilst the following predicative relevance effect sizes have been proposed in the literature: 1) small: $0 < Q2 < 0.25$; 2) medium: $0.25 < Q2 < 0.5$; 3) large: $Q > 0.5$ (Hair et al. 2020). Per Figure 2, the obtained values for both endogenous constructs imply that the model has medium predictive capability.

Finally, to assess model fit, and to ascertain how well the hypothesised model structure fits the empirical data (Hair et al. 2021), the standardised root mean squared residual (SRMR) was computed (Benitez et al. 2018b, 2020; Hair et al. 2021; Henseler et al. 2014). This measures the discrepancy between “the empirical correlation matrix and the model-implied correlation matrix” (Benitez et al. 2018b:513), and is reported in recent studies applying PLS-SEM (Benitez et al. 2018b; Mikalef and Gupta 2021). The obtained SRMR value of 0.048 was below the recommended value of 0.08, thus inferring model fit for the PLS path model (Hair et al. 2017; Mikalef et al. 2020). However, considering that the effectiveness and appropriateness of model fit indices are still an area of active research (Hair et al. 2021; Rigdon et al. 2017), especially in “applied research” settings (Hair et al., 2021, p. 117), following the suggestions made in the literature (Hair et al., 2020; Hair et al., 2021; Hair et al. 2019a), the obtained results were interpreted cautiously and used as a descriptive measure.

Figure 2: Estimated relationships of the structural model



6. Discussion

6.1 Summary of Results

The literature on AI adoption in organisational settings remains scant. The available studies indicate that AI initiatives fail to create and capture business value, essentially due to the lack of a holistic approach to AI adoption. Given the technical complexity associated with the technology, recent work has argued that organisations need to nurture AI-complementary resources (Mikalef and Gupta 2021) and, more precisely, their tangible (for example data), intangible (for example interdepartmental coordination) and human resources (for example technical and business skills) to ensure the successful deployment of AI. Building on this IT-complementary perspective (Bharadwaj 2000; Irfan et al. 2019; Mikalef and Gupta 2021; Mikalef et al. 2020), in this study it was maintained that an organisation-level AIC is required to ensure that business value can be obtained from AI-initiatives. As a departure point from prior work, using the DCV of the firm to theoretically ground the study, we theorised that, if the resources associated with an AIC are reconfigured appropriately, they can lead to the development of ITA and the harnessing of the higher-order dynamic capability of OA. The proposed theory was tested on a sample of firms, primarily in South Africa, and the empirical results support the theory. We found that AIC has a direct, positive effect on (1) ITA; and (2) OA, whilst a robust PLS-SEM analysis illustrated the in-sample statistical significance, relevance and explanatory power of the hypothesised relationships between the constructs (Hair et al. 2017, 2019a, 2020).

The relationship between the AIC and OA constructs was positioned in the IT-enabled agility literature, where an IT-agility contradiction exists (Ghasemaghaei et al. 2017; Liang et al. 2017; Liu et al. 2018; Park et al. 2017). In this regard, some studies have found that IT capabilities have a positive effect on OA (Gunasekaran et al. 2018; Lee et al. 2015; Liu et al. 2018; Mikalef and Pateli 2017; Ravichandran 2018), whilst others have found that IT capabilities have a neutral or negative influence on OA (Ghasemaghaei et al. 2017; Liang et al. 2017; Liu et al. 2013; Swafford et al. 2008). For example, Ghasemaghaei et al. (2017) and Liang et al. (2017) both found that IT capabilities have an impeding effect on OA. In contrast, Ravichandran (2018) reported that general IS capabilities had a statistically significant, direct impact on OA, while Mikalef and Pateli (2017) found that general IT capabilities were an essential, direct enabler of OA. Given the IT-agility contradiction, the findings suggest congruence with the view that IT capabilities have a positive, direct impact on OA.

We also analysed the effect of an AIC on ITA and OA and found that the effect size for AIC → ITA was approximately 3.3 times larger than the effect size for AIC → OA. A potential explanation for this could be related to the hierarchical IT-enabled capabilities perspective of the DCV used to theoretically anchor this study (Steininger et al. 2022; Teece 2007; Teece et al. 1997, 2016). It seems likely that, in comparison to OA, which is a strategic higher-order dynamic capability (Ghasemaghaei et al. 2017; Lee et al. 2015; Park et al. 2017; Queiroz et al. 2018; Ravichandran 2018; Steininger et al. 2022; Teece et al. 2016), AIC conceptualised as a functional lower-order capability is closer in the capability hierarchy (Benitez-Amado and Walczuch 2012; Liu et al. 2020) to ITA – also conceptualised as a functional capability.

The potential mediating role of ITA between an AIC and OA was also theorised. Given the IT-agility contradiction, it was hypothesised that ITA could potentially translate AICs into OA; however, the empirical results did not support the hypothesised relationship (AIC → ITA → OA). To explain the lack of mediating effect of ITA, we turned to the non-significant link between ITA and OA. A potential reason for the low path coefficient and non-significant relationship ($\beta = 0.106$, $p > 0.05$) for the ITA → OA link, which contributed to the non-significant indirect effect (AIC → IT → OA), could be the distance between the ITA and OA capabilities in the organisational capability hierarchy (Benitez-Amado and Walczuch 2012; Liu et al. 2020). It is possible that, for ITA to enable OA, it needs to interact with other organisation-level capabilities, such as operational ambidexterity (Lee et al. 2015), organisational fit (Ghasemaghaei et al. 2017) or business coordination (Liang et al. 2017), which potentially are closer to OA in the organisational capability hierarchy (Benitez-Amado and Walczuch 2012; Liu et al. 2020).

Another possible explanation for the lack of mediation could be the research methodology adopted. Testing mediation paths using cross-sectional data could have resulted in biased estimates (Aguinis et al. 2017; Pan et al. 2018; Ramayah et al. 2018), since “mediated models contain causal paths that imply the passage of time” (Aguinis et al. 2017:677). In addition, several recent studies on ITA have suggested that a longitudinal time horizon may be required to understand how ITA influences organisational capabilities, such as OA, at different points in time (Lee et al. 2021; Nwankpa and Datta 2017; Syed et al. 2020a, 2020b), suggesting an area of future research. Moreover, the lack of a sampling frame for the current study could have also contributed to the lack of mediation. With non-probability sampling, it is difficult to ascertain if the non-significant effect emerged due to the idiosyncrasies of the qualified sample, or if it existed in the population (Sarstedt et al. 2018).

6.2 Implications for Theory and Research

This study makes three key contributions to IS research. First, building on prior work adopting a theoretical approach inspired by the RBV of the firm to conceptualise an AIC, this study advances this theoretical underpinning by positioning the AIC within the DCV of the firm (Mikalef et al. 2021a), which is considered an extension of the RBV (Mikalef and Pateli 2017; Schilke et al. 2018; Steininger et al. 2022; Teece, 2018b). More precisely, it positions an AIC and ITA as lower-order capabilities in the latest IT-enabled organisational capability literature, and argues theoretically how these capabilities could enable OA, which is an intermediate higher-order dynamic capability (Ghasemaghaei et al. 2017; Lee et al. 2015; Queiroz et al. 2018; Teece et al. 2016). The theoretical positioning of this study in the dynamic capability literature supports the emerging IT-enabled organisational capabilities perspective and contributes to a developing consensus (Benitez et al. 2018b; Mikalef and Gupta 2021; Steininger et al. 2022) that IT “capabilities enable firms to generate performance gains through intermediate organizational capabilities” (Mikalef et al. 2021a:81).

Second, through the evaluation of the hypothesised measurement model, it was possible to confirm the reliability and validity of the newly proposed AIC construct, as well as its sub-measures and items (Mikalef and Gupta 2021; Mikalef et al. 2021b). By doing so, this study contributes to recent calls in the information systems community to conceptualise and empirically validate the complementary organisational capabilities required to leverage AI to derive business value (Enholm et al. 2021; Mikalef and Gupta 2021; Mikalef et al. 2019, 2021a; Wamba-Taguimdje et al. 2020; Wirtz et al. 2019).

Third, the study advances prior empirical work on the impact of an AIC on organisation-level capabilities, such as creativity (Mikalef and Gupta 2021) and flexibility (Bag et al. 2021), by demonstrating the in-sample impact, explanatory power and predictive capability of an AIC on OA and ITA. Although the outcome variables of ITA and OA have been either explicitly or implicitly suggested to be influenced by an AIC (Björkdahl 2020; Dubey et al. 2020; Dwivedi et al. 2021; Enholm et al. 2021; Keding 2021; Nwankpa and Datta 2017), this appears to be the first large-scale study that empirically validates these conjectured relationships. It was empirically demonstrated that, by harnessing an AIC, organisations can enable OA and ITA, a finding that highlights the strategic potential of AI in driving an ambidextrous and agile strategic approach, which in turn could lead to enhanced performance and sustained competitiveness (Lee et al. 2015; Mithas and Rust 2016; Tallon et al. 2019; Teece 2007; Teece et al. 2016).

6.3 Implications for Practitioners

The outcome of this study offers several pragmatic insights for IS practitioners. Whilst the practice-based literature (for example, Brynjolfsson and McAfee 2017; Davenport and Ronanki 2018; Fountaine et al. 2019; Ransbotham et al. 2018, 2019) has positioned the importance of tangible AI resources such as data, hardware and algorithms to operationalise AI in organisational settings, this study, following recent academic literature (Mikalef and Gupta 2021; Mikalef et al. 2019, 2021b), advocates a more holistic approach to developing an organisational AIC. In particular, the study highlights the importance of developing and leveraging human and intangible resources as key complementary resources to support the tangible (i.e., technical) resources of an AIC (Mikalef and Gupta 2021). The findings indicate that business practitioners should focus on the development of technical skills to develop and execute AI technologies, as well as business skills to identify and prioritise AI initiatives to derive business value (Mikalef and Gupta 2021; Wamba-Taguimdje et al. 2020). Training and upskilling staff on AI techniques and their potential applications are important to ensure the successful and sustained deployment of AI initiatives in an organisation (Dwivedi et al. 2021; Mikalef and Gupta 2021; Spector and Ma 2019).

The findings also indicate that business managers should focus on improving interdepartmental coordination, fostering an organisational capacity to change, and promoting a greater appetite towards embracing risks (Mikalef and Gupta 2021; Mikalef et al. 2021b), as these intangible resources are essential in developing an AIC. The different types of resources studied in this work (tangible, intangible and human) suggest that intangible resources are the “most difficult" to replicate by competing organisations (Mikalef and Gupta 2021:6). Furthermore, it has been suggested that intangible resources are of even greater significance in dynamic, volatile and uncertain markets (Mikalef and Gupta 2021; Morgan et al. 2006), thus further highlighting the need for management to focus on them to improve competitiveness, given the current volatile and dynamic environment of business (Mikalef and Pateli 2017; Tallon et al. 2019; Walter 2020).

Although this study focused on evaluating an organisation’s AIC, the adopted instrument, measures and items (Mikalef and Gupta 2021; Mikalef et al. 2021b) can be used by IT practitioners and managers as a self-assessment instrument to evaluate organisational readiness for AI initiatives (Lokuge et al. 2019). In doing so, they will be able to: 1) assess the organisation's tangible, intangible and human capabilities; 2) understand where building capabilities are required; 3) and minimise the risk of future AI initiatives failing (Bharadwaj 2000; Lokuge et al. 2019; Mikalef and Gupta 2021). The adopted survey instrument can therefore be used by practitioners and management as a precursor to the successful implementation of AI deployment within their organisations (Lokuge et al. 2019; Mikalef and Gupta 2021).

Finally, the study demonstrated the impact of harnessing an AIC on strategic business capabilities, specifically on agility and ITA. Thus, the research model may be used by strategists to highlight areas within the organisation that need to be developed to foster agility and ambidexterity. As noted by Mikalef and Gupta (2021), value-generating mechanisms from AI initiatives are likely to be derived in different ways, since different types of AI technologies and business contexts could lead to different outcomes. For example, using certain forms of AI could enhance OAA through the automation of manual tasks, while AI algorithms could be used to improve market segmentation, contributing to MCA (Enholm et al. 2021; Keding 2021).

6.4 Limitations and Recommendations for Future Research

Despite the study's promising results, it has theoretical and methodological limitations which should be addressed in future studies. First, it used a deductive research approach, which assumed that the adopted AIC construct was appropriate across geographical locations and organisational contexts (Mikalef and Gupta 2021). Yet AI adoption rates vary in different economies and industrial sectors due to context-specific challenges and nuances (Bag et al. 2021; Lokuge et al. 2019; Sutherland 2020). To uncover these nuances, an interpretivist approach could potentially provide enriched information on some of the challenges and limitations contributing to the poor performance of AI in the organisational context (Mikalef and Gupta 2021; Ransbotham et al. 2019). Also, since organisational AICs are still in their infancy (Enholm et al. 2021; Mikalef and Gupta 2021; Wamba-Taguimdje et al. 2020), further work to understand what constitutes an AIC, and how it affects organisational performance, is required. Second, to limit bias from using a single key informant, future empirical studies could use a matched-pair survey approach, which samples technology officials and business executives from the same organisations. It has been argued that this approach can reduce CMB (Lee et al. 2015; Liang et al. 2017; Podsakoff and Organ 1986).

Third, future work should explore the latest advances in PLS-SEM and use them to enhance the quality of the model's out-of-sample predictive capability, thereby enhancing the validity of the results. It is recommended that the model is evaluated using the PLSpredict algorithm (Shmueli et al. 2016, 2019). PLSpredict can estimate the out-of-sample predictive capability of the structural model, which is important, especially when drawing conclusions that influence business practices and have management implications (Hair 2020; Hair et al. 2019a, 2020). Although statistical tests unveiled that the biased industrial sector demographic had a non-significant effect on the key outcome variable (OA), future work should test for heterogeneity in the qualified sample, since unobserved heterogeneity can have a considerable adverse impact on PLS-SEM results and could lead to misrepresentative interpretations (Becker et al. 2013; Sarstedt et al., 2017).

Finally, the cross-sectional time horizon inhibited testing the predictive validity of the measurement model (Hair et al. 2020) and could have adversely affected the results of the mediation analysis, since mediation models have causal paths that conjecture the conduit of time (Aguinis et al. 2017). Future work should consider testing the relationships longitudinally, as this could also facilitate an explanation of the evolutionary characteristics of the impact of AI and ITA on OA, which are key capabilities in a dynamic business environment (Lee et al. 2015; Mithas and Rust, 2016 Tallon et al. 2019; Teece et al. 2016).

7. Conclusion

Inspired by the surge in interest in understanding the business value of AI in the organisational context, this study developed and tested the relationship between AICs, and OA and ITA, which have been positioned as important organisational capabilities that can foster competitiveness in the dynamic environment of business. Built on the DCV, as well as emerging AIC and ITA research, the empirical results highlight the importance of investing in complementary AI resources (i.e., tangible, intangible and human) that collectively can help harness an AIC. The empirical results indicate that AICs can foster OA, and ITA, but that ITA does not translate an AIC into OA. The theorised relationships, and substantive results from this work, will hopefully be used pragmatically to enhance AI deployments within organisations, and for future research on the emergence of AIC and its impact on other organisational capabilities required for competitiveness.

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Appendix A: Summary of Selected Recent Studies Focused on Organisational AICs

Source	Definition of AIC	Methodology	Key contributions
Wamba-Taguimdje et al. (2020: 1900)	"AICs could be defined as the firm's ability to create a bundle of organizational, personnel and AI resources for business value creation and capture"	Multiple case study/ secondary data analysis	Conceptual model suggesting that AI management capabilities, personnel expertise, and infrastructure flexibility contribute to process and organisational level business value creation
Schmidt et al. (2020:3)	"AIC is the ability of organizations to use data, methods, processes and people in a way that creates new possibilities for automation, decision making, collaboration, etc. that would not be possible by conventional means"	Design science research	Conceptual multi-level framework that describes business value creation based on different layers of AICs. Specifically, AI assets foster basic AICs, which foster process-level capabilities, subsequently leading to value creation
Schmidt et al. (2020:4)	"AICs are digital capabilities that integrate AI-specific assets, for instance, AI-algorithms, training data, etc. to enable value creation"		
Mikalef et al. (2019:410)	An AIC is "the ability of a firm to orchestrate organizational resources and apply computer systems able to engage in human-like throughout processes such as learning, reasoning, and self-correction towards business tasks"	Theoretical concept development	Theoretical development arguing that competitive performance from AI initiatives is achieved in specific business areas through an AIC, which consists of organisational data, infrastructure, culture, learning and skills
Mikalef and Gupta (2021:2)	"An AIC is the ability of a firm to select, orchestrate, and leverage its AI-specific resources"	Survey	Conceptualisation and empirical validation of AIC construct, empirical evidence showing AICs impact performance

Appendix B: Survey Instrument

Construct	**AI capability** (Mikalef and Gupta 2021; Mikalef et al. 2021)
Measures	**Tangible**
Data	D1. We have access to very large, unstructured, or fast-moving data for analysis
	D2. We integrate data from multiple internal sources into a data warehouse or mart for easy access
	D3. We integrate external data with internal to facilitate high-value analysis of our business environment
	D4. We have the capacity to share our data across business units and organisational boundaries
	D5. We are able to prepare and cleanse AI data efficiently and assess data for errors
	D6. We are able to obtain data at the right level of granularity to produce meaningful insights
Technology	T1. We have explored or adopted cloud-based services for processing data and performing AI and machine learning
	T2. We have the necessary processing power to support AI applications (e.g. CPUs, GPUs)
	T3. We have invested in networking infrastructure (e.g. enterprise networks) that supports efficiency and scale of applications (scalability, high bandwidth, and low-latency)
	T4. We have invested in scalable data storage infrastructures
	T5. We have explored AI infrastructure to ensure that data is secured from to end to end with state-of-the-art technology
Basic resources	BR1. The AI initiatives are adequately funded
	BR2. The AI project has enough team members to get the work done
	BR3. The AI project is given enough time for completion
	Human resources
Technical skills	TS1. The organisation has access to internal and external talent with the right technical skills to support AI work
	TS2. Our data scientists are very capable of using AI technologies (e.g. machine learning, natural language processing, deep learning)
	TS3. Our data scientists are provided with the required training to deal with AI applications
	TS4. Our data scientists have suitable work experience to fulfil their jobs
Business skills	BS1. Our managers are able to understand business problems and to direct AI initiatives to solve them
	BS2. Our managers are able to work with data scientists, other employees and customers to determine opportunities that AI might bring to our organisation

	BS3. The executive manager of our AI function has strong leadership skills
	BS4. Our managers are able to anticipate future business needs of functional managers, suppliers and customers and proactively design AI solutions to support these needs
	BS5. We have strong leadership to support AI initiatives and managers demonstrate ownership of and commitment to AI projects
	Intangible
	Please indicate to what extent do departments (e.g., marketing, R&D, manufacturing, information technology, and sales) within your organisation engage in the following activities:
Inter-departmental coordination	IC1. Collaboration
	IC2. Teamwork
	IC3. Same vision
	IC4. Mutual understanding
Organisational change capacity	OCC1. We are able to anticipate and plan for the organisational resistance to change
	OCC2. We consider politics of the business reengineering efforts
	OCC3. We are capable of communicating the reasons for change to the members of our organisation
	OCC4. We are able to make the necessary changes in human resource policies for process reengineering
	OCC5. Senior management commits to new values
Risk proclivity	RP1. In our organisation we have a strong proclivity for high risk projects (with chances of very high returns)
	RP2. In our organisation we take bold and wide-ranging acts to achieve firm objectives
	RP3. We typically adopt a bold aggressive posture in order to maximise the probability of exploiting
Construct	**Organisational agility** (Lu and Ramamurthy, 2011)
Measures	
Operational adjustment agility	OA1: We fulfil demands for rapid-response, special requests of our customers whenever such demands arise; our customers have confidence in our ability.
	OA2: We can quickly scale up or scale down our production/service levels to support fluctuations in demand from the market.
	OA3: Whenever there is a disruption in supply from our suppliers we can quickly make necessary alternative arrangements and internal adjustments
Market capitalising agility	MA1: We are quick to make and implement appropriate decisions in the face of market/customer-changes.
	MA2: We constantly look for ways to reinvent/reengineer our organisation to better serve our market place.

	MA3: We treat market-related changes and apparent chaos as opportunities to capitalise quickly.
Construct	**ITA** (Lee et al. 2015; Zhen et al. 2021)
Measures	
IT exploration	ITER1: We acquire new IT resources (e.g., new generation of IT architecture, potential IT applications, critical IT skills)
	ITER2: We experiment with new IT resources
	ITER3: We experiment with new IT management practices
IT exploitation	ITEI1: We make extensive use of the existing IT components, such as hardware, software, and network resources.
	ITEI2: We offer IT applications and services sufficiently
	ITEI3: We have a high level of IT-related skills.

Appendix C: Industrial Sector Granular Analysis

Industrial sector	Frequency	Overall percentage	Sector percentage
Manufacturing			
Motor vehicles, Parts and Accessories and other Transport Equipment	50	28.90%	40.32%
Food, Beverages and Tobacco	12	6.94%	9.68%
Utilities, Energy, and Extraction	11	6.36%	8.87%
Petroleum, Chemical Products, Rubber and Plastic Products	10	5.78%	8.06%
Basic Iron and Steel, Non-ferrous Metal Products, Metal Products and Machinery	7	4.05%	5.65%
Electrical Machinery	4	2.31%	3.23%
Textiles, Clothing, Leather and Footwear	4	2.31%	3.23%
Pharmaceuticals	4	2.31%	3.23%
Retail & Consumer Durables	4	2.31%	3.23%
Airlines & Aerospace (including Defence)	3	1.73%	2.42%
Radio, Television and Communication Apparatus and Professional Equipment	3	1.73%	2.42%
Agriculture	1	0.58%	0.81%
Construction and Homes	1	0.58%	0.81%
Wood and Wood Products, Paper, Publishing and Printing	1	0.58%	0.81%
Manufacturing Other	9	5.20%	7.26%
Manufacturing support			
Transportation & Delivery	3	1.73%	30.00%
Business Support & Logistics	7	4.05%	70.00%
Technology services			
TTIE	39	22.54%	100.00%
Total	173	100.00%	

Appendix D: Reflective Indicator Loadings, Squared Loadings, t-Statistics, and p-Values

Item / Construct	Loadings	Squared loadings	T-Statistics	P-values
First-order indicators				
TS1	0.847	0.717	33.730	0.000
TS2	0.944	0.891	86.281	0.000
TS3	0.935	0.874	74.524	0.000
TS4	0.894	0.799	28.942	0.000
BS1	0.879	0.773	33.784	0.000
BS2	0.893	0.797	49.669	0.000
BS3	0.761	0.579	16.841	0.000
BS4	0.896	0.803	43.703	0.000
BS5	0.892	0.796	49.362	0.000
IDC1	0.860	0.740	32.500	0.000
IDC2	0.891	0.794	49.419	0.000
IDC3	0.880	0.774	37.338	0.000
IDC4	0.885	0.783	48.232	0.000
OCC1	0.834	0.696	26.223	0.000
OCC2	0.741	0.549	11.627	0.000
OCC3	0.833	0.694	25.258	0.000
OCC4	0.792	0.627	20.437	0.000
OCC5	0.805	0.648	24.706	0.000
RP1	0.917	0.841	54.041	0.000
RP2	0.922	0.850	48.423	0.000
RP3	0.906	0.821	34.838	0.000
OA1	0.903	0.815	45.655	0.000
OA2	0.929	0.863	71.547	0.000
OA3	0.894	0.799	41.727	0.000
MA1	0.855	0.731	31.575	0.000
MA2	0.910	0.828	51.651	0.000
MA3	0.916	0.839	53.622	0.000
ITEI1	0.858	0.736	29.558	0.000
ITEI2	0.902	0.814	42.457	0.000
ITEI3	0.898	0.806	47.207	0.000
ITER1	0.864	0.746	30.287	0.000
ITER2	0.930	0.865	64.502	0.000
ITER3	0.870	0.757	28.072	0.000
Second-order indicators				
BS	0.952	0.906	116.273	0.000
TS	0.941	0.885	77.480	0.000
IDC	0.841	0.707	31.127	0.000
OCC	0.893	0.797	58.478	0.000
RP	0.822	0.676	26.512	0.000
ITEI	0.916	0.839	65.627	0.000
ITER	0.913	0.834	52.820	0.000

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