Determinants of the Adoption of Digital Technologies in South African Manufacturing: Evidence from a Firm-level Survey

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Abstract

Digital technologies and digitalisation are emerging as the new drivers of structural transformation in developing countries. At the firm level, the adoption of advanced digital technologies offers prospects for improved productivity and competitiveness, and hence digital industrialisation. However, the determinants of adoption of digital technologies in manufacturing firms in developing countries remain anecdotal. Using unique online survey data on 516 manufacturing firms in South Africa, and a multivariate probit model, this paper examines the determinants of digital technology adoption in South African manufacturing firms. Our results show heterogeneity in the factors that explain the adoption of digital technologies across business functions. Overall, the empirical results reveal that innovation, foreign ownership, exposure to export markets, and higher-skilled human capital push the adoption of digital technologies, while a lack of capital constrains the adoption of digital technologies in our sampled firms. We discuss the possible policy implications of our findings and how they fit into the South African Digital Skills policy discourse.

Keywords: digital technology, technology adoption, manufacturing, South Africa

JEL codes: 014

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1. Introduction

The emergence of new technologies has reshaped and revolutionised industrial production and human society as a whole (Selase and Selase 2019). Early technological innovations such as steam power, and later computers, ushered in entirely new eras of production and facilitated significant shifts in how businesses organise and conduct their operations, while also broadening their reach into new markets and customers. The adoption of advanced technologies has been fundamental to how firms and economies both develop and perform.[1] Today, digital technologies and digitalisation are also emerging as new drivers of structural transformation. This is due to digitalisation upending traditional industries while also opening entirely new markets and influencing innovation, production, trade, consumption, and a host of business processes across industries and geographies (Andreoni et al. 2021; Barnes et al. 2019).

From a manufacturing perspective, the prospects and potential if he widespread diffusion and adoption of advanced digital technologies offer firms benefits that range from improved customer experiences to completely altering their existing business and organisational models for the better (Hammer 2019; Liere-Netheler et al. 2018). The growing discussions on these new digital technological advancements (often described as Industry 4.0), driven in some degree by the Covid-19 pandemic, also allude to the potential benefits of these technologies, including increased competitiveness and productivity, among other measures of manufacturing firm performance (see, for instance, Barnes et al. 2019). However, these potential benefits also come with potential costs (Baldwin and Lin 2002). These costs may include the costs of acquiring the technology, and the retraining and reskilling of workers with the requisite technological and foundational capabilities to adapt and use the acquired advanced technology (Andreoni et al. 2021; Baldwin and Lin 2002).

There is a debate on the possible implications and benefits of advanced technologies for developing countries, such as South Africa, that are experiencing de-industrialisation. The debate, in fact, heralds digitalisation and the adoption of advanced digital technologies as having the potential to reignite South Africa's ailing manufacturing sector (Barnes et al. 2019). Studies on the manufacturing sub-sectors in South Africa have referenced poor and ageing technological infrastructure as key reasons for the country's lagging competitiveness in global markets (see Bell et al. 2019 for an assessment of technological capabilities in the plastics industry). The country therefore is at an important juncture and there is an urgent need to develop policy responses to these challenges and opportunities that promote the broader objective of inclusive growth. In response to this and other challenges, South African policymakers have drafted policy strategies aimed at addressing the digital gaps in many South African industries (Department of Communications and Digital Technologies 2020).

[1] Advanced digital technologies are defined as including computer-managed inventory systems, machine-to-machine (M2M) communication systems, big data and artificial intelligence, i.e. Generations III and IV technologies (see Delera et al. 2022; Ferraz et al. 2020).

However, most of the studies on technological change approach the issues from an industry- or sector-focused analysis (Blume 1992; Brown and Campbell 2002; Rosenberg 1963). Indeed, from a South African perspective too, studies tend to take the shape of analyses of an industry or system owing to a lack of available data (see, for example, Reardon et al. 2004 for an investigation of agrifood systems). However, there is a crucial gap in our knowledge of the dynamics of technological change, specifically digital technological change, at the firm level. The related empirical literature analysing the adoption and implications of digital technologies at the firm level in developing countries is nascent. Despite this, the evidence emerging from the scant literature suggests that the adoption of advanced digital technologies remains limited and may not fully generate the expected gains in developing countries (Delera et al. 2022; Ferraz et al. 2019). This may be due to several factors, including the inadequacy of digital skills, the wide heterogeneity in the adoption patterns of firms, as well as the poor integration of firms in global value chains (GVCs) (Delera et al. 2022).

Given the difficulties in adopting and implementing new digital technologies in developing countries, several questions on the adoption processes, and the drivers of digital technologies in manufacturing, remain unanswered in the literature.[2] The current paper adds to this body of literature by focusing on digital technology adoption across business functions in South African manufacturing firms, using knowledge gleaned from a unique online survey of firms that are classified under three manufacturing sector education and training authorities (SETAs[3]).[4] These include the Chemicals Industry SETA (henceforth CHIETA), the Manufacturing, Engineering and Related Services SETA (MerSETA), and the Fibre-processing and Manufacturing SETA (FP&M SETA). These sectors were chosen partly because of their role as important root industries for (digital) industrialisation. This paper contributes to this growing research by evaluating the behaviours and attitudes of manufacturing firms to the adoption of digital technologies using micro-level data. An understanding of the ongoing changes in manufacturing due to digitalisation provides policymakers an opportunity to influence and shape the digital technology adoption behaviours of manufacturing firms in South Africa. In addition, the use of micro-level data is essential for understanding the drivers and implications of advanced digital technologies in developing countries (Delera et al. 2022).

In line with the literature, we find that the adoption of digital technologies is limited across all surveyed business functions in our data. Our empirical analysis suggests that there is some heterogeneity in the factors that explain the adoption of digital technologies across business functions in the sampled manufacturing firms. Overall, the empirical results reveal that innovation, foreign ownership and human capital push the adoption of digital technologies, while the lack of capital constrains the adoption of digital technologies in the sampled firms.

[2] This is besides Delera et al. (2022), who examined the role of value chains in the adoption of digital technologies in developing countries. However, the authors analysed the determinants of technology adoption by generations, while our paper examines the determinants of digital technology adoption by business functions, thereby allowing us to identify specific factors that affect the adoption of digital technologies based on their use.
[3] SETAs provide information and assistance on education, skills and training in their sectors.
[4] The digital skills survey encompassed 516 firms across several areas of digital technologies and skills.

In addition, we find that the negative effect of capital constraints on adoption is mitigated by exports, innovation, and human capital.

The rest of the paper proceeds as follows. Section 2 conceptualises digital technologies in developing countries, followed by a discussion of our data and empirical strategy in Section 3. In Section 4 we present and discuss the results of our empirical analysis, and we conclude the paper with some policy recommendations in Section 5.

2. Conceptual Framework

2.1 Digital Technologies and Manufacturing

Globally, digital technologies are changing the landscape of many sectors. Since their full-scale introduction into many sectors of the economy, dating back to the computer revolution in the 1980s, technological upgrades have been a catalyst for structural transformation. While technological breakthroughs of the past have led to many significant changes in the labour force, thereby offering some level of uncertainty about the future, they have also created growth and employment opportunities in entirely new occupations and industries, and augmented production in some 'traditional' manufacturing industries (Berger and Frey 2016).

From a manufacturing perspective, digital technologies, and more broadly digitalisation, offer the promise of increasing the productivity and global connectedness of South African manufacturing industries (Barnes et al. 2019). The adoption of upgraded technologies can also create, and in some cases strengthen, backward and forward linkages to other domestic sectors, while also facilitating growth in the quality of output in these sectors (Bell et al. 2019). Nevertheless, there is still ongoing debate about what the adoption of improved digital technologies entails for the future of work and the manufacturing sector in the context of Industry 4.0. For instance, some authors see the coming digital revolution as a 'Second Machine Age' – one in which technological innovations promise to radically increase productivity in a wide range of industries, but also that new technologies also having adverse effects on particularly low- and middle-skilled workers (Brynjolfsson and McAfee 2014). These potential social consequences of the digital revolution are echoed by Krzywdzinski et al. (2018), who argue that, while this sudden technological breakthrough may in fact have positive aggregate employment effects, there are more urgent issues that require attention, such as the increasing inequality and increased alienation of the workforce through greater levels of standardisation and surveillance.

Moreover, the widespread adoption of digital technologies in manufacturing has the potential to have a massive impact on the environment. It is unclear, however, whether digitalisation will have an overall positive or negative environmental impact from applications in manufacturing (Chen et al. 2020). In terms of the benefits, digitalisation results in positive environmental sustainability through increased resource efficiency from the integration of Industry 4.0 technologies over the entire product lifecycle. The negative effects on manufacturing from rapid digitalisation come in the form of waste and emissions arising from increased energy use.

The success of the adoption of advanced digital technologies (intimately linked with Industry 4.0) is keenly linked to the ability of firms to reorient their digital infrastructure around automation, the internet of things (IoT), cloud computing, and big data and analytics. Some authors have expressed hesitance about the ability of firms to properly extract benefits. Piccarozzi et al. (2018), for example, suggest that these technologies need to be introduced into the organisation purposefully in order to experience the benefits of Industry 4.0.

2.2 Digital Technologies: Implications for Manufacturing in Developing Economies

In the context of a highly competitive global marketplace in which firms are competing with other firms to gain market share, digital technologies offer firms in developing countries the potential to carve out niches and offer improved products and customer service. Furthermore, digital technologies can assist firms in developing economies to expand their reach regionally and internationally, and to improve the efficiency of production and supply chain processes. Digital technologies are also creating new opportunities for smaller firms to enter into GVCs, due to lower barriers to export in the digital era, even in longer and more complex GVCs (Banga 2019).

From the perspective of individual firms, digital technologies are expected to bring about transformation along three main avenues (Hammer 2019). Firstly, advancements in digital technologies are believed to assist firms in developing a deeper understanding of their customers through digitally enhanced selling, predictive marketing, analytics-based marketing and streamlining. These improvements will lead to greater synergies between customers and producers. Secondly, from the perspective of improvements in the operational process, digital technologies are seen as important catalysts for performance improvement, operational transparency and data-driven decision-making, while also enabling workers to work better and faster through the advancements in communication and knowledge sharing. Thirdly, and perhaps most crucially from the firm perspective, is the effects that digital technologies and digitalisation will have on their business models. Firms that readily adopt and adapt to the advancements in digital technology will be able to extract the benefits of reshaped organisational boundaries, while also being able to augment their products and services.

However, our understanding of the drivers of technology (specifically digital technologies) is less concrete. This lack of understanding of the drivers of digital technology adoption is all the more pressing given the Covid-19 pandemic, which has accelerated the push towards digitalisation as firms seek to gain efficiency and improve competitiveness in response to the upending of global supply chains. At the same time, the pandemic is highlighting the challenges of the digital divide and the lack of digital skills in many African countries (the dtic, 2018).

Moreover, while the adoption of digital technologies has the potential to bring about enormous economic and social benefits in developing countries, it is crucial to recognise that the impact of digital technologies will not be homogenous across countries, regions, cities and firms. Therefore, developing countries are facing a two-pronged problem in the digital economy, centred around persistent divides in access to and use of digital technologies (Banga 2019).

The existence of a digital divide has implications that extend beyond the productivity and competitiveness of individual firms and industries. For example, the unequal adoption of digital technologies can have ramifications that weaken the capabilities and performance of the wider industry, particularly in terms of the aforementioned ability of these developing economy firms to integrate into GVCs. Moreover, the problems associated with the digital divide also tend to be exacerbated in developing countries, particularly on the African continent. This sentiment is echoed in other case studies, that show what appears to be a stark digital divide between developing economies themselves.

In India, for instance, the digital divide also transcends industry and sector boundaries, with digital technologies and digitalisation concentrated in only a few sectors, such as computers and electronics, metals, pharmaceuticals, and other transport equipment (Banga 2019). In addition to this, differing firm-level performance in response to digitalisation is very much linked to the firm capitalising on the benefits of the digitalisation of the market, as referenced in a case study of the experiences of Latin American firms (Sanchez-Riofrio et al. 2021). Another study, of 240 Serbian manufacturing firms, found that the use of digital technologies was limited in high-technology firms. Instead, the results of the survey found that medium-sized firms were greater adopters of digital technologies (Lalic et al. 2020).

The different experiences and heterogeneity that exist in the adoption of digital technologies among and within developing economies highlight the need for a deeper understanding of the behaviours of firms in the digital age. Of crucial importance here is the attitudes of firms and workers in the context of the potential effects of the greater adoption of evermore advanced digital technologies. For example, of the South African workers surveyed in a PwC survey of 22 000 people in 11 countries, 70% answered positively about the future effects of digital technologies on their jobs (PWC 2020).

This sentiment was echoed by respondents in India and China, where around eight in 10 respondents answered favourably on the impact of digital technologies. European and Australian respondents were less positive about the future effects of digital technologies on their jobs. Similarly, around 56% of the South African respondents expressed concerns about the potential risk of jobs losses from automation. Moreover, these results highlighted a stark divide between female and male workers, with female workers expressing more concerns about the risks of the impacts of future technologies.

While the results of the PwC research offer unique insights into the attitudes of individual workers to the future uptake of digital technologies, the results do not offer any insights into the attitudes of firms to digital technologies. One high-level commentary on the potential for technology as a catalyst for growth in South Africa has argued that more positive attitudes towards technology can help the economy unlock tremendous productivity gains in many sectors (Magwentshu and Rajagopaul 2019).

The true uptake of advanced digital technologies will most likely be mixed and, in many cases, uneven. This is because of different levels of existing technological infrastructure and organisational capabilities that allow some firms to adapt to advancements in digital technologies more easily. The different abilities of firms to integrate and extract benefits from digitalised business and production models will result in the escalation of the digital divide.

These issues are likely to increase the risks of exclusion of firms in developing countries from GVCs, for instance. To combat this, firms in developing economies must begin engaging with digital technologies to improve their respective capabilities. The adoption of digital technologies can act as a starting point towards igniting this process of technological catch-up in many economies whose current technological infrastructure lags well behind those of more developed economies. Moreover, concerns should also be focused on the potential for digital technologies to worsen existing divides between small and large firms (Andreoni et al. 2021). The heterogeneity stemming from differing levels of digital technology adoption, itself a function of technological infrastructure, foundational capabilities and financial affordability, may ultimately lead to the creation of a larger digital divide (Turianskyi 2020).

However, at this stage, little is known about how firms from different industries operating in South Africa's current economic climate are approaching and navigating the many complexities that come with a potential overhaul of business strategies and operations of this magnitude. Moreover, less is known about the baseline drivers of digital technology adoption in South African firms and the relative degrees and directions of their effects. The existing literature discussing drivers of adoption offers only some useful insights, and few from a micro-level and industry analysis, into the *a priori* directions and degree of influence of these individual factors, which can combine to determine the ability of a firm to adopt digital technologies.

This research therefore seeks to contribute to the knowledge base by analysing the perspectives of South African firms on the adoption of digital technologies and digital skills at different industry (or SETA) levels. The specific nuances that exist between a set of industries means that tailoring approaches and policies to a given industry's experience and plans around the adoption of digital technologies is paramount to facilitating a smooth transition to Industry 4.0. Understanding how South African firms in different industries are approaching these complex issues is essential to deepen our current knowledge of digitalisation in the South African context. This research thus presents the insights gained through the first iteration of the digital skills survey conducted across three South African SETAs in 2020/2021.

3. Methodology

This section discusses the digital skills survey in Section 3.1, the empirical strategy employed for the analysis in Section 3.2, and finally the presentation of basic descriptive statistics of key variables in the data in Section 3.3.

3.1 Data

The analysis uses the digital skills survey – a first of its kind in South Africa – that drew from similar surveys in Argentina and Brazil. The South African survey was conducted in March 2021, covering firms organised into three manufacturing sector education and training authorities (SETAs) – manufacturing and engineering services (MerSETA), chemicals (CHIETA), and textiles and fibre processing (FP&M SETA). The survey was conducted as part of an ongoing joint project under the IDTT supported by the Department of Trade, Industry and Competition, and as well the SETAs that govern skills training.

The survey aimed to understand the current and possible future levels of adoption of digital technologies, and the state of digital skills and technological capabilities in South African manufacturing firms. There are nine sections in the digital skills survey questionnaire. The first four sections examined the current and future adoption behaviours of firms in our sample across four key business functions: supplier relationship, production management, customer relations, and product development. In this paper, we use this data to measure our digital technology variable. In sections five to seven, the survey explores the technological capabilities and skills of workers, the implications of technologies for firm outcomes, and the relevant factors that affect the adoption behaviours of firms. The last two sections examine the firm-level characteristics, employment, and innovation and export activities of firms between the 2017/2018 and 2019/2020 financial years.

We then combined the data from the survey with data obtained from the SETAs on the industry, levies, size and location characteristics of firms. These variables were used as additional controls in our analysis.

In total, the digital skills survey obtained 516 responses from all sampled firms (about 7% response rate), with the MerSETA, CHIETA and FP&M SETA firms accounting for 67%, 17% and 16% of the responses, respectively. However, after merging with the SETAs dataset, we obtained and used data on 440 firms for our analysis. The drop in the number of firms is due to our inability to uniquely link the information of 76 firms in the digital skills survey to that of the SETA databases. Detailed descriptive statistics of our main variables of interest are reported in Section 3.3.

3.2 Empirical Strategy

In order to identify and examine the determinants of digital technology adoption separately across different business functions for which we have good data,[5] we formulated three separate simple probit models as:

$$Supplier\_relations_{iqt+5} = a_0 + X_{iqt}\delta_1 + Industry_{qt}\delta_2 + \varepsilon_{iqt} \quad (1)$$

[5] In this paper, we define digital technologies as generation 3 and 4 technologies, following the UNIDO elaboration based on the Indústria 2027 Survey (IEL 2018) and on Ferraz et al. (2019). See Appendix 1 for digital technology classifications across business functions.

$$Customer\_relations_{iqt+5} = b_0 + X_{iqt}b_1 + Industry_{qt}b_2 + \mu_{iqt} \tag{2}$$

$$Production\_development_{iqt+5} = b_0 + X_{iqt}b_1 + Industry_{qt}b_2 + \gamma_{iqt} \tag{3}$$

where $Supplier\_relations_{iqt+5}$, $Customer\_relations_{iqt+5}$ and $Production\_development_{iqt+5}$ are binary variables that equal 1 if the firm plans to introduce supplier relations, customer relations and production development disruptive technologies in firm i of industry q in time t+5 respectively, and 0 otherwise.[6] In the survey, firms were asked to indicate technologies they would adopt in five to 10 years. Based on this, we defined digital technology adoption in t+5 as firms that have indicated that they would use digital technologies in the next five to 10 years. The use of the expected adoption of digital technologies in t+5 was to avoid possible bidirectional causality between our dependent and independent variables. $Industry_{qt}$ is a vector of industry-level classification of the firm in 2019, while ε_{iqt}, μ_{iqt} and γ_{iqt} are multivariate, normally distributed error terms with 0 mean, constant variance, and correlation rho12, rho13 and rho23.

In line with Delera et al. (2022) and Ferraz et al. (2020), we define X_{iqt} as a vector of all firm-level and location variables that may affect the probability to introduce disruptive technologies across business functions. In addition, the literature also identifies specific factors that influence the ability of a firm to adopt digital technologies. Specifically, we control for exports, given that there is a noted technology premium associated with exports, and firms with exporting capabilities are more likely able to adopt new, advanced digital technologies (Cirera et al. 2021; Cirillo et al. 2021; Lee et al. 2020). A multitude of foundational capabilities (that extend to general skills, infrastructure and the presence of a well-functioning industrial ecosystem) influence the adoption of digital technologies (Andreoni et al. 2021). In this regard, we also control for a host of variables such as the importance of human-computer skills, and science, technology, engineering and mathematics (STEM) qualifications.

Based on Baldwin and Lin (2002), we regrouped all firm-level variables into six main categories: institution-related constraints; cost-related constraints; information-related constraints; labour-related characteristics; organisation-related characteristics; and firm characteristics. In our analysis, institution-related constraints refer to a lack of adequate digital infrastructure, while cost-related constraints covers the lack of capital. Specifically, institution-related constraints emerge from the operating environment, while cost-related constraints pertain to the price associated with acquiring advanced technology and its adoption. Information-related constraints cover firms' lack of information and awareness of digital technologies. Organisation-related characteristics are those attributes that require firms to make internal modifications to their operations, such as innovation, export, and research and development (R&D). Firm characteristics are the general demographic variables such as age, size of the firm, capital ownership, and the SETA of the firm. Finally, and of

[6] The analysis excluded the production management business function due to data and convergence issues.

particular interest, are the labour-related firm characteristics that cover the skills of workers, including issues such as the importance of the general training of workers, human-computer interaction skills for workers, as well as human capital in STEM. We consider these labour-related firm characteristics as a summary of the level of skills and capabilities within the digital ecosystem of the firm or industry in question.

Given that firms may simultaneously introduce all or a combination of digital technologies for the business functions under consideration, we estimated equations 1 to 3 with a multivariate probit model, where the error terms across the different models are correlated (in line with Delera et al. 2022). In extension, we also analysed the determinants that influence the introduction of digital technologies for at least one business function. This analysis helped us to examine heterogeneity in the factors that may influence the simultaneous introduction of the digital technologies across all business functions under consideration.

To estimate our multivariate probit model simultaneously, we employed the flexible conditional mixed process (cmp) estimator framework developed by Roodman (2011). The cmp allows us to fit the three multi-probit equations into a mixed process with digital technology adoption behaviours across three different business functions that have different observations. Using the cmp framework, we conducted the analysis in a full-information maximum likelihood (FIML), where errors from all equations are correlated and normally distributed. This estimation of our equations, jointly using maximum-likelihood estimation, uses the full covariance matrix of the residuals across our models, and hence was identified as being more efficient (Roodman 2011).

3.3 Basic Descriptive Statistics

Table 1 shows the definition and descriptive statistics of all variables in our model. As noted, we used data on 440 firms.[7] Given the missing observations, our data show that most of our sampled firms were small (54%), and about 25% and 21% were medium-sized and large firms respectively.[8] Only a small proportion of our sampled firms were fully or partly owned by foreigners (about 15%). A large proportion of sampled firms export (about 45%), innovate (about 51%), are relatively old (average of 56 years since establishment), and lack financial capital (90%). In terms of human capital, about 63% of firms had employees with STEM qualifications.

[7] See Table 5 in Appendix 2 for the definition and measurement of all variables.

[8] The size of firms was determined by annual sales value: Micro (sales valued below R10 million per financial year), small (sales valued at between R11 and 50 million per financial year), medium (sales valued at between R51 and R250 million per financial year), and large (sales valued at more than R250 million per financial year).

Table 1: Definition and descriptive statistics of key variables

>	Definition	N	Mean	SD	Min	Max
Digital technologies						
Supplier relations	A dummy variable that takes a value of 1 if the firm's primary method of communicating with suppliers (to place orders) in five to 10 years will be through real-time monitoring of orders and logistics of suppliers (e.g., computer-managed inventory systems), and 0 if the firm will place orders manually (e.g., over the phone or via email) or through electronically using computerised systems.	426	.370	.483	0	1
Customer relations	A dummy variable that takes a value of 1 if the firm's primary method of managing production in five to 10 years will be through a machine-to-machine (M2M) communication system, and 0 if it will manage production through a partially or fully automated process or simple automation with unconnected machines.	321	.140	.347	0	1
Product development	A dummy variable that takes a value of 1 if the technology the firm would use in five to 10 years is virtual development systems (such as manufacturing) or integrated data product systems (such as product data management and/or product lifecycle management), and 0 otherwise.	106	.613	.489	0	1
Human capital	A dummy variable that takes a value of 1 if the firm has employees with STEM qualifications, and 0 otherwise.	260	.630	.483	0	1
Lack of capital	A dummy variable that takes a value of 1 if the firm considers the lack of capital/funds as an obstacle, and 0 otherwise.	257	.898	.302	0	1
Age	A continuous variable defined as the total number of years the firm has been in operation, constructed as the natural logarithm of the total number of years plus 1.	435	56.078	38.071	1	100
Capital ownership	A dummy variable that takes a value of 1 if the firm is partly or fully foreign owned, and 0 otherwise (in the 2019/2020 financial year).	268	.145	.353	0	1
Export	A dummy variable indicating if the firm exports (1), and 0 if otherwise (in the 2019/2020 financial year).	270	.451	.498	0	1
Innovation	A dummy variable indicating if the firm has introduced new production processes or made significant improvements to products between the 2017/2018 and 2019/2020 financial years.	344	.508	.500	0	1
Industry	A categorical variable that shows the 20 South African industrial classifications of the firms in our sample.	435			1	20
Size of firm	A categorical variable that takes the value 1 if the size of the firm is large (21%), 2 if medium (25%), and 3 if small (54%) (in the 2019/2020 financial year).	435			1	3
Province	A categorical variable that assumes a value between 1 and 9 to indicate the province in which firm is located.	435			1	9

Our data further shows that, of 426 firms that responded to the question on the adoption of advanced digital technologies for supplier relations, about 37% indicated that they would use digital technologies in the next five to 10 years. For customer relations and product development, we found 14% and 61% future adoption of advanced digital technologies rates respectively. These figures suggest some level of heterogeneity in the expected adoption of digital technologies across the three business functions in our data in the next five to 10 years.

Given that the decision to adopt advanced digital technologies is dependent on the expected net benefits (Baldwin and Lin 2002), we examined the specific factors that drive the adoption of advanced digital technologies and the observed heterogeneity across business functions.

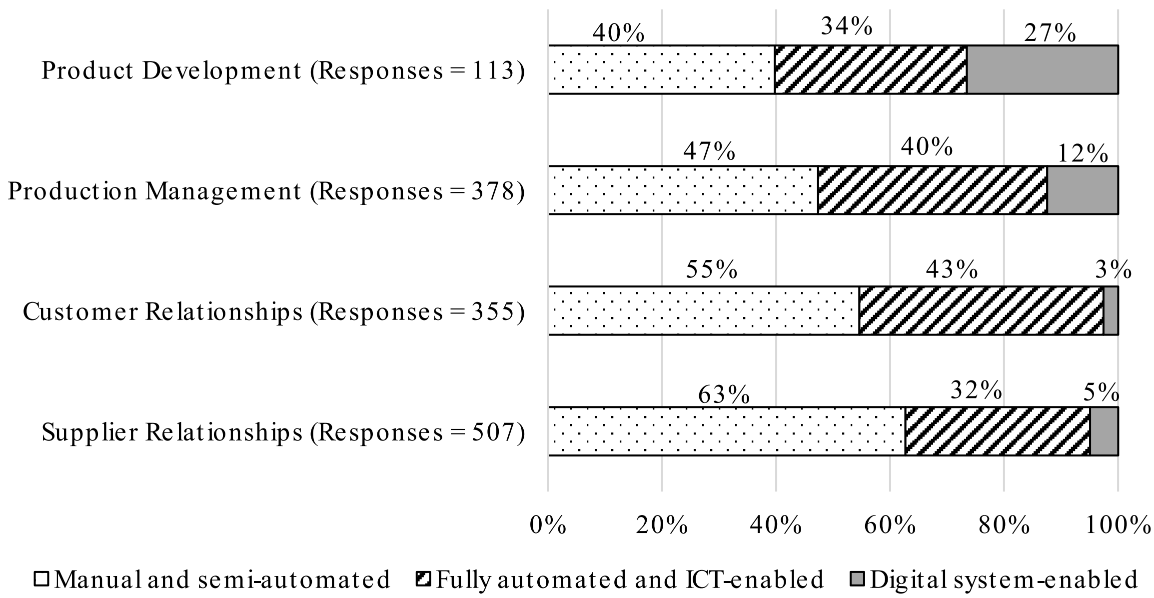
4. Empirical Results and Discussion

This section presents and discusses the evidence from our online survey data for all business functions (Section 4.1), and the econometric analysis in which we examined the determinants of technology adoption across three business functions (supplier relationships, customer relationships, and product development) in sections 4.2 and 4.3. In the empirical estimation, we first estimate, separately, probit models for each business function, followed by our preferred model – multivariate probit – with which we jointly estimate all three equations as a seemingly unrelated regression (SUR). All correlations are heteroskedasticity-robust.

4.1 Evidence from Firm-level Survey

Here, we first provide basic graphical representations and descriptions of some of the variables in our data. Figure 1 shows the distribution by types of technologies firms employ in the four respective business functions. Of the firms surveyed, there is some level of heterogeneity in their technological infrastructure, with some business functions displaying greater affinity for fully-automated, ICT-enabled and digital-enabled systems (Figure 1). The production management business function, for example, displays the highest degree of technological heterogeneity, while the supplier and customer relationship business functions display the least technological heterogeneity.

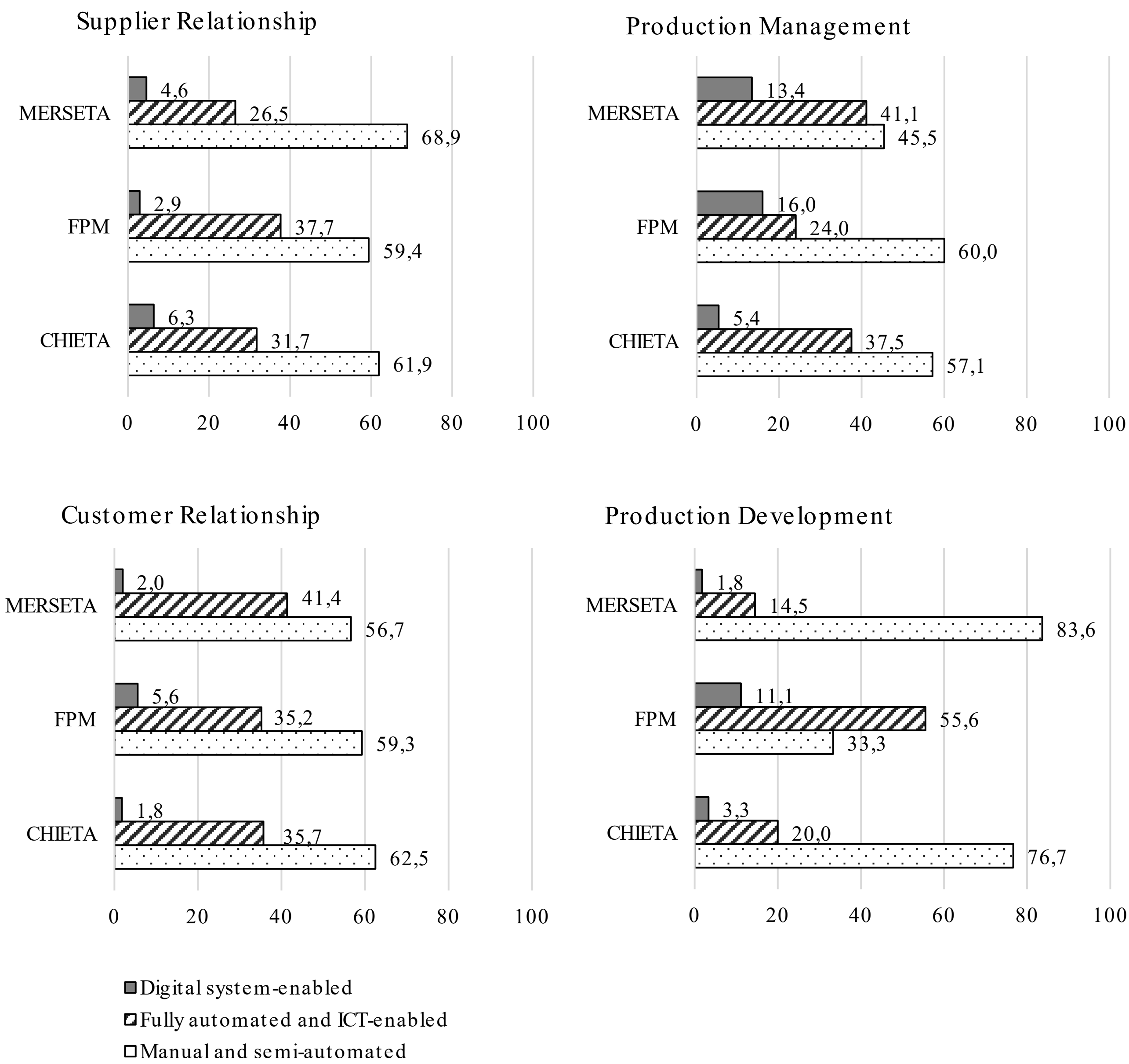
Figure 1: Distribution of technology adoption across business functions



Source: Authors

The current rate of technology adoption within business functions across the three SETAs shows that technology is concentrated in manual and semi-automated processes (Figure 2). Among the three SETA groupings, MerSETA's surveyed firms appear to have the highest affinity for advanced levels of technology. However, this finding appears to be specific to the production management business function, with at least 54% of its processes being fully automated and ICT enabled, or digitally enabled. On the other hand, across the three business functions, MerSETA's surveyed firms are overwhelmingly dependent on manual and semi-automated processes.

Figure 2: Distribution of technology adoption across business functions by SETA

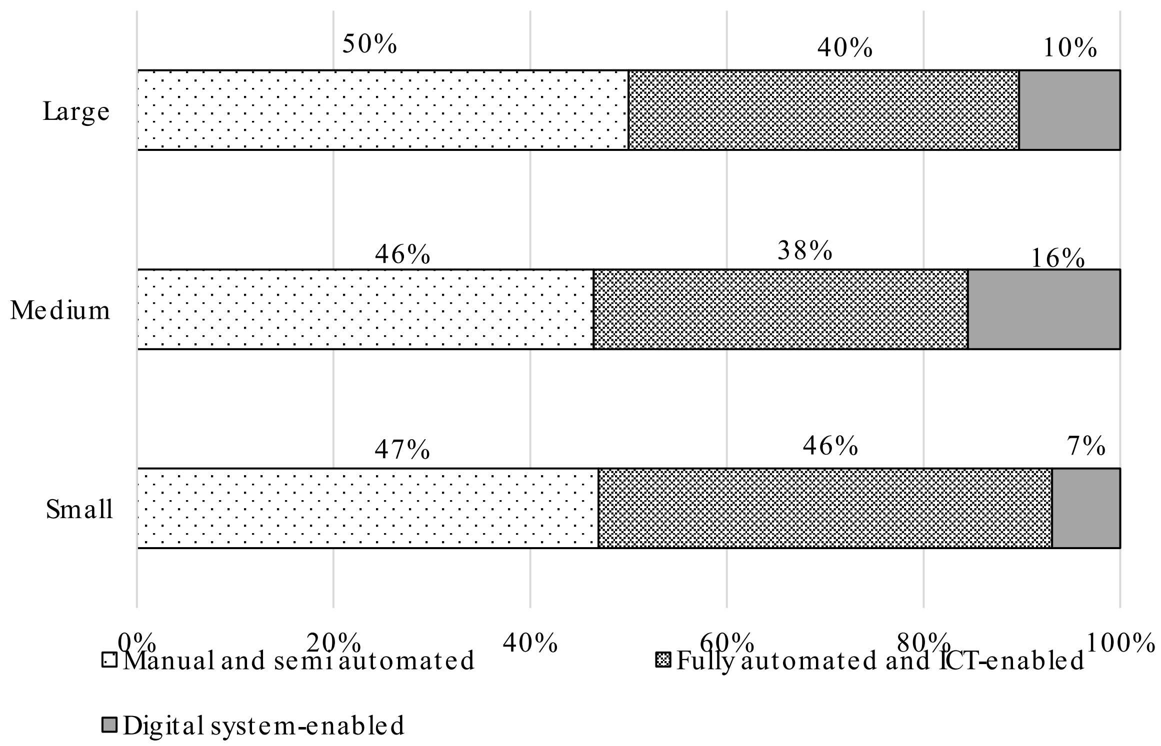


Source: Authors

The FP&M SETA's surveyed firms display slightly less heterogeneity than MerSETA, with, on average, a majority of its product development business function employing fully-automated and ICT-enabled technologies (66.7%). However, this uptake of advanced technology seemingly only occurs in isolated pockets, as the other three business functions of the FP&M SETA firms, on average, mostly employ manual and semi-automated processes and technologies. CHIETA's technological infrastructure, according to the surveyed firms, is the least technologically advanced across all business functions, with CHIETA firms subjectively reporting to conduct their operations across all of the four business functions using manual and semi-automated technologies, displaying the least heterogeneity across the three SETAs.

Evaluating the current technological infrastructure across firms according to size is critical for understanding the technological adoption and innovation affinity in the future (Figure 3). It further offers explanatory power for how different degrees of technological heterogeneity might affect the industries and SETA groupings dominated by a specific size of firm. From the surveyed firms, the vast majority (85%) classified themselves as either micro, small or medium-sized enterprises. However, there are significant variations and nuances within and across these different firm-size classifications in terms of their respective affinity towards, and ability to engage in, technological upgrading.

Figure 3: Firm size and technology adoption



Source: Authors

Notes: Small - Sales valued at between R11 and R50 million in the 2019/2020 financial year; Medium - Sales valued at between R51 and R250 million in the 2019/2020 financial year; and Large - Sales valued at more than R250 million in the 2019/2020 financial year.

Based on our sample, all firms display some technological heterogeneity, with medium and large firms having the most diverse technological infrastructure. Small firms display the least heterogeneity and affinity for the adoption of sophisticated technology infrastructure when compared strictly to medium and large firms. This could be due to several reasons that are specific to the exact nature of these small firms, and the specific business or industry in which they operate. If an expanded grouping combining both fully automated, ICT-enabled and digitally enabled systems is used, all the firms across all sizes display high affinity towards technology adoption in their current operations. However, at this high level, there is little nuance and depth of understanding about the technology-adoption habits of different sizes of firms.

4.2 Determinants of Technology Adoption by Business Function

Table 3 reports the estimation results from our probit (columns 1 to 3) and multivariate probit (columns 4a to 4c) estimation procedures. The correlation coefficients of the error terms (atanhrho_12, atanhrho_13, and atanhrho_23) across all the three equations are positive and statistically significant (see column 4a). This highlights the importance of estimating the three equations as an SUR rather than as separate probit models. Based on this, we proceeded to interpret and discuss the results of the multivariate probit estimation (columns 4a to 4c).

The basic estimation results showing the determinants of digital technologies across the three business functions are reported in Table 3. Our results show that a mix of factors influence the adoption of digital technologies across the three business functions under consideration. For all business functions, our results identify cost-related constraints as key determinants of digital technology adoption in our sampled firms. Specifically, we find that the lack of financial capital negatively affects the likelihood of adopting digital technologies for supply relations and customer relations business functions, suggesting that the technologies for these business functions and their adoption are cost-intensive. Our results also suggest that organisation-related characteristics, such as investments in R&D, matter for the likelihood of adopting advanced technologies for supply relations, while innovation is found to matter for customer relations. This suggests the important roles of innovation activities and investment in capabilities in the adoption of new digital technologies, in line with Delera et al. (2022).

In contrast to our expectations, our results show that institution-related constraints (specifically lack of infrastructure) and labour-related constraints, such as the lack of digital training centres, tend to lead to a higher probability of adopting supplier relations and customer relations digital technologies respectively. This suggests that institution-related and labour-related constraints force firms to invest in in-house training and infrastructure, leading to higher levels of digital technology adoption. Firms may also require bespoke technological systems for supplier-related and customer-related technologies, hence higher levels of investment and digital technology adoption. This is in contrast with product development, in relation to which labour-related constraints such as a lack of human-computer interaction skill reduces the likelihood of adopting digitalisation. South African manufacturing firms with skilled human capital – firms with higher proportions of employees with STEM qualifications – have been identified as having a higher likelihood of adopting customer relations digital technologies, suggesting the importance of emphasising the generation of STEM skills in the labour force. Also, these results highlight the importance of ‘foundational’ capabilities (Andreoni et al. 2021) in fostering the adoption of new digital technologies.

For product development, our analysis shows that older firms tend to have a higher likelihood of introducing digital technologies, while manufacturing firms with foreign ownership tend to have a higher likelihood of adopting digital technologies for supply relations and customer relations business functions, suggesting the key role of experience and foreign linkages in (stimulating) the digitalisation of production processes. The result that foreign ownership of capital enhances the adoption of digital technologies is in contrast with the work of Delera et al. (2022), who found a negative but statistically insignificant effect.

To understand the possible indirect mechanisms that may influence the determinants of adoption, we interacted the main variables of interest – export, innovation, lack of capital, and capital ownership. The results are reported in Table 4. For supplier relations, our results show that firms with a lack of capital tend to have a lower likelihood of adopting digital technologies, but this negative effect is mitigated in firms that have skilled human capital. That is, having a STEM employee in a firm moderates the negative effect that a lack of capital generates on the digital technology adoption behaviours of firms. We found similar indirect mechanisms between a lack of capital and human capital when we considered the customer relations and product development business functions. We did not find other, indirect mechanisms for supplier relations.

In addition, our results show that skilled human capital tends to enhance exporting firms’ likelihood of adopting customer-related digital technologies, while it enhances innovative firms’ ability to adopt product development-oriented digital technologies. Also, our results show that firms that export products but lack capital tend to have a higher likelihood of adopting product development digital technologies than those that do not export, suggesting the importance of participation in international markets in the adoption of advanced digital technologies. The favourable adoption behaviours of these firms may be due to the revenue and/or the knowledge generated from selling in international markets.

In sum, our results suggest that firms that possess a certain level of internal (skills and innovation) and external (foreign-ownership and exports) ‘foundational’ capabilities tend to have a higher likelihood of adopting digital technologies. In line with the literature, our findings corroborate the evidence that foundational capabilities are crucial in fostering the adoption of new digital technologies at the firm level (Andreoni et al. 2021).

Table 2: Determinants of digital technology adoption in SA manufacturing: By business function

	(1)	(2)	(3)	(4a)	(4b)	(4c)
	Probit			Multivariate probit		
	Supplier relations	Customer relations	Product development	Supplier relations	Customer relations	Product development
Age (log)	0.120	-0.128	0.290	0.0966	-0.189	0.591*
	(0.90)	(-0.69)	(0.62)	(0.74)	(-0.99)	(1.90)
Size – medium	-0.0748	-0.298	-0.0919	-0.0275	0.0151	-0.440
	(-0.23)	(-0.66)	(-0.10)	(-0.09)	(0.03)	(-0.44)
Size – small	-0.254	-0.531	3.653**	-0.247	-0.245	0.627
	(-0.89)	(-1.31)	(2.54)	(-0.86)	(-0.56)	(0.70)
Export	0.287	0.128	0.226	0.318	0.138	0.0868
	(1.21)	(0.42)	(0.37)	(1.33)	(0.43)	(0.17)
Innovation	0.374	1.111***	0.399	0.371	0.678**	0.473
	(1.57)	(3.71)	(0.53)	(1.59)	(2.38)	(0.93)
Lack capital	-1.376***	-1.882***	-1.400	-1.112**	-1.352***	-0.339
	(-2.78)	(-3.54)	(-1.40)	(2.50)	(2.59)	(-0.33)
Lack awareness	0.138	0.00902	-0.833	-0.0620	-0.161	-0.232
	(0.46)	(0.02)	(-0.88)	(-0.21)	(-0.43)	(-0.35)
Lack digital infrastructure	0.575*	0.0477	4.999***	0.527*	-0.0399	1.507
	(1.85)	(0.13)	(2.72)	(1.75)	(-0.10)	(1.59)

RD&I – Initial	1.294**	-0.725		1.109**	-0.212	
	(2.08)	(-1.10)		(2.04)	(-0.30)	
RD&I – Approved	1.739***	1.149*	2.968**	1.487***	0.870	0.234
	(2.76)	(1.88)	(2.36)	(2.72)	(1.21)	(0.27)
RD&I – Execution	1.603***	0.287	0.468	1.427***	0.187	1.820
	(2.61)	(0.47)	(0.32)	(2.68)	(0.26)	(1.05)
Human capital	0.442	3.072***	7.006**	0.492	1.882*	3.355
	(0.72)	(2.94)	(2.38)	(0.80)	(1.96)	(1.40)
Training centre – Indifferent	-0.0763	8.008***		-0.337	1.960*	
	(-0.08)	(4.75)		(-0.40)	(1.81)	
Training centre – Important	0.620	7.117***	-4.038	0.309	1.339	-1.232
	(0.71)	(4.04)	(-0.51)	(0.40)	(1.36)	(-1.00)
Human-computer skills – indifferent	0.626	-1.254	-3.408***	0.225	-0.674	-2.000**
	(0.99)	(-1.59)	(-2.79)	(0.38)	(-0.93)	(-2.34)
Human-computer skills – important	1.077*	-0.257		0.649	-0.0384	
	(1.85)	(-0.38)		(1.20)	(-0.06)	
Capital ownership	0.751**	0.971***	0.956**	0.741**	0.845**	0.953
	(2.32)	(2.65)	(2.48)	(2.42)	(2.30)	(1.02)
atanhrho_12						

_cons				0.476***
				(3.00)
atanhrho_13				
_cons				0.0502**
				(2.13)
atanhrho_23				
_cons				0.0239**
				(2.38)
pseudo R^2	0.257	0.307	0.636	
N	212	188	63	212

t statistics in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Note: All regressions include sector and province controls, and all coefficients are probit regression coefficients.

Table 3: Determinants of digital technology adoption in SA manufacturing: Indirect mechanisms

Multivariate probit	(1a)	(2a)	(3a)	(4a)	(1b)	(2b)	(3b)	(4b)	(1c)	(2c)	(3c)	(4c)
	Supplier relations				Customer relations				Product development			
Export	0.342	0.319	1.685	0.0548	0.164	0.137	1.316*	1.742**	0.0838	0.496	1.836	1.486
	(1.42)	(1.34)	(1.36)	(0.06)	(0.57)	(0.48)	(-1.95)	(-2.18)	(0.16)	(1.00)	(0.58)	(1.35)
Innovation	0.385	0.361	0.339	0.373	0.659**	2.587	0.763**	0.756***	0.470	1.980**	0.577	0.679
	(1.63)	(0.33)	(1.46)	(1.60)	(2.55)	(1.57)	(2.50)	(2.76)	(0.93)	(1.98)	(1.10)	(0.91)
Lack capital	-1.866*	-1.113**	-1.133***	-0.843	-1.077*	-1.325***	-1.353**	-1.122**	-0.343	-0.113	-0.332	-3.863**
	(-1.84)	(-2.53)	(-2.59)	(-1.28)	(-1.95)	(2.95)	(2.44)	(2.11)	(-0.36)	(-0.10)	(-0.30)	(2.33)
Human capital	0.994*	0.488	0.255	0.486	3.111	1.017	0.303	0.277	3.350	8.167	4.183	4.218
	(-1.93)	(0.62)	(-0.34)	(0.79)	(-1.23)	(0.95)	(0.24)	(0.24)	(1.54)	(1.39)	(1.37)	(0.91)
Capital ownership	0.734**	0.741**	0.771**	0.732**	0.832**	0.858***	0.944**	0.933***	0.953	0.813	0.871	1.393
	(2.34)	(2.39)	(2.46)	(2.36)	(2.44)	(2.63)	(2.52)	(2.75)	(1.14)	(0.88)	(0.92)	(1.48)
Human capital*Lack capital	0.548**				1.043*				1.133***			
	(2.14)				(1.94)				(2.59)			
Human capital*Innovation		0.0111				1.975				1.378*		
		(0.01)				(1.22)				(1.79)		
Human capital*Export			2.018				0.437**				-1.721	
			(1.64)				(2.11)				(-0.57)	

Lack capital*Export				0.413	0.381	1.876***
				(0.45)	(0.45)	(-2.72)
N	212	212	212	212		

t statistics in parentheses; * p < 0.10, ** p < 0.05, *** p < 0.01.

Note: Table controlled for same set of variables as presented in Table 3, and all coefficients are probit regression coefficients.

4.3 Determinants of Technology Adoption – Complementarity of Business Functions

As discussed above, firms can adopt digital technologies for one or more business functions. To analyse the determinants of the possible complementary adoption of technologies for either one of the business functions under consideration, we constructed a new, dependent variable as a dichotomous dummy (1 if the firm adopted digital technologies for at least two business function, and 0 otherwise). Our empirical results using the new, dependent variable are reported in Table 4.

Column 1 examines the determinants of digital technology adoption using our new construct. Columns 2 to 5 introduce interaction terms to examine possible indirect factors that influence the adoption of digital technologies. In all, our results are similar to our previous findings, with R&D, lack of digital infrastructure, human capital, human competitive skills, and capital ownership emerging as the key determinants of digital technology adoption.

Table 4: Determinants of digital technology in SA manufacturing: Interactions and complementarity

Multivariate probit	(1)	(2)	(3)	(4)	(5)
		Supplier_customer_product			
Age (log)	0.0159	0.0159	0.00656	0.0116	0.0435
	(0.11)	(0.11)	(0.04)	(-0.08)	(0.28)
Size – medium	-0.0234	-0.0234	-0.0151	-0.0715	-0.0243
	(-0.07)	(-0.07)	(-0.05)	(-0.21)	(-0.07)
Size – small	0.194	0.194	0.250	0.128	0.302
	(0.63)	(0.63)	(0.81)	(0.42)	(0.95)
Export	0.0420	0.0420	0.0449	1.639**	1.048**
	(0.17)	(0.17)	(0.18)	(1.99)	(2.09)
Innovation	0.313	0.312	-0.451	0.263	0.330
	(1.28)	(1.28)	(-0.30)	(1.08)	(1.32)
Lack capital	-0.520	-7.987	-0.774	-0.635	-2.219**
	(-1.12)	(-1.57)	(-1.39)	(-1.38)	(-2.52)
Lack awareness	0.346	0.346	0.366	0.356	0.306
	(1.15)	(1.15)	(1.21)	(1.19)	(1.03)
Lack digital infrastructure	0.980*	0.980*	0.908*	0.806	0.981*
	(1.95)	(1.95)	(1.83)	(1.57)	(1.94)
RD&I – Initial	1.826***	1.826***	1.700***	1.850***	1.945***
	(3.67)	(3.67)	(3.48)	(3.61)	(3.85)

RD&I – Approved	1.441***	1.441***	1.418***	1.388***	1.486***
	(3.06)	(3.06)	(3.03)	(2.88)	(3.18)
RD&I – Execution	0.793**	0.793**	0.841***	0.783**	0.858**
	(2.47)	(2.46)	(2.62)	(2.43)	(2.56)
Human capital	1.141*	7.938***	0.580	0.0799	1.227*
	(1.82)	(11.12)	(0.69)	(0.11)	(1.91)
Training centre – Indifferent	-0.596	-0.595	-0.705	-0.628	-0.620
	(-0.82)	(-0.82)	(-0.98)	(-0.88)	(-0.83)
Training centre – Important	-0.194	-0.194	-0.301	-0.0754	-0.263
	(-0.31)	(-0.31)	(-0.49)	(-0.13)	(-0.41)
Human-computer skills – Indifferent	0.710	0.710	0.723	0.839	0.754
	(1.06)	(1.06)	(1.11)	(1.21)	(1.09)
Human-computer skills – Important	1.315**	1.315**	1.271**	1.318**	1.297**
	(2.15)	(2.15)	(2.12)	(2.10)	(2.06)
Capital ownership	1.650***	1.650***	1.665***	1.771***	1.864***
	(3.43)	(3.43)	(3.32)	(3.36)	(3.60)
Human capital*Lack capital		6.797***			
		(-16.04)			
Human capital*Innovation			1.268		
			(1.05)		
Human capital*Export				2.759**	
				(2.05)	
Lack capital*Export					2.148**
					(-2.05)
pseudo R^2		0.328	0.333	0.343	0.339
N		212	212	212	212

t statistics in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Note: All regressions include sector and province controls, and all coefficients are probit regression coefficients.

The additional analyses (columns 2 to 5) identify that the adoption behaviours of firms are influenced by similar indirect mechanisms as those identified in the previous section: firms with capital constraints tend to adopt digital technologies if they have STEM employees; firms that export tend to have a greater likelihood of adopting digital technologies if they have STEM employees; and firms that have capital constraints have a higher likelihood of adopting digital technologies if they export. These findings suggest that human capital (STEM employees) on the one hand, and export activities on the other hand, mitigate the negative effect of capital constraints, while human capital reinforces the positive effect of exporting on digital technology adoption in our sampled manufacturing firms.

5. Conclusions

Digital technologies and digitalisation are fundamental to the structural transformation and industrialisation of middle-income countries. However, the literature on the factors that affect the adoption of digital technologies remains nascent and anecdotal, particularly in developing countries such as South Africa. This paper contributes to this growing literature on digital industrialisation by analysing the determinants of advanced digital technology adoption by South African manufacturing firms, using unique firm-level data on three SETAs covering 516 manufacturing firms, and a simple multivariate probit model for the empirical analysis.

Our findings highlight the key drivers of the adoption of digital technologies in our sampled manufacturing firms. Our results identify a lack of capital and a lack of digital infrastructure as the main factors that inhibit the adoption of digital technologies, while human capital, foreign ownership of capital, exporting and innovation enhance the adoption of digital technologies. However, these factors are identified as affecting firms' digital technology adoption across business functions differently. These findings are important baseline results that confirm the evidence from other countries, as well as existing qualitative/case study-based evidence from South Africa.

The findings bring some level of awareness of what determines the adoption of digital technologies in South Africa and, as a result, have the potential to influence policy discussions on the specific firm- and industry-level characteristics that drive digital transformation in the country's manufacturing. Based on the findings, for instance, we find that there is heterogeneity in the factors affecting the adoption of digital technologies across business functions. In the light of this finding, we suggest the need for targeted policy actions for specific functions of firms, rather than blanket sector-based digital policies, to resolve the diverse array of constraints firms face in the adoption of digital technologies. This is confirmed by the empirical literature, which also identifies heterogeneity in similar constraints across industries and different categories of firms.

In promoting the adoption of digital technologies by manufacturing firms, our findings also highlight the need for the development of targeted 'foundational' capabilities in STEM skills across different firms and industries. Policy and relevant skill-based institutions could help to promote the re-training and re-skilling of employees to meet the human capital demand for digital transformation. Deliberate policies that enable 'local' manufacturing firms to collaborate on and leverage the experience and know-how of foreign-owned firms, for instance, are critical. Collaborations between foreign-owned firms and lead local firms can help to shape a new 'industrial ecosystem' in which the opportunities of digital industrialisation can be captured fully.

Given that the area of research is in its early stages, several aspects of our paper can be extended. For instance, and analysis of the industry and the extent of firm heterogeneity in the adoption of digital technologies are natural extensions of the paper. Also, our data is not representative of all the firms in the three SETAs we considered, and hence our conclusions cannot be generalised to SETAs and/or the manufacturing sector in South Africa. A follow-up survey that covers a representative sample of manufacturing firms across SETAs would provide more useful data and evidence for policy. Despite these caveats, the paper provides first-level empirical evidence that has the potential to stir the conversation around digitalisation in manufacturing, and also provides evidence-based direction to digital technologies and skills policy in South Africa.

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Appendix 1: Digital Technology Generations and Business Functions

Generations of digital technologies		Business function				
		Supplier relationship	Product development	Production management	Client relationship	Business management
G 4.0	Fourth generation: Smart production	Real-time web-based relation	Virtual development systems (such as manufacturing)	Machine-to-machine systems, robots, augmented reality, additive manufacturing	Client relationship-based online monitoring of product use (such as artificial intelligence in customer services)	Business management supported by big data analytics
G 3.0	Third generation: Integrated production	Digital system for processing orders, stock and payments	Integrated data product system (such as product data management and/or product lifecycle management)	Computerised process for execution of system	Internet-based support for sales and after service (such as mobile app, customer data analytics	Integrated platform to support decision-making (such as advanced enterprise resource planning)
G 2.0	Second generation: Lean production	Automated electronic transmission of orders (such as email)	Computer-aided design and computer-integrated manufacturing, computer-aided engineering, computer-aided process planning	Partially or fully integrated computer-aided manufacturing	Automated devices to support sales (such as customer relationship management)	Enterprise resource management in a few areas (such as enterprise resource planning)
G 1.0	First generation: rigid production	Manual electronic transmission of orders (such as email)	Stand-alone computer--aided design	Stand-alone automation	Electronic contact (such as spreadsheet registry, email)	Information systems by area/ department
G 0.0	Zero generation: analogue production	Manual transmission of orders (such as personal contact, telephone)	Manual generation of designs (such as 2D/3D drawings in 2D space)	Non-micro-electronic-based machinery	Manual handling of contacts (such as personal contact, telephone)	No software support to business management

Appendix 2: Definition and measurement of variables

Variable	Definition and measurement
Supplier relations technologies	A dummy variable that takes a value of 1 if the firm's primary method of communicating with suppliers (to place orders) is through real-time monitoring of orders and logistics of suppliers (e.g., computer-managed inventory systems), and 0 if the firm places orders manually (e.g., over the phone or via email) or through electronically using computerised systems in 5-10 years' time.
Customer relations	A dummy variable that takes a value of 1 if the firm's primary method of managing production in five to 10 years will be through a machine-to-machine (M2M) communication system, and 0 if it manages production through a partially or fully-automated process or simple automation with unconnected machines.
Product development	A dummy variable that takes a value of 1 if the technology firms would use in five to 10 years is virtual development systems (such as manufacturing) or integrated data product systems (such as product data management and/or product lifecycle management), and 0 otherwise.
Age (log)	A continuous variable defined as the total number of years a firm has been in operation, constructed as the natural logarithm of the total number of years plus 1.
Size	A categorical variable that assumes the value 1 if the firm is large (sales valued at more than R250 million per financial year), 2 if the firm is medium (sales valued at between R51 and R250 million per financial year), 3 if the firm is small (sales valued at between R11 and R50 million per financial year), and 4 if the firm is micro (sales valued at below R10 million per financial year) in the 2019/2020 financial year.
Export	A dummy variable indicating if the firm exports (1), and 0 if otherwise, in the 2019/2020 financial year.
Innovation	A dummy variable indicating if the firm has introduced new production process or has made significant improvements to products between the 2017/2018 and 2019/2020 financial years.
Lack of capital	A dummy variable that takes a value of 1 if the firm considers a lack of capital/funds as an obstacle, and 0 otherwise.
Lack awareness	A dummy variable that takes a value of 1 if the firm indicates a lack of awareness and knowledge of an obstacle to adopting digital technologies, and 0 otherwise.

Lack of adequate digital infrastructure	A dummy variable that takes a value of 1 if the firm considers the lack of adequate digital infrastructure as an obstacle, and 0 otherwise.
RD&I	A categorical variable that assumes the value 1 if the firm is not engaged in research, development and innovation, 2 if there are initial studies, 3 if plans are approved, and 4 if plans are in execution.
Human capital	A dummy variable that takes a value of 1 if the firm has employees with STEM qualifications, and 0 otherwise.
Training centre	A categorical variable that takes the value 1 if the firm considers digital training centres for skills development as not important, 2 if indifferent, and 3 if important.
Human-computer skills	A categorical variable that takes the value 1 if the firm considers human-computer interaction skills as not important when hiring employees, 2 if indifferent, and 3 if important.
Capital ownership	A categorical variable that takes the value 1 if the capital of the firm is foreign-owned, 2 if fully South African-owned, 3 if mixed (South African and foreign-owned), and 4 if state-owned in the 2019/2020 financial year.
SETA	A categorical variable that takes the value 1 if the firm belongs to MERSETA, 2 if FP&M, and 3 if it belongs to CHIETA.
Industry	A categorical variable that shows the 20 South African industrial classifications of the firms in our sample.
Province	A categorical variable that assumes a value between 1 and 9 to indicate the province in which the firm is located.

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