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Investigating the relationship between digital business strategy and business performance in a financial services organisation

22961209

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ABSTRACT

The evolution of digital technologies (e.g., social, mobile, analytics, cloud and Internet of Things [IoT]) is disrupting companies and their ecosystems. In response, companies are leveraging digital resources to formulate and implement business strategies underpinned by digitality. In this study, the relationship between digital business strategy and business performance was examined. As strategy refers to the plan of action developed to achieve an objective or goal, company capabilities are essential ingredients. As such, managerial capabilities and operational capabilities were identified as the main dimensions of digital business strategy.

The research used structural equation modelling to establish the relationship between digital business strategy and business performance in a financial services organisation in South Africa. The results predict a positive effect of managerial capabilities on business performance. The insights also show a positive effect of operational capabilities moderated by dynamic capabilities on business performance. However, the model predicts a neutral effect on business performance in relation to operational capabilities and managerial capabilities moderated by dynamic capabilities.

Although extant literature examined the role of digital business strategy in creating and capturing value, existing approaches are mostly abstract, and the research setting is often in developed countries. Thus, this study contributes to the evolving literature discussion in digital business strategy from a developing country perspective.

KEYWORDS

Digital technologies, business performance, configurational theory, digital business strategy, dynamic capabilities, managerial capabilities, operational capabilities, resource-based view, systems theory

DECLARATION

I declare that this research project is my own work. It is submitted in partial fulfilment of the requirements for the degree of Master of Philosophy in Corporate Strategy at the Gordon Institute of Business Science, University of Pretoria. It has not been submitted before for any degree or examination in any other University. I further declare that I have obtained the necessary authorisation and consent to carry out this research.

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1. INTRODUCTION TO THE RESEARCH PROBLEM

1.1. Background to the research problem

In 2014, JP Morgan Chase Chairman and Chief Executive Officer, Jamie Dimon in a letter to shareholders cautioned that the bank is facing competition not only from traditional banks, both local and foreign, but also "startups with a lot of brains and money working on various alternatives to traditional banking" (JP Morgan Chase, 2014, p. 29). The startups that Dimon was referring to are Fintechs that have been entering the financial services industry worldwide with innovative business models that leverage Big Data to simplify business processes such as credit underwriting leading to loan applications that can be processed in minutes as opposed to days (Sia et al., 2016).

Fintechs are defined as "new generation of financial technology startups that are revolutionizing the financial industry, from payment to wealth management to peer-to-peer lending to crowdfunding" (Sia et al., 2016, p.105). The proliferation of Fintechs is disrupting financial services industry traditional business models of intermediating between clients that need to borrow and clients that need to invest. Fintechs business models connect borrowers and investors through an online marketplace (JP Morgan Chase, 2014). According to the PWC, the emergence of non-traditional players in the South African banking industry has created a marketplace without boundaries. The new players are considered to be innovative, creating new products and services that position their businesses to be more competitive than the traditional players.

Their competitiveness is attributed to leveraging low operating costs business models enabled by digital solutions which allow them to serve customers with tailor-made banking solutions at a fraction of the cost that traditional banks charge (Camarate & Brinckmann, 2017). Although the banking industry always had other financial services industry players such as insurance companies proving banking services, there is a notable increase in these companies "diversifying their financial services offerings by introducing digitally-enabled banking solutions to provide better customer experience at a reduced cost" (Camarate & Brinckmann, 2017, p. 6).

Other than Fintechs and insurance companies, the banking industry is also faced with the emergence of industry specific banking players. Among these players are retail and commercial companies that have sensed the opportunity to provide personalised and, in some cases, affordable financial services products that traditional banks also offer. For example, SA Taxi has developed an innovative credit underwriting business model which gives them the ability to manage high risk clients by leveraging digital capabilities, big data and analytics (Transactional Capital, 2023). In the same vein, African Bank traditionally specialised in micro-lending but recently, as part of its expansion strategy to become a retail bank in a highly competitive market segment, it has been focusing on providing clients with a "digitally-enabled bank account, which is competitively priced and [offer] a great product with additional value-added features" (Camarate & Brinckmann, 2017, p. 7).

Amongst others, new entrants such as Bank Zero, Discovery Bank and TymeBank are disrupting the South African banking sector by exploiting the opportunities offered by digital platforms which significantly reduce costs. What sets apart the new players from traditional players, dubbed 'the big four': Absa, FirstRand, Nedbank and Standard Bank, is the ability to combine product innovation with leading digital capabilities to manage risk. For example, Discovery Bank leverages big data and digital capabilities to understand clients behaviour which gives them unparalleled ability to manage clients risk undergirded by their shared value business model (Discovery Group, 2022).

However, the emergence of a marketplace without boundaries appears to be the biggest threat facing 'the big four'. This change is also reshaping the banking industry structure. Anecdotal evidence suggests that 'the big four' appear to be slow in responding to the threat of increasing competition as they continue to be "weighed down by their legacy IT systems and cumbersome legacy processes" (Sia, et al., 2016, p. 106). Furthermore, traditional players often lack agility to experiment with digital innovation due to endless compliance requirements attached to their operating licenses. New players are nimbler as they are not burdened by a string of heavy regulatory requirements borne out of complex structures that evolved over time when the industry structure was characterised by high barriers to entry (Porter, 1991).

The context above may give the impression that digital technologies are disrupting only the financial services industry. This assumption cannot be further from the truth, digital technologies are touching and influencing almost every aspect of our social and economic lives (Piccinini et al., 2015 & Redwood et al., 2017). One such example is the research conducted by Karimi & Walter (2015) in the newspaper industry that revealed that the "convergence of inexpensive digital information goods and computing and communication devices are changing not only the newspaper industry but also business and society as a whole" (p. 40). In the banking industry, however, Sia et al. (2016) discovered that "with the rapid adoption of the Internet, ecommerce and smartphones, consumers are increasingly turning to computers, tablets, mobile phones and smartphones to interact and transact with banks" (p. 121).

Despite the ongoing discourse about the existential threat from new players entering the banking industry such as Fintechs, insurance, retailors and others, Adarkar et al. (2022) is of the view that incumbent banks will continue to be around and possibly lead in the Retail Banking environment but survivors "will operate like tech companies, with advanced data capabilities, a cutting-edge tech stack, and an agile operating model" (p. 2). This implies that incumbent banks that continue to run the 'old playbook' will find it challenging to compete in an increasingly digital marketplace gradually opening and accommodating new thinking (Sia et al., 2016). However, what is important to remember is when thinking about technology, "as sexy as it is to speculate about new technologies such as AI, robots, and the internet of things (IoT), the focus on technology can steer the conversation in a dangerous direction. Because when it comes to digital transformation, digital is not the answer, transformation is" (Westerman, 2018, pp. 1-2).

1.2. The research problem

Although researchers in the field of information systems and strategic management continue to demonstrate the benefits of digital shifts, many organisations continue to treat digital through the traditional lens of managing functional areas as distinct businesses implementing individual strategies without integration with IT strategy. It is, therefore, not surprising that organisations driving digital adoption without focused integration across the enterprise are likely to realise limited benefits. It has been over a decade since Bharadwaj et al. (2013) argued that "the time is right to shift our thinking about IT, not as a functional-level response, but as a fundamental driver of business value creation and capture" (p. 480) but research focusing on digital business strategy continues to be limited.

Digital technologies are envisaged to continue to disrupt industries and, invariably, organisations. The emergence of the marketplace without boundaries in the financial services industry is not only disrupting existing business models but also reshaping the financial services industry ecosystem resulting in the creation of new business models that improve customer experience and reduce costs (Camarate & Brinckmann, 2017).

Sebastian et al. (2017) refers to some of these digital technologies as “SMACIT (social, mobile, analytics, cloud and Internet of Things [IoT])” (p. 197).

As organisations increasingly endeavour to identify opportunities offered by adopting digital capabilities, they also redefine their digital strategies. “These are not merely technology strategies. Rather, they are business strategies that incorporate the opportunities that the digital economy presents” (Sebastian et al., 2017, p. 198). Bharadwaj et al. (2013) term this formation a digital business strategy (DBS) which is defined as an “organizational strategy formulated and executed by leveraging digital resources to create differential value” (p. 472). The DBS definition is said to transcend the traditional view of business strategy that is in general disentangled from organisational functional areas strategies such as IT strategy (Bharadwaj et al., 2013 & Chi et al., 2016). In this regard, DBS elevates digital resources beyond the IT functional area thereby treating them as part of strategic resources that can be deployed in line with the resource based view of competitive advantage (Barney, 1991).

In the same vein, under the DC perspective, digital resources can be harnessed to enable the organisation to be innovative in order to respond to rapidly changing environment (Teece, 2018a & Rantala et al., 2019). This can be achieved by following a three pronged process of sensing, seizing and reconfiguring digital resources. According to Vial (2019), sensing involves “the identification, development, codevelopment, and assessment of technological opportunities in relationship to customer needs” (p. 133) and seizing is about the “mobilization of resources to address needs and opportunities, and to capture value from doing so” (p. 133), and lastly, reconfiguration is related to a systematic process of creating and renewing digital resources with agility to gain competitive advantage.

The research problem presented in this study is, although researchers present DBS as a solution in response to digital disruptions (Bharadwaj et al., 2013; El Sawy et al., 2016; Uhlig & Remané, 2022; Vial, 2019 & Wessel et al., 2021), adopting DBS is not a straightforward process. On the other hand, “companies that fail to adopt new technologies and fail to heed the need for digital transformation are likely to be left trailing behind in the dust” (Sebastian et al., 2017, p. 208). According to Setia & Patel (2013), “although IT investments are required to create a robust digital infrastructure, investments in IT are only the first step and do not necessarily translate directly into higher performance” (p. 409).

Vial (2019) argues that there is evidence to suggest that corporates tend to embed traditional separation between IT and business functions as part of their values system and culture. As such, to change existing set of beliefs and mental models takes time. Thus, companies need to find a suitable path to integrate IT strategy with business strategy and it may be necessary to apply a modulated approach before scaling up across the organisation to enable the process of unlearning, deeply ingrained cultural practices not conducive to the formulation and implementation of a successful DBS, to take effect. According to Hess et al. (2016), “regardless of the strategic role of IT, companies can take different approaches to the process of diffusing new digital technologies. More conservative firms may adopt established and widely used technology solutions, while others may deploy new technology solutions at the early stages of their development” (p. 130). The latter tend to be the path that startups follow to innovate in order to create new products and services that eventually enter the market on the back of new technological solutions.

1.3. Research questions

There are several gaps that the study identified in the literature. Increasingly, organisations are adopting digital resources to guide their DBS but few empirical studies focus on investigating the relationship between the adoption of DBS and its influence to business performance. Extant literature largely focuses on developed countries with minuscule, if any, relevance to developing countries. Nonetheless, by leveraging existing literature on DBS by researchers such as Wang & Ahmed (2007), Bharadwaj et al. (2013), Leischnig et al. (2017), Ukko et al. (2019), Bitencourt, et al. (2020), to name a few, an examination of the relationship between digital business strategy and business performance in a financial services organisation in a South African context was conducted, and the research question asked was: **RQ 1 “to what extent does adopting a digital business strategy improve business performance in a moderately changing environment”.**

The research question above assumes that the setting of digital business strategy is in an industry that is relatively stable but facing some disruptions as a result of new players entering the market (Wilden et al., 2016). However, in an industry where the business environment is rapidly changing, for digital business strategy to be effective, it must be integrated with dynamic capabilities (DC) to enable the organisation to sense, seize and reconfigure opportunities. In this context, to survive and gain competitive advantage, organisations are compelled to transform (Eisenhardt & Martin, 2000, Wang & Ahmed, 2007, Teece, 2014 & Wilden et al., 2016) and the research question asked was: **RQ 2 "to what extent does adopting a digital business strategy improve business performance in a rapidly changing environment".**

1.4. The research aims

The aim of this study was to investigate the relationship between DBS and business performance in a financial services organisation. Consequently, the study aims to bridge the existing gap in the literature regarding the benefits of adopting DBS to gain competitive advantage. Of significant importance is the examination of the role that managers play in the enablement of the organisation to develop the necessary capabilities that drive a digital business strategy.

This is because digital technologies are forcing organisations to rethink the role of IT in relation to organisational strategy (Wang & Ahmed, 2007). DBS foundational research conducted by Bharadwaj et al. (2013) argue that for companies to compete in dynamic business environments, they need to treat IT as part of digital resources. In support of this view, Vial (2019) maintains that further research should be directed towards understanding the factors that drive IT solutions beyond the traditional lens. Despite growing interest in understanding the impact of digital technologies to traditional business models and the significance for companies to have dedicated DBS, research in this is still in its infancy but evolving which calls for further research to fully realise the benefits of DBS (Matt et al., 2015).

The study postulated that in undertaking the digital journey, it is not enough for an organisation to simply align the IT strategy with DBS (Henderson & Venkatraman, 1993), rather organisations must aim to embed IT resources in every aspect of the entity to improve business performance (Bharadwaj et al., 2013; El Sawy et al., 2016; Uhlig & Remané, 2022; Vial, 2019 & Wessel et al., 2021) underpinned by "a clear digital strategy supported by leaders who foster a culture able to change and invent the new" (Kane et al., 2015, p. 3). It is, therefore, important to note that strategy not technology is the main driver of digitality (Rantala et al., 2019).

1.5. Research contribution

1.5.1 Managerial contribution

Although there is an abundance of academic research related to digital transformation and digital business strategy, few provide practical insights to managers on how to implement a successful DBS to impact business performance, particularly, in developing countries. Thus, the insights from this study will help companies to focus on how to develop a successful DBS in a manner that its effects to business performance are measurable (Ukko et al., 2019). One of the key ingredients that facilitates the adoption of DBS is the possession of digital capabilities. Managers are required to have the necessary capabilities to lead the process of developing and implementing digital strategies.

Ismail et al. (2017) argue that to develop and implement a successful DBS, managers have to articulate the business case for DBS adoption. The fundamental question to be asked is what is the real motivation to transform, is it internally driven to increase business performance by improving operational efficiencies and effectiveness or response to clients' expectations and increased competition? Another critical driver that managers cannot ignore when considering to orchestrate a digital journey is human capital that has the "ability to operate with digitality" (Ukko et al., 2019, p. 2).

Kane et al. (2015) found that increasingly "employees want to work for digital leaders" (p. 4) because digital leaders are likely to have a clear digital strategy anchored on a culture of innovation and foresight for long-term company sustainability. El Sawy et al. (2016), asserted that a different kind of workplace is emerging as a result of digitisation. This new workplace requires that organisations recognise that "as more 'born digital' younger employees enter the workforce with different values, they will have different expectations of the workplace in terms of flexibility of location and working hours, sophistication of mobile online access, and the extent to which the workplace environment is humanized" (p. 143).

1.5.2. Theoretical contribution

The theoretical grounding of this research is based on DC as an extension of the resource based view framework (Eisenhardt & Martin, 2000 and Wang & Ahmed, 2007). The literature review in Chapter 2 dives deeper into the theoretical opportunities and limitations of both resource based view (RBV) and dynamic capabilities (DC) frameworks. This paper, however, followed DC thinking of integrating configurational/ systems theories with DC in order to provide the necessary theoretical grounding to DC models. These theories are said to be ideal for DC because they "complement variance theories and process theories to help better understand [dynamic capabilities]" (Wilden et al., 2016, p. 26). In the same vein, Teece (2018b) is of the view that by reframing DC to include a systematic approach that is comprehensive and yet practical will strengthen DC models.

Undoubtedly, the process of adopting DBS requires that managers follow the DC process of sensing, seizing and reconfiguring opportunities. According to Teece (2007), the process of sensing new opportunities requires deliberate actions to gather relevant information that is necessary to making informed decisions about the sensed opportunity. This is because, more often than not, companies have to make the necessary investments with the long-term view to capture value. Once the company has enough information about the technology or market, the next step is to seize the new opportunity which involves designing and refining business models and commit resources required for new products or services development. But before taking the products or services to market, there is a need to clearly understand the capabilities required to successfully deliver the desired results. This process requires that the company transform or reconfigure its organisational structures and culture. In summary, this study has demonstrated that a successful DBS enables the company to be intentional in identifying opportunities offered by digital technologies, how to seize that opportunity and reconfigure the organisation to achieve sustained competitive advantage in an effort to position the organisation as a market leader.

1.6. Conclusion

This chapter provided an overview of the challenge that traditional financial services organisations are facing due to the changing industry landscape as a result of increased competition from non-traditional players such as Fintechs, insurance, retailors and so on. The paper concluded that the threat of new entrants is pushing existing financial services organisations to create completely new business strategies anchored on digitality to transform their organisations. According to Adarkar et al. (2022), financial services organisations of the future "will operate like tech companies, with advanced data capabilities, a cutting-edge tech stack, and an agile operating model" (p. 2). Furthermore, the paper argues that DBS is the solution for traditional financial services organisations to respond to increasing threats of competition but more importantly, DBS will allow them to reinvent themselves to stay competitive in an industry that is increasingly becoming boundaryless (Uhlig & Remané, 2022).

2. LITERATURE REVIEW

2.1. Introduction and roadmap

The purpose of this chapter is to review the main constructs, which are the building blocks of a theory (Gehman et al., 2018) related to this research topic. First, the literature on resource-based view (RBV) was reviewed. Second, building on the RBV theoretical perspective, the concept of DC, as it relates to competitive advantage and business performance, was discussed. Finally, the review deconstructs the relationship between information technology and digital business strategy. Table 1 below provides the structure of the literature review.

Table 1: Literature review structure

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	2.4. Dynamic capabilities and digital business strategy	2.5. Digital business strategy and business performance
	2.6. Conclusion	

Source: Author's compilation

2.2. Theoretical overview

2.2.1. Resourced-based review framework

The RVB perspective focuses on internal characteristics of a company in relation to gaining competitive advantage (Penrose, 1959; Wernerfelt, 1984; Barney, 1991 & Peteraf, 1993). RBV emerged “as a response to the criticism that relying on external factors alone to achieve competitive advantage may render strategies reactive and short-term” (Wilden et al., 2016, p. 1). As such, the RBV theoretical framework departs from traditional strategic management view which focuses on strength, opportunities, threats and weaknesses of a company as propagated, for example, by Porter’s (1980) five forces model which is designed to identify and analyse the competitive landscape of an industry.

Key to the RBV perspective is the assumption that companies have access to a bundle of strategic resources, which are heterogeneous and immobile, that can be leveraged to enhance their competitive advantage (Barney, 1991 & Hart, 1995). To that end, it is assumed that competitive advantage is gained through the deployment of a company’s idiosyncratic resources. However, to effectively position company’s resources for superior performance, certain attributes are necessary. According to Barney (1991), a company will have competitive advantage against its competitors if the resources that under its auspices are valuable, rare, imperfectly imitable and non-substitutable (VRIN).

2.2.1.1. Company resources

Lockett et al. (2009) asserts that RBV focuses on “the resource as the unit of analysis … to explain the extent to which a company may be able to sustain a position of competitive advantage” (pp. 10-11). Barney (1991) consider company resources to “include all assets, capabilities, organisational processes, firm attributes, knowledge, etc. controlled by a firm that enable the firm to conceive of and implement strategies that improve efficiency and effectiveness” (p. 101). Within the RBV context, resources can be classified into three broad categories: physical, human and organisational resources. Physical resources are viewed as plant and equipment, the technology that company possesses and geographic location which offers strategic leverage to access raw materials and customer base. Although, on average, most physical resources are valuable, there may not be rare, inimitable and non-substitutable.

On the other hand, human attributes such as culture, experience, relationships and the insights that key and critical talent possesses are almost impossible to replicate. In the same vein, organisational resources such as the planning process, coordination of different systems and the networks that groups of employees have built overtime within an organisation can also be hard to imitate or substitute. Considering that the RBV framework only offers guidance on what can be classified as VRIN resources, and possessing idiosyncratic resources (Eisenhardt & Martin, 2000), managers have an important role to develop models geared towards enabling the company to identify resources that meet the VRIN criteria in a manner that position the company to gain competitive advantage (Lockett et al., 2009).

2.2.1.2. Competitive advantage and sustained competitive advantage

Porter & Heppelmann (2014) is of the view that competitive advantage is achieved when a company is “able to differentiate itself and thus command a price premium, operate at a lower cost than its rivals, or both” (p. 14). In a nutshell, competitive advantage allows a company to enjoy superior profitability relative to competitors. Thus, a company that has competitive advantage is the one that is “implementing a value creating strategy not simultaneously being implemented by any current or potential competitors” (Barney, 1991, p. 102). However, for competitive advantage to be sustainable, other players in the industry must not be able to imitate the benefits of the value creating strategy.

2.2.1.3. Company resources and sustained competitive advantage

As remarked by Eisenhardt & Martin (2000), “resources are at the heart of resource based view” (p. 1106). As a result, to gain sustained competitive advantage, a company must possess resources that are both heterogeneous and immobile. According to Barney (1991), strategic resources must have the following attributes: 1) valuable, in the sense that resources must enable the company to seize the opportunity whilst addressing threats from competitors, 2) rare, which implies that resources must not be easily accessible, 3) imperfectly imitable, and d) non-substitutable by current and potential competitors. In summary, the RBV perspective assumes that in an environment where companies possess exactly the same resources, it would be inconceivable for one particular company to develop and implement strategies that enable the company to have sustained competitive advantage.

2.2.1.4. Resource recombinations

In general, companies have innumerable resources under their control. To gain competitive advantage, the RBV perspective assumes that managers have the ability to identify the resource that creates most value. However, more often than not, “resources are seldom valuable in isolation” (Lockett et al., 2009, p. 14). In this regard, identifying resources which are complimentary in order to combine them for maximum benefit allows managers to derive maximum benefits form those resources.

Interestingly, the concept of resource recombination ventures into the literature of capabilities. A capability is viewed as the company's competence to embark on value creation activities by deploying its resources (Lockett et al., 2009 & Teece et al., 1997). However, in an ever-changing business environment, ordinary capabilities are said not to be sufficient to enable the organisation to gain competitive advantage hence the need to possess dynamic capabilities (Teece et al., 2016).

Although related to building capabilities, managers have different reasons for recombining company resources. Eisenhardt & Martin (2000) argue that "at a more strategic level … managers reconnect webs of collaborations among various parts of the firm to generate new and synergistic resource combinations among businesses" (p. 1107). Confronted with low uncertainty, managers make minor incremental improvements to resources to maintain their current competitive advantage position (Sirmon et al., 2007). This practice is called *stabilising strategy* of resource recombinations. However, managers are said to embark on *enriching strategy* which involves "extending and elaborating current capabilities through activities such as learning or adding a complementary resource" (Lockett et al., 2009, p. 14) in response to increasing competitive environment. But in uncertain competitive environments, managers are likely to pursue a *pioneering strategy* which entails recombinations of newly acquired resources into the organisation.

As discussed above, the concept of resource recombinations has to do with building capabilities by managers who, ironically, also form part of company resource base. It can be argued that a pool of key and critical talent form a strategic resource for a company that enables sustained competitive advantage. Although individual human capital practices may not lead to a competitive advantage, complex human capital management systems and routines that companies invest in and mature overtime embedded in the company's culture thereby creating difficult to imitate/ replicate processes, may offer sustained competitive advantage (Barney et al., 2001).

2.2.2. Dynamic capabilities framework

Dynamic capabilities framework originated from the resource based view (Peteraf et al., 2013 & Yeow et al., 2018). Dynamic capabilities extend the RBV framework beyond competencies that come from merely owning resources to renewal of those resources thereby positioning the company to stay competitive in a rapidly changing environment (Teece et al., 1997; Eisenhardt & Martin, 2000; Pavlou & El Sawy, 2011, Vial, 2019, and Hitt et al., 2021). In developing the DC framework, Teece et al. (1997), recognised that although RBV focuses on resources and routines that enhance company performance, it "does not attempt to explain the nature of the isolating mechanisms that enable entrepreneurial rents and competitive advantage to be sustained" (p. 510).

According to Teece et al. (1997), DC provides the company with the ability to "integrate, build and reconfigure internal and external competencies to address rapidly changing environments. Dynamic capabilities thus reflect an organisation's ability to achieve new and innovative form of competitive advantage" (p. 516). In support of creating DC to gain competitive advantage, Bitencourt, et al. (2020) found that the following antecedents: resources, knowledge management & learning, alliances, and environmental dynamism have positive effects to DC which in turn improve company's performance. This implies that "the firm's performance consists of the organisation's tangible and intangible objectives, for example, increased sales, product success, competitive advantage, efficiency, quality and profitability" (p. 110).

Dynamic capabilities are, therefore, perceived to be critical moderators of performance in turbulent business environments because "they allow organizations to systematically generate and modify their organizational capabilities to gain long-term competitive advantages" (Konopik et al., 2022, p. 2). Central to DC effectiveness is the ability to deploy resources, both tangible and intangible, in a manner that proactively responds to threats and opportunities related to changing customer preferences due to, among others, the rapid spread of digital technologies. Teece (2018a) argues that DC enable companies to "continuously sense and seize opportunities, and to periodically transform aspects of the organization and culture so as to be able to proactively reposition to address yet newer threats and opportunities as they arise" (p. 43).

In their critique of the DC framework, Williamson (1999) and Priem & Butler (2001) suggested that similar to RBV, the DC framework is "tautological, vague and endlessly recursive" (Eisenhardt & Martin, 2000, p. 1116). In their study, Eisenhardt & Martin, (2000) refuted this claim by arguing that dynamic capabilities have observable processes that can be examined empirically ranging from agile product development to strategic alliances and are also found to "have greater equifinality, homogeneity, and substitutability"

(Eisenhardt & Martin, 2000, p. 1106) than the traditional RBV perspective thereby allowing companies to respond to the prevailing market dynamics. The authors' view is the value of DC "lies in their ability to alter the resource base: create, integrate, recombine, and release resources" (p. 1116).

It is to be noted that the reasoning advanced by Eisenhardt & Martin, 2000 (EM) is noticeably different to that advanced by Teece et al., 1997 (TPS) in that the former view DC as inherently susceptible to shocks in rapidly changing environments (Peteraf et al., 2013). Although complimentary in some form, EM and TPS divergent views have created two schools of thought wherein TPS argue that dynamic capabilities are a source of competitive advantage whereas EM view DC as a source of limited competitive advantage as a result of inherent boundary conditions in rapidly changing environments.

To overcome what they consider to be the main DC limitations, Eisenhardt & Martin (2000) developed a contingency-based framework to augment DC with a set of tools to enable managers to understand how to achieve sustainable competitive advantage notwithstanding the degree of change in their environment. The contingency-based perspective is aimed at moderating DC into simple rules, processes and routines that organisations deploy in high turbulent business environments, and best practices in moderately changing business environments. Thus, the moderation is intended to mitigate the one-size-fits-all notion advanced by Teece et al. (1997).

In later years, Teece (2007, 2014) enhanced the DC framework by focusing on three types of routines: sensing, seizing and reconfiguring/ transforming routines. These routines are useful in explicating the nature and microfoundations of DC in relation to how competitive advantage is sustained albeit for short period of time until a new cycle of creating new resources is repeated to position the company ahead of its competitors. The main thesis is DC do not only enable companies to adapt to the changing market conditions but also shape their ecosystems through developing innovative products, routines and fit-for-purpose dynamic business models (Teece, 2007 & Fieldston et al., 2013).

2.2.2.1. Sensing routines

The DC framework enables "the firm's capacity to innovate, adapt to change, and create change that is favorable to customers and unfavorable to competitors" (Teece et al., 2016, p. 18). Therefore, the process of sensing "new opportunities is very much a scanning, creation, learning, and interpretive activity” (Teece, 2007, p. 1322). There are numerous ways to sense new opportunities. According to Teece et al. (2016), sensing opportunities can be achieved by leveraging “generative sensing, sense-making, use of scenario planning, and the purchase of real options” (p. 21).

Accordingly, to develop and maintain resilient DC, companies may purchase real options through commissioned research and development. On the contrary, the entrepreneurial mind-set orientation emphasises less organisational process with its focus on individual contribution as the sensing process is more interested in harnessing individual creativity to innovate (Wilden et al., 2016 & Bitencourt et al., 2020). However, it is important to recognise that the ability to sense opportunities is neither uniform nor linear across the organisation. As such, developing and building support structures to nurture innovation becomes essential.

2.2.2.2. Seizing routines

Although sensing the new opportunity is a vital step, translating an idea into new products, processes and services necessitate that a company understand the best way to create and derive value (Teece, 2007). This is an execution process which requires that a company conducts, among others, value chain analysis to identify bottlenecks and make the necessary changes or adjustments which may entail the implementation of “flexible sourcing arrangements, building “slack” into the organization itself, reengineering rule-bound hierarchies, and adopting open innovation processes” (Teece et al., 2016, p. 22). Undoubtedly, the execution process requires effective lobbying and influencing key people in the organisation to get buy-in on the fly. This is because in DC environment, making quick decisions within reasonable time is of essence in order seize the identified opportunity.

2.2.2.3. Reconfiguring/ transforming routines

The ability to identify opportunities offered by technological developments and changing market conditions followed by deliberate strategic choices and investments can lead to superior performance above industry norms (Teece, 2007). To sustain superior performance, companies may have to reconfigure their strategic resources, processes and internal structures. According to Teece (2007) “reconfiguration is needed to maintain evolutionary fitness and, if necessary, to try and escape from unfavorable path dependencies” (p. 1335).

Eisenhardt & Martin (2000) argue that "since the functionality of dynamic capabilities can be duplicated across firms, their value for competitive advantage lies in the resource configurations that they create, not in the capabilities themselves" (p. 1106). As a result, managers have to figure out how to transform and reconfigure, particularly, a large organisation in an agile manner. One such avenue is to divisionalise the change into multi-divisions, e.g. embarking on managed evolution to increase digital adoption by starting with the IT division with the aim of evolving the adoption into other functional areas. Pavlou & El Sawy (2011) maintain that the process of reconfiguration is related to "the appropriateness, timeliness, and efficiency by which operational capabilities are reconfigured to fit the environment" (p. 243). To reconfigure existing operational capabilities, the authors have developed the following DC tools: sensing; learning, integration, and coordination capabilities.

a) Sensing capability

The process of reconfiguring requires an entity to constantly scan the environment for trends likely to influence the industry and, invariably, the company. Pavlou & El Sawy (2011) define sensing capability "as the ability to spot, interpret, and pursue opportunities in the environment" (pp. 243-244). The argument is possessing the sensing ability allows the company to reconfigure its existing operational capabilities to be more responsive to customer needs, identify new market opportunities or develop new products through innovative processes and design (Leischnig et al., 2017).

b) Learning capability

New opportunities are identified by developing and leveraging sensing capabilities. However, sensing an opportunity in itself does not lead to value creation unless this can be translated into new products and services. Learning capability which is "the ability to revamp existing operational capabilities with new knowledge" (Pavlou & El Sawy, 2011, p. 244) leads to innovative solutions to develop new products and services that meet customer needs.

c) Integration capability

In the DC context, learning is an integral part of the reconfiguration process. However, new knowledge generated through learning is dispersed or reside with individual managers. To embed new knowledge into collective processes and routines, integration through knowledge management and learning reinforcement has to take place (Setia &

Patel, 2013 and Bitencourt et al., 2020). According to Teece (2007), DC only become effective when new knowledge is integrated into collective activities and sense-making through socialisation across the organisation. It can be argued that without collective ownership of knowledge in an organisation, there can be no dynamic capabilities (Pavlou & El Sawy, 2011).

d) Co-ordination capability

Dynamic capabilities require that managers allocate resources and assign tasks to the relevant people in an agile manner to create new operational capabilities (Wilden et al., 2016) or core competencies (Prahalad & Hamel, 2003). This level of co-ordination enables the organisation to fully realise the benefits of new opportunities. As defined by Pavlou & El Sawy (2011), co-ordination capability is "the ability to orchestrate and deploy tasks, resources, and activities in the new operational capabilities" (p. 246). Teece et al. (1997) argue that "capability is embedded in distinct ways of coordinating" (p. 519). Invariably, companies that master co-ordination pursue new opportunities more optimally than those that do not.

2.2.2.4. Dynamic capabilities theoretical grounding

Despite the contribution that the DC framework has made to the field of strategic management since the conceptual work of Teece et al (1997) & Eisenhardt & Martin (2000), and later Teece (2007, 2014), DC has been criticised for not being grounded in theory. As a response to this challenge, Wilden et al. (2016) developed what they termed the 'House of Dynamic Capabilities' framework aimed at integrating DC with configuration theory. Wilden et al. (2016) argue that configurational theories are ideal for DC thinking as they "complement variance theories and process theories to help better understand [dynamic capabilities]" (p. 26). As one of the co-founders of the DC framework, Teece (2018b) proposed the integration of DC with systems theory as both frameworks "adopt a holistic view that calls for all elements of an organization to be in alignment, and both recognize the importance of some form of learning for the purpose of adaptation" (p. 359). Thus, the two approaches have the potential to provide the theoretical grounding that the DC framework is purported to lack.

2.2.2.4.1. Configurational theory

Configurational theories are receiving attention in the field of strategic management research as a result of their usefulness in understanding and analysing complex systems (Wilden et al., 2016). According to Meyer et al. (1993), "rather than trying to explain how order is designed into the parts of an organization, configurational theorists try to explain how order emerges from the interaction of those parts as a whole" (p. 1178). To that end, configurational theories are ideal for studying complex social systems such as organisations and communities as these social systems are characterised by a high degree of interconnectedness and contingency (Doty et al., 1993 and Park & Mithas, 2020).

In this context, the 'House of Dynamic Capabilities' framework provide a practical application to DC (Wilden et al., 2016). The authors have used a simple but effective logic of a house to explain the interaction of a company with its environment within the DC milieu. The authors equate the weather outside the house with the business environment that the company has to respond to when it changes. The industry where the company is located is seen as the neighbourhood and part of the company ecosystem. In DC language, the owners of the house must gather enough information about the neighbourhood to thrive and survive. Furthermore, similar to company strategy, the roof is seen as one of the most important components of the house that holds the structure together protecting the house from the elements. Different joints of the house are equated to the company's operational backbone in the form of systems and processes that without the house is not likely to be functional. The logic is without a strong roof and joints the house would be susceptible to the weather and, overtime, this may lead to a total collapse.

To avoid the destruction of the house, dynamic capabilities are deployed to strengthen the company's strategy and, more importantly, operational capabilities. Quite simply, the argument is the house is as good as its structure. It is all good and well to have a beautiful house but without a strong foundation and pillars that carry and support the weight of the house, eventually the house will collapse. In this analogy, the pillars of the house are characterised as the DC routines, namely, to sense, seize and reconfigure the opportunities. Ultimately, the value of the house is company performance enabled by DC practices. Thus, the 'House of Dynamic Capabilities' provide a useful framework for managers and researchers alike to understand the different components of DC and how they inter-relate with one another. The framework also demonstrates that although there may be similarities in architectural typologies of the house plans in the neighbourhood, ultimately the value of the house is likely to hold and even appreciate depending on how the owners have built and continue to maintain the house.

2.2.2.4.2. Systems theory

Although the basic idea of systems theory can be traced as far back as Aristotle's era, its tenets remain relevant in analysing management systems such as dynamic capabilities (Teece, 2018b). The application of systems theory is useful in understanding how organisations work considering that organisations are a total sum of its sub-units which are likely to operate independently in the absence of a shared vision, purpose, culture and practices. To co-ordinate the organisation effectively, Teece (2018b) argues that combining systems theory with DC provides a suitable framework given that organisations are "social systems made up of sub-units that must inter-relate in a harmonious (congruent) manner for the organisation to be effective" (p. 360).

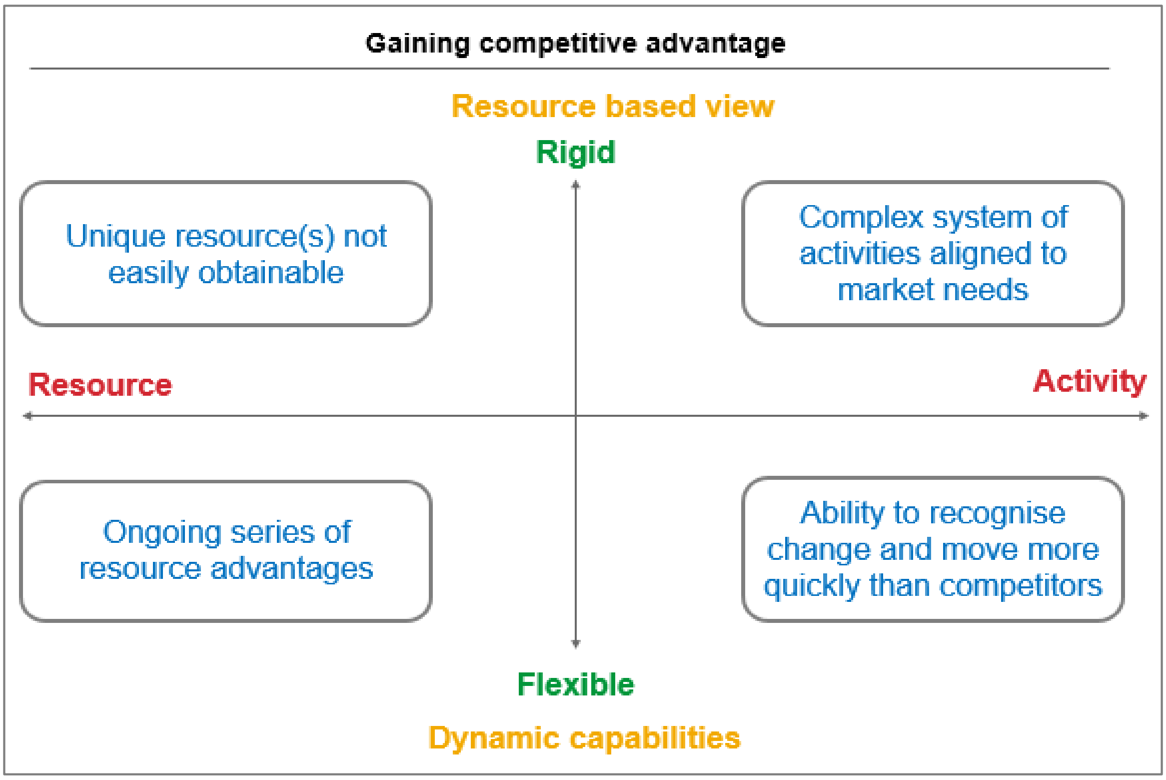
Thus, integrating the two frameworks is intended to facilitate the recognition of both evolutionary path dependences tied to resources and entrepreneurial acumen to create new opportunities. As discussed under the RBV framework, resources can be classified broadly into three categories: physical, human and organisational. However, most generic resources are not strategic. To qualify as strategic, resources have to meet the VRIN criteria. Under the DC framework, resources have to be renewed and/ or created to gain and maintain competitive advantage. It is the opaque nature of this process of resources renewal and creation that needs to be understood systematically, at a micro-level, in order to structure the DC process in a manner that makes it easily comprehensible and measurable.

The other component that requires systematic evaluation is strategy. Although possessing DC and resources is critical for the development of products and services, it is strategic insights that informs managers whether to enter a particular market and at what point whilst keeping the competition from doing the same. According to Teece (2018b) "the goal of strategy is to outmaneuver competitors by taking advantage of their mistakes and leveraging in-house strengths" (p. 365). In Teece's (2018b) view, although DC, resources and strategy are separate elements that can be studied separately, together they form a system that can be examined collectively to establish competitive advantage.

2.2.3 Resource based view versus dynamic capabilities

Despite their short-comings, RBV and DC frameworks have made significant contributions to the field of strategic management. Figure 1 below provides a schematic comparison of the two frameworks. RVB advances the view that to gain sustained competitive advantage and superior performance, companies have to possess heterogeneous and immobile resources that are valuable, rare, inimitable and non-substitutable. The RBV framework has been criticised for being too internally focused and light on providing the necessary guidance to enable companies to fathom how to create value and gain competitive advantage. At the heart of the RBV criticism is the opaque nature of the framework thereby making it hard for managers and researchers to decipher what success looks like in the RBV context (Wilden et al. 2016).

Figure 1: Resource-based view versus dynamic capabilities frameworks



Adapted from Barney (1991) & Teece et al. (1997).

As depicted in figure 1 above, the DC framework is an extension of the RBV framework. Instead of focusing on owning resources as a source of competitive advantage, DC focuses on resource creation and renewal which in turn enables the company to generate superior performance above industry norms. The distinction between RBV and DC is in how resources are perceived and deployed as a source of competitive advantage. Whereas RBV views ownership of VRIN resources to be long-term which enables sustained competitive advantage, DC view strategic resources to have short span that requires constant renewal in order to create new competencies and routines that facilitate quick adaptations in rapidly changing environments.

2.2.4. Theoretical debate and conclusion

By focusing on company resources as a unit of analysis, the RBV framework "seeks to explain the extent to which a firm may be able to sustain a position of competitive advantage" (Lockett et al., 2009, p. 10). This is achieved through building tangible and intangible competencies. However, the RBV framework came in for criticism for providing little guidance on how managers could build such competencies and how organisations should respond to changes in the competitive environment, particularly, in rapidly changing high velocity business environments. More specifically, RBV was criticised for being tautological (Eisenhardt & Martin, 2000 and Lockett et al., 2009) and the point in case is the framework's proposition that only valuable and rare resources can be considered to be a source competitive advantage.

Furthermore, by focusing on idiosyncratic resources, managers and researchers struggle to identify specific resources that influence performance. Lockett et al. (2009) noted that "a significant body of empirical research on the RBV has parallels with the proverbial drunk looking under the street light for his keys" (p. 17). The implication is under these circumstances; researchers are likely to measure easy to identify attributes that may not correlate with performance or have negligible influence thereof. RBV is also criticised for making it difficult for researchers to focus on measurable and testable attributes due to attributes being heterogeneous and unique to a company making the data not analogous across industry (Lockett et al., 2009). Undoubtedly, lack of homogeneous sample present significant challenges for researchers intending to measure attributes that contribute to competitive advantage.

In addition, the concept of causal ambiguity is said to be inherent in RBV which restrict company outsiders to fully comprehend causal relationships thereby making it difficult to socialise new managers to identify core competencies or researchers to perform meaningful empirical research. As a result, RBV was criticised for not providing generalizable and predictable inferences between identifiable set of resources and company performance making it almost impossible to discern and fathom RBV best practice (Lockett et al., 2009 & Wilden et al., 2016). The inability to develop best practice makes it unclear to managers and researchers in terms of how a company should respond to exogenous market dynamics.

The DC framework is a significant departure from the RBV framework particularly in dynamic markets because, in modern business milieu, responding to threats and opportunities presented by digital technologies goes beyond leveraging the company's resources to create, deliver and capture value (Barney, 2001). Although the DC framework has made progress in attempting to explicate the behaviour of firms in rapidly changing environments, its critics argue that the framework has not moved away from the RBV perspective and, as such, it remains vague and continues to advance circular reasoning that appears not to escape the RBV perspective. In contrast, Eisenhardt & Martin's (2000) argue that DC "exhibit commonalities across firms that are associated with superior effectiveness" (p. 1116) which implies that DC can become a useful and valuable tool that enables the company to gain competitive advantage.

However, DC emphases agile learning in high velocity markets in order to add new competencies whilst shredding the old ones. In this regard, the speed at which the company is required to assimilate new knowledge may prove to be unrealistic. This suggests that DC may not be as responsive in high velocity markets as Teece and other DC proponents make it to be. One of the most important process that the DC framework provides is the ability transform and reconfigure key competencies and routines. This process enables a company to apply its strategy regarding, for example, the timing of entering a market and, broadly, the implementation of strategic choices. As suggested by Wilden et al. (2016) and Teece (2018b), reframing DC to include a systematic approach that is comprehensive and yet practical is expected to provide the necessary theoretical grounding for DC.

2.3. Digital business strategy

2.3.1. Overview

2.3.2. The rise of digital technologies

Digital technologies are increasingly becoming part of business processes, structures and people (Park & Mithas, 2020, Ukko, 2019 & Vial, 2019). This phenomenon, according to Vial (2019), triggers "strategic responses from organizations that seek to alter their value creation paths while managing the structural changes and organizational barriers that affect the positive and negative outcomes of this process" (p. 118). It is, therefore, important to unpack what digital technologies are in order to understand how they interact with an organisation and indeed, society.

According to (Porter & Heppelmann, 2014), digital technologies are changing traditional businesses and every part of our lives at an exponential rate. Bharadwaj et al. (2013) defines digital technologies as “combinations of information, computing, communication, and connectivity technologies” (p. 471). It can be argued that the pervasiveness of these technologies present both opportunities and threats to companies. Sebastian et al. (2017) refers to some of these technologies as “SMACIT (social, mobile, analytics, cloud and Internet of Things [IoT]) technologies” (p. 197).

SMACIT technologies are viewed as powerful capabilities intended on “delivering unique, integrated business capabilities in ways that are responsive to constantly changing market conditions” (Sebastian et al., 2017, p. 198). The authors maintain that the omission of other digital technologies such as AI, blockchain, machine learning, robotics, virtual reality and so on was intentional since the SMACIT acronym refers to those digital technologies which are readily accessible. It is, therefore, critical that companies pay close attention to other (stated above) technologies as they have the potential to be as disruptive (if not more) as the SMACIT technologies.

2.3.3. Digital business strategy conceptual framework

Bharadwaj et al. (2013) developed the concept of digital business strategy a decade ago anchored on four themes: scope, scale, speed and sources of value creation and capture. Thus, the authors are widely credited with developing the original DBS concept after realising that digital technologies were “fundamentally transforming business strategies, business processes, firm capabilities, products and services, and key interfirm relationships in extended business networks” (p. 471).

This was a departure from the traditional of thinking which view IT strategy as subordinate to business strategy. In this regard, the conceptual framework of DBS was viewed as “going beyond the traditional view, thinking of IT strategy as a function within firms and recognizing the pervasiveness of digital resources in other functional areas such as operations, purchasing, supply chain, and marketing” (p. 472). Uhlig & Remané (2022) argue that DBS emerged as an “interdisciplinary research field, primarily combining strategic management research and IS research” (p. 10). It has been observed that, notwithstanding the evolutionary nature of DBS and its infancy as a research field, empirical research has been on the rise since 2015. Based on a systematic literature review on DBS conducted by Uhlig & Remané (2022), there are “key components that must be defined when developing and executing a DBS" (p. 6). These components include the following: "digitalization of products and processes, business model execution, IT governance and principles, IT investment and prioritization, digital resources, ecosystem compatibility, capabilities, leadership and culture" (p. 6).

2.3.3.1. Digitalization of products and processes

To enable DBS, this process involves carefully selecting a portfolio of technologies geared towards formulating and executing on DBS optimally. Some of these technologies may be grouped as SMACIT (Sebastian et al., 2017). However, depending on the level of organisational digital maturity, this may also include ERP and CRM as well as complementary platforms. It is important, therefore, to remember that the purpose of acquiring digital technology stack is ultimately to meet customer needs in a manner that competitors cannot.

2.3.3.2. Business model execution

Business model execution in the context of DBS involves ensuring that business models can cope with the digital demands from a technology and customer perspectives. Considering that in the digital environment business models have to do with "value proposition, value creation and delivery, and value capture elements and the interactions between these elements within an organisational unit" (Geissdoerfer et al., 2018, p. 402), to be effective, they have to be multisided. Uhlig & Remané (2022) argue that multisided business models or platforms "creates value by reducing distribution, transaction, and search costs, and it creates network effects" (p. 7).

2.3.3.3. IT governance and principles

The process of integrating IT strategy with business strategy requires that the role of IT in the organisation is clearly defined including the role of the Chief Information Officer (CIO). This is to ensure that, the role of IT is elevated to be more strategic than functional. Therefore, IT need to be included throughout the entire business value chain to enable co-creation and ownership that is required for a successful implementation of DBS.

2.3.3.4. IT investment and prioritization

Similar to IT governance, to execute digital business strategy effectively, IT investment decisions have to be considered holistically informed by corporate strategic choices. This implies that IT decisions, no matter how trivial or small, they have to be considered within the context of a corporate strategy beyond IT as a functional area.

2.3.3.5. Digital resources

To drive effective DBS, there is a need to establish which resources offer competitive advantage. Within the RBV framework, resources offer differential value if they are considered VRIN (Barney, 1991). Thus, within the DBS context, “digital resources enable new strategic digital opportunities by laying the foundation for the effective use of digital technologies in the business context” (Uhlig & Remané, 2022, p. 8).

2.3.3.6. Ecosystem compatibility

The proliferation of digital technologies continues to reshape industries and their ecosystems which in turn redefines the ecosystems on an ongoing basis. Uhlig & Remané (2022) view value networks to be made up of the following: “the closed vertically integrated model, loosely coupled coalitions, and multisided platforms” (p. 8). Thus, when developing DBS, it is critical that leadership teams understand opportunities and threats that ecosystems present as these networks are prone to unexpected changes.

2.3.3.7. Capabilities

Understanding organisational capabilities is a critical part of DBS execution. These capabilities can be divided into operational and managerial. However, ordinary capabilities may not be sufficient to deliver DBS. Consequently, organisations must strive to adopt dynamic capabilities to sense, seize and reconfigure new opportunities (Teece, 2007, 2014).

2.3.3.8. Leadership

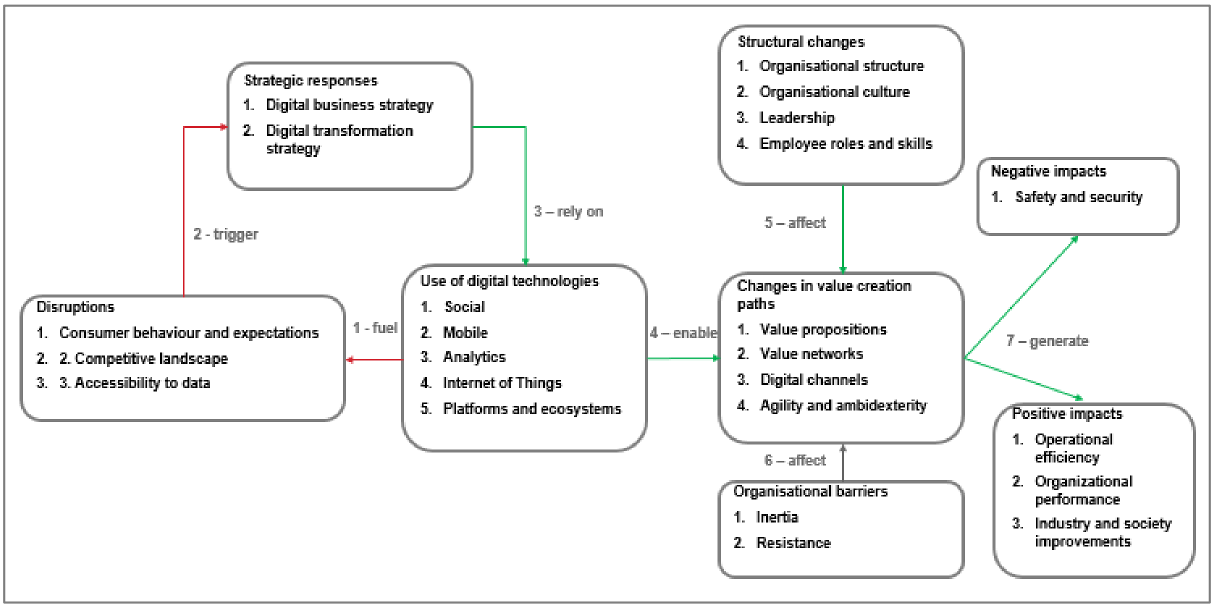
Developing DBS requires unique leadership skills and abilities anchored on digitality. This is because DBS need to be “supported by leaders who foster a culture able to change and invent the new” (Kane et al., 2015, p. 3). Hence DBS execution will only successful if is led by digital leaders.

2.3.3.9. Culture

Nurturing a culture of innovation is a critical part of formulating and executing on DBS. Uhlig & Remané (2022) argue that "one crucial aspect of DBS is the IT knowledge of managers, as well as employees, as this enables a hard-to-imitate organizational innovativeness" (p. 9). However, for the innovation culture to take shape, the organisation need to create a conducive environment for creative thinking and continuous learning.

Although understanding DBS components is useful in the development of a robust DBS plan, at a conceptual level, there is a need to understand other key concepts that interrate with DBS. It is, therefore, important that we differentiate between DBS and digital transformation (DT). Whereas DBS is transformative in nature in its attempts to fuse IT strategy with business strategy, its main focus is in driving business strategy than transforming the organisation into a completely new one. Consequently, it can be argued that DBS focuses on incremental change rather than radical change (Wessel et al., 2021). This differs from the DT perspective which focuses on transforming the organisation into a completely new one (Vial, 2019 & Wessel et al., 2021). However, the differences between DBS and DT are not always obvious and it is therefore necessary that these concepts are aligned to avoid creating confusion. As depicted in the figure 2 below, the process of DBS follows the same path as DT.

Figure 2: Building blocks of DBS and DT processes



Source: Adapted from Vial (2019)

According to Vial (2019), the DT framework above is depicted as a process flow because it is based on the outcome of "relationships that emerged through [the] analysis across eight overarching building blocks describing DT as a process where digital technologies play a central role in the creation as well as the reinforcement of disruptions taking place at the society and industry levels" (p. 122). Notwithstanding, the lack of clear delineation of differences between DBS and DT, the framework above makes a useful contribution to the understanding of both DBS and DT processes.

In relation to DBS, the framework above generates two outcomes, positive impacts (operational efficiency, organisational performance and industry and society improvements) and negative impacts (safety and security). The assertion, therefore, is positive outcomes have close associations with DBS dimensions: managerial capabilities and operational capabilities.

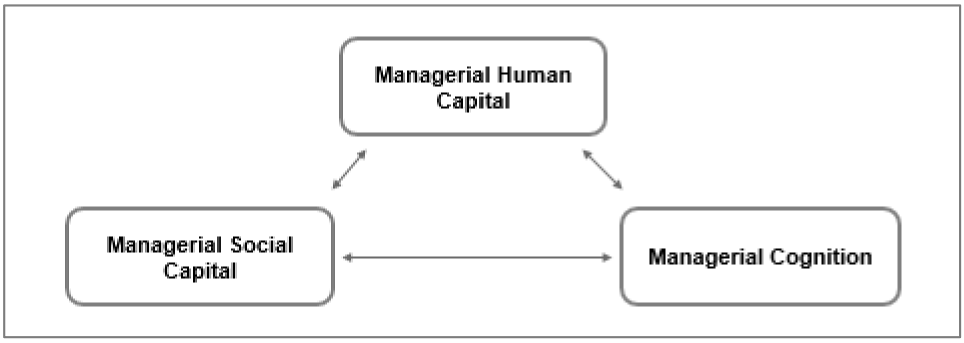
2.3.4. Managerial capabilities

To navigate the complexity of fusing IT strategy and business strategy, managers are required to demonstrate the ability to orchestrate organisational capabilities to lead in a dynamic business environment (Bharadwaj et al., 2013; Hanelt et al., 2021; Park & Mithas, 2020, Ukko et al., 2019 & Vial, 2019). According to Ukko et al. (2019) "managerial capability as a dimension of a digital business strategy included items related to managers' knowledge of and skills in digital tools, managers' clear vision for utilizing digitality, and managers' support for digitality" (p. 5) which is essential in formulating and implementing DBS.

The concept of managerial capabilities presumes that managers possess ordinary capabilities that enable them to make decisions in stable environments. However, in rapidly changing environments, dynamic managerial capabilities are required (Teece, 2018a). Adner & Helfat (2003) introduced the concept of dynamic managerial capabilities "to help explain differences in managerial decisions that in turn lead to heterogeneity in firm performance" (p. 1012). Unsurprisingly, the authors linked the concept with dynamic capabilities as articulated by Teece et al. (1997) which suggests that dynamic managerial capabilities enable managers to "integrate, build, and reconfigure internal and external competences to address rapidly changing environments" (p. 516).

Dynamic managerial capabilities "draw on a set of underlying managerial resources, namely, managerial cognition, managerial social capital, and managerial human capital" (Helfat & Martin, 2015, p. 1285). Adner & Helfat (2003) view the underlying managerial resources as key drivers of dynamic managerial capabilities. The three drivers are depicted in figure 3 below.

Figure 3: Dynamic managerial capabilities drivers



Source: Adner & Helfat (2003).

i) Managerial human capital

Human capital is defined as "learned skills that require some investment in education, training, or learning more generally" (Adner & Helfat, 2003, p. 1020). Heterogeneity in human capital is believed to be the main driver of performance differences between organisations (Adner & Helfat, 2003). Therefore, access to scarce and critical skilled talent is seen as a necessary condition to increase the propensity of an organisation to sense, seize and reconfigure new opportunities in a rapidly changing environment (Helfat & Martin, 2015).

ii) Managerial social capital

The relationships that manages have built and nurture both internally and externally can play an important role in driving business performance (Adner & Helfat, 2003). This is because "social ties … may help to transfer information from one setting to another" (p. 1021). Therefore, in a rapidly changing environment, access to information becomes currency.

iii) Managerial cognition

Helfat & Martin (2015) and Adner & Helfat (2003) view managerial cognition as a set of beliefs, mental models and processes that managers use to perceive, interpret and respond to information from the environment. By applying dynamic managerial capabilities, organisations can position themselves to better understand the extent to which their underlying decision making processes impact business performance in rapidly changing environments.

2.3.5. Operational capabilities

Technologically driven disruptions causes changes on a continuous basis. This requires companies to be agile in their adaptations within the context of DBS (El Sawy et al., 2008 & Ukko et al., 2019). The ability to be proficient in deploying digital solutions without disrupting business operations is an integral part of embedding operational capabilities in DBS. Ukko et al. (2019) states that operational capabilities "includes digitality in internal processes, the integration of digitality across the whole business, and the existence of digitality in all business functions" (p. 5).

Applying the RBV perspective as a foundation, Wu et al. (2010) view operational capabilities as "firm-specific sets of skills, processes, and routines, developed within the operations management system, that are regularly used in solving its problems through configuring its operational resources" (p. 726). In this regard, operational capabilities are said to be the 'secret ingredient' that serve as a source of competitive advantage. The authors argue that although operational capabilities are closely related to operational practices, they are not synonymous.

To explain the difference, the authors use the analogy of a restaurant kitchen wherein resources such as the stove and staff members' skills only offer the potential whereas operational practices involve the process of combining kitchen resources to prepare a meal. However, possessing required resources and the process of preparing a meal does not guarantee success since they are dependencies such staff members' skill sets and experience. Operational capabilities, therefore, enable the kitchen to "leverage the staff's skill sets to deploy resources in creating dishes that reflect the restaurant's history, style of cooking, and the preferences of its customers" (p. 726).

Thus, understanding operational capabilities enable the company to leverage opportunities offered by digitality (Sebastian et al., 2017). According to Ross et al. (2017), this implies that companies require "an integrated platform of distinctive capabilities - we call it an operational backbone - that ensures efficient, reliable transactions and customer interactions” (p. 9). In an attempt to achieve these operational capabilities, many companies continue to make substantial investments in enterprise resource planning (ERP) and customer relationship management (CRM) systems. However, success in DBS can only be achieved by mastering optimal configuration and customisation that enable the company to have “access to a single authoritative source of information for key data about finances, customers and products; reliable end-to-end global supply chain processes; or back office shared services” (p. 9).

For example, although financial services organisations may have SAP as their backbone system, success is achieved when employee and customer world-class experience is achieved. The bottom line is companies that lack scalable operational capabilities across the enterprise “will not be able to deliver reliable operations and thus will not be able to compete digitally” (p. 9). This is because operational capabilities are “firm specific and are developed over time through complex interactions among the firm’s resources” (Amit & Schoemaker, 1993, p. 35).

Considering that operational capabilities are a critical component of organisational resource base, to respond to digital threats, organisations must reconfigure their operational capabilities to gain competitive advantage in a rapidly changing environment. The concept of reconfiguring operational capabilities has been widely discussed above under dynamic capabilities. According to Pavlou & El Sawy (2011), operational capabilities can be reconfigured to become dynamic by applying the following DC tools: sensing; learning, integration, and coordination. Invariably, the process of revamping operational capabilities involves transforming basic routines such as increasing the speed and quality of gathering market intelligence (Leischnig et al., 2017), deliberate exploitation and assimilation of new knowledge in a manner that positions the organisation to be competitive (Wilden et al., 2013), orchestration of resources and activities to create dynamic operational capabilities (Pavlou & El Sawy, 2011). In summary, competitive advantage is achieved when companies offer unique value propositions to its customers that cannot be replaced or imitated. In the era of digital, unique value proposition “stems from a digital strategy that is focused on either a set of digitized, integrated offerings or a relationship that engages customers in ways that competitors can’t match” (Ross et al., 2017, p. 9). In essence, this is real value of possessing operational capabilities.

2.4. Dynamic capabilities and digital business strategy

Due to the disruptive nature of digital technologies, it is necessary to understand the role that DC play within the context of DBS. Dynamic capabilities are viewed as critical moderators of performance in turbulent business environments because “they allow organizations to systematically generate and modify their organizational capabilities to gain long-term competitive advantages” (Konopik et al., 2022, p. 2). In a classical sense, dynamic capabilities are about “two important aspects of achieving competitive advantage: dynamics and capabilities” (Bitencourt et al., 2020, p. 109). The term ‘dynamic’ is related to the execution of innovation when the organisation requires it whereas the term ‘capabilities’ is related to agile adaptability in a changing business environment (Teece et al., 1997).

Invariably, DC denote the ability to innovate and adapt in a rapidly changing environment. This is the moderating effect that is required to enhance both managerial capabilities and operational capabilities as the two main dimensions of DBS. El Sawy (2008) defines operational capabilities as “planned ability to effectively execute substantive day-to-day activities, such as manufacturing, logistics, and sales” (p. 140). In relation to managerial capabilities, the DC framework provides key insights to DBS based on its ability to enable managers to sense unknown futures, mobilise resources to capture value (seizing) and transform/ reconfigure the business environment for maximum adaptability (Teece et al., 2016).

2.5. Digital business strategy and business performance

In strategic management, the concept of “competitive advantage helps strategists understand and analyse within industry differences in performance” (Ghemawat et al., 2014, p. 8105). Central to conducting industry comparisons is consistent industry measures. Matured industries such as the banking industry tend to have consistent indicators e.g. headline earnings per share, cost to income ratio, net promoter score and so on. Therefore, to measure if DBS dimensions are having the desired effects to improve business performance, indicators that measure business performance such as financial performance and customer performance are essential and they must be measured where possible.

2.6. Conclusion

The literature in this chapter demonstrated that for the past three decades there has been a great deal of research focusing on examining what makes a company competitive. One such perspective is RBV that view company resources to be a source of competitive advantage. However, to gain sustained competitive advantage, a company must possess resources which are considered valuable, rare, imperfectly imitable, and non-substitutable by current and potential competitors. The RBV perspective, therefore, assumes that in an environment where companies possess exactly the same resources, it would be inconceivable for one particular company to develop and implement strategies that enable them to have sustained competitive advantage. This implies that competitive advantage can only be derived in an environment where company resources are heterogeneous and immobile.

In contrast, the DC perspective go beyond competencies that come from merely owning resources to renewal of those resources in a rapidly changing environment. By focusing on three types of routines: sensing, seizing and reconfiguring/ transforming routines, the DC framework view competitive advantage in turbulent environments to be short-term which requires that companies renew their routines on a regular basis to stay competitive. However, to augment the DC framework, a systems approach has been proposed aimed at building a DC model that is both effective and replicable. It is the argument of this paper that a robust DC framework is required to strengthen both managerial capabilities and operational capabilities which are essential to realise digitality underpinned by strategy and not technology.

3. RESEARCH QUESTIONS AND HYPOTHESES

3.1. Introduction and roadmap

In this chapter, the research questions and their commensurate hypotheses are presented. Considering that this study is anchored on two different but related questions, each question will be analysed and discussed separately. Table 2 below provides main headings of the chapter.

Table 2: Research questions and hypotheses roadmap

Main headings		
	3.1. Introduction	
	3.2. Research question 1	3.3. Research question 2
	3.2.1. Managerial capabilities	3.3.1. Managerial capabilities moderated by DC
	3.2.2. Operational capabilities	3.3.2. Operational capabilities moderated by DC
	3.4. Conceptual framework	

Source: Author’s compilation

3.2. Research question 1

Developing suitable research questions enables a researcher “to focus on what is it about the [the] area of interest that the [researcher] want to know” (Bell et al., 2019, p. 31). This research study investigated the relationship between DBS and business performance in a financial services organisation. Thus, to examine the relationship between DBS and business performance the following research question was asked: **RQ 1 “to what extent does adopting a digital business strategy improve business performance in a moderately changing environment”.** This research question presupposes that the adoption of DBS is prevailing in an industry that is in a relatively stable environment but is gradually facing disruption as new players enter the market (Wilden et al., 2016).

To answer this research question, there is a need to understand the key dimensions of DBS. Ukko et al. (2019) concluded that there are two main dimensions of DBS, managerial capabilities which “refers to managers' abilities to utilize digitality in a business strategy, employees’ mindsets and skillsets, as well as the workplace” and operational capabilities which is about “the company's capability to integrate digitality into the overall business” (p. 2).

In attempting to unpack how multiple capabilities lead to systematic patterns of high performance in health, education, manufacturing and service industries, Park & Mithas (2020) discovered that information analytics capabilities as well as other key organisational capabilities such as leadership, strategic planning, customer focus, human resources and process management are parts of a system form within the DBS context that influence business performance conjunctively. Consequently, to investigate the relationship between DBS and business performance, the study focused on managerial capabilities and operational capabilities as the key dimensions of DBS in a stable to moderately changing environment.

3.2.1. Managerial capabilities

To navigate the complexity of fusing IT strategy and business strategy, managers are required to demonstrate the ability to orchestrate organisational capabilities to lead in a dynamic business environment (Bharadwaj et al., 2013; Hanelt et al., 2021; Park & Mithas, 2020, Ukko et al., 2019 & Vial, 2019). In line with this argument, the following hypothesis was proposed:

H1: Managerial capabilities are positively related to business performance.

3.2.2. Operational capabilities

Technologically driven disruptions causes changes on a continuous basis. This requires companies to be agile in their adaptations within the context of DBS (El Sawy et al., 2008 & Ukko et al., 2019). The ability to be proficient in deploying digital solutions without disrupting business operations is, therefore, an integral part of embedding operational capabilities in DBS. In line with this argument, the following hypothesis was proposed:

H2: Operational capabilities are positively related to business performance.

3.3. Research question 2

In addition, to further expand the two hypotheses above in a rapidly changing environment, the study investigated the relationship between managerial capabilities and operational capabilities on business performance when moderated by DC. Thus, in an industry where the business environment is rapidly changing, it can be argued that the adoption of DBS is effective when it is moderated by DC to enable the organisation to sense new opportunities, seize identified opportunities and reconfigure resources/ routines within a short period of time (Teece, 2007, 2014). To respond to major disruptions, the incumbent organisations are compelled to transform to survive and be competitive (Teece, 2014 & Wilden et al., 2016). To that end, the following research question was asked: **RQ 2 “to**

what extent does adopting a digital business strategy improve business performance in a rapidly changing environment”.

3.3.1. Managerial capabilities moderated by dynamic capabilities

The literature revealed that both managerial capabilities and operational capabilities are relevant antecedents to DBS (Ukko et al., 2019). It is, therefore, postulated that DC has a moderating effect to both managerial capabilities and operational capabilities. Li et al. (2018), argue that dynamic capabilities, which are “the capabilities with which managers build, integrate, and reconfigure organisational resources and competences” (p. 1132), provides a useful theoretical orientation to managerial capabilities. In line with this argument, the following hypothesis was proposed in relation to managerial capabilities:

H3: Dynamic capabilities positively moderates the relationship between managerial capabilities and business performance.

3.3.2. Operational capabilities moderated by dynamic capabilities

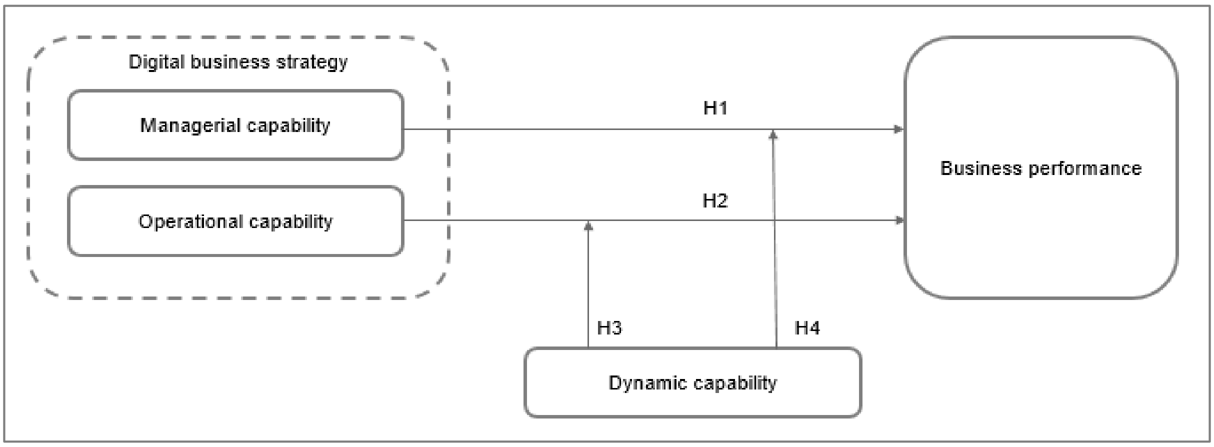
The link between operational capabilities and DC was made by El Sawy et al. (2008), who view DC as “the ability to effectively reconfigure existing operational capabilities to match the changing business environment” (p. 140). In line with this argument, the following hypothesis was proposed:

H4: Dynamic capabilities positively moderates the relationship between operational capabilities and business performance.

3.4. Conceptual framework

The research conceptual framework below in figure 4 provides the research logic for developing the four hypotheses.

Figure 4: Conceptual framework



Source: Adapted from Ukko et al. (2019).

The hypotheses are based on the following DBS dimensions: 1) managerial capabilities (H1) and 2) operational capabilities (H2). These capabilities are therefore the independent variables and they are hypothesised to influence business performance which is the dependent variable. Hypotheses H1 and H2 were intended to answer RQ 1: “to what extent does adopting a digital business strategy improve business performance in a moderately changing environment”.

Furthermore, the framework further hypothesised that dynamic capabilities moderates both managerial capabilities (H3) and operational capabilities (H4) in order to attain superior business performance in rapidly changing environments. To that end, hypotheses H3 and H4 were intended to answer RQ 2: “to what extent does adopting a digital business strategy improve business performance in a rapidly changing environment”.

4. RESEARCH METHODOLOGY

4.1. Introduction and roadmap

This chapter provides the research methodology that was applied to conduct this study as well as the research design used to test the hypotheses related to RQ1 and RQ2. Table 3 below provides the structure of this chapter.

Table 3: Research methodology roadmap

<table>
<tr><td rowspan="11">Main headings</td><td colspan="2">4.1. Introduction</td></tr>
<tr><td>4.2. Research philosophy</td><td>4.3. Data collection design</td></tr>
<tr><td>4.2.1. Research design and time horizon</td><td>4.3.1. Population, sampling and setting</td></tr>
<tr><td rowspan="2">4.2.2. Methodological choice and approach</td><td>4.3.2. Level and unit of analysis</td></tr>
<tr><td>4.3.3. Sampling frame</td></tr>
<tr><td colspan="2"></td></tr>
<tr><td>4.4. Research instrument</td><td>4.6. Quality control</td></tr>
<tr><td>4.4.1. Survey questionnaire</td><td>4.6.1. Research quality and rigour</td></tr>
<tr><td rowspan="2">4.4.2. Instrument scale</td><td>4.6.2. Reliability</td></tr>
<tr><td>4.6.3. Validity</td></tr>
<tr><td colspan="2">4.5. Ethical considerations</td></tr>
</table>

Source: Author’s compilation

4.2. Research philosophy

A research philosophy is viewed as a set of beliefs and assumptions related to how knowledge is developed and generated (Saunders et al., 2019). These assumptions can be classified into two categories: 1) ontology “refers to assumptions about the nature of reality” and 2) epistemology “refers to assumptions about knowledge, what constitutes acceptable, valid and legitimate knowledge, and how we can communicate knowledge to others” (p. 130). In a nutshell, ontology examines the nature of reality whilst epistemology examines how that reality can be examined.

Ontological assumptions are, therefore, presuppositions that researchers display about the nature of reality, either explicitly or implicitly, that shapes the framing of their research. Bell et al. (2019) argue that there are two types of ontological assumptions: objectivism and constructionism. Objectivist position “implies that social phenomena confront us as external facts beyond our reach or influence and they exist whether we are aware of them or not” (p. 11) whereas constructionist position asserts that “social phenomena and categories are not only produced through social interaction but are also in a constant state of revision” (p. 12).

According to Bell et al. (2019), epistemological positions follow on ontological guardrails. For example, if we take an objectivist ontological position, “logically we can gain knowledge of the world only by direct or indirect observation or measurement of aspects of it” (p. 14). Conversely, if we take a constructionist ontological position, we can gain knowledge by “observing and interviewing social actors in an attempt to understand how they shape and understand the world” (p. 14). Ontological positions are, therefore, antecedents of epistemological positions. Articulating both ontological and epistemological positions clearly is important when conducting business research because this understanding allow researchers “to answer the question of how we should conduct research” (p. 14).

Therefore, the process of combining ontology and epistemology positions enable researchers to get a holistic view of how to understand knowledge. In the language of research, this understanding is called a research paradigm that provides the philosophical basis of a research project. One such paradigm is positivism. Bell et al. (2019), argue that this is an “epistemological position which is informed by an objectivist ontological position” (p. 14). Saunders et al. (2019) maintain that “positivism relates to the philosophical stance of the natural scientist and entails working with an observable social reality to produce law-like generalisations” (p. 144). Thus, the positivist paradigm is interested in a scientific research method that is designed to investigate a social or business phenomenon based on pure data and facts free of human bias.

In contrast, interpretivism research paradigm is “underpinned by a social constructionist ontology, which holds that reality is constituted by human action and meaning-making, rather than existing objectively and externality” (Bell et al., 2019, p. 15) to accommodate the state of constant change that characterises social interaction as opposed to the natural order. The main difference between positivism and interpretivism, therefore, is that the former is interested in explaining human behaviour whereas the latter seeks to understand human behaviour.

4.2.1. Research design and time horizon

The purpose of research design is to turn “research questions into a research project” (Saunders et al., 2009, p. 136). This process guides how research is conducted from data collection to data analysis in a manner that answers the relevant research questions. It is worth noting that the manner in which the research is structured flows from the chosen research philosophy. Thus, an objectivist ontological position that is positivist in nature logically follows a quantitative research design approach. To that end, to answer RQ1 and RQ2, this research project followed a survey questionnaire design which was cross-sectional, that is, the data collection time-horizon was at a specific point in time (Saunders et al., 2019).

4.2.2. Methodological choice and approach

There are three common research approaches: quantitative, qualitative, and mixed methods (Williams, 2007, Saunders et al., 2019 & Bell et al., 2019). According to Bell et al. (2019), the quantitative research approach is interested in explaining a social or business phenomenon from data and facts with a view of generalising the results across the entire population. The qualitative method, on the other hand, is interested in collecting in-depth information on a particular topic. “This approach assumes a single person represents the group feelings and emotions of a person are equally important to interpret which are ignored by the quantitative method” (Rahi, 2017, p. 2). The aim of the researcher is to observe or interpret the phenomenon in order to develop a theory (Gehman et al., 2018). This is an interpretive paradigm that holds the view that that “true knowledge can only be obtained by deep interpretation of [the] subject” (Rahi, 2017, p. 1).

An emerging research approach that attempts to close the gap between quantitative and qualitative approaches is the mixed research method. This approach is less applied due to the under-appreciation of the value of leveraging both methods to investigate complex social and business phenomena that cannot be explained or understood based on positivist or interpretivist approaches applied separately. Accordingly, this led to the creation of a pragmatist approach which is “concerned with the practical consequences of action and does place problem solving at the center of its understanding of human action” (Farjoun et al., 2015, p. 1789).

Although there is value in applying any of the three research approaches, after critically assessing the research approach that is fit-for-purpose to answer the two research questions in this study, a quantitative research approach was followed to collect and analyse data which, in principle, enables the researcher to generalise the results to the entire population (Rahi, 2017).

4.3. Data collection design

In general, researchers plan their research based on the research questions that need to be answered. Saunders et al. (2019) used the analogy of a research 'onion' to compare the research process to the process of delayering an onion wherein the outer part of the onion represents the chosen research philosophy whilst the middle layer represents research methods and the core of the onion represents data collection and analysis. Thus, to develop a robust research process, researchers need to understand and explain each layer of their research process from research philosophy to data collection and analysis.

In this research project, RQ1 and RQ2 are framed to be answered by testing hypotheses related to managerial capabilities and operational capabilities (independent variables) and business performance (dependent variable). As a result, the study applied a Structured Equation Model (SEM) which is statistical technique that is used to confirm the measurement model of latent variables. The measurement model specified how the observed variables measure the latent variables. As such, confirmatory factor analysis (CFA) was used to test whether the observed variables measure the latent variable in a way that is consistent with the hypotheses. According to Pallant (2007), CFA is used in research to "test (confirm) specific hypotheses or theories concerning the structure underlying a set of variables" (Pallant, 2007, p. 179).

4.3.1. Population, sampling and setting

The purpose of this study was to investigate the relationship between digital business strategy and business performance in a financial services organisation. The research setting, is therefore, in a South African financial services organisation where data was collected around the organisation's digital transformation journey. In this regard, the population groups were employees at managerial levels: executives, senior managers, middle managers and junior managers. The rationale for targeting managerial employees was based on the need to address the research aim which sought to explain the relationship between managerial capabilities and operational capabilities (as the main dimensions for DBS) and business performance.

4.3.2. Level and unit of analysis

This study was interested in understanding the relationship between DBS and business performance. Therefore, the level of analysis, which can be classified, broadly, as the research scope wherein a business phenomenon is being observed, is the financial services organisation. According to Hair et al. (2019), the unit of analysis is considered to be "the basic element of …[a] research. In other words, it is the "who" or "what" in … [a] study that you want to understand and describe" (p. 34). Accordingly, the unit of analysis in this research project is the employees.

4.3.3. Sampling frame

Hair et al. (2019) defines sampling frame as "a comprehensive list of the elements from which the sample is drawn" (p. 183). Given the volume of data that contains all managers' information in the organisation under review, it was not possible for the researcher to gain access to a complete list of managers. As a result, there was a limitation in selecting a probability sample. Invariably, the researcher applied a purposive non-probability sample method. Purposive sampling method "is a form of convenience sampling in which the researcher's judgment is used to select the sample elements" (Hair et al., 2019, p. 193). Accordingly, the researcher targeted selected managerial employees on the assumption that managers ought to have some level of understanding and insights regarding the organisation's digital journey (Hess et al., 2016).

4.4. Research instrument

4.4.1. Survey questionnaire

In a positivist paradigm, the research purpose is to test hypotheses using objective measures free from value judgement (Burns & Burns, 2008). Given that this study follows a positivist approach, an online self-administered survey questionnaire instrument was used. The questionnaire was designed on Microsoft Forms, an online survey platform. The survey was deployed to respondents via email with an embedded link to the Microsoft Forms survey platform (Bell et al. 2022) which allowed easy access to participants. A number of statements were adapted from academic research studies that formed part of the literature review section in chapter two. Noteworthy academic contributors to the development of the survey questionnaire are: Barney (1991), Teece et al. (1997), Eisenhardt & Martin (2000), Pavlou et al. (2011), Bharadwaj et al. (2013), Chi et al. (2016), El Sawy et al. (2016), Teece et al. (2016), Leischnig et al. (2017), Sebastian et al. (2017), Ukko et al. (2019), and Vial (2019).

Ukko et al. (2019) investigated the relationship between DBS and financial performance. The authors theorised that "both managerial capabilities and operational capabilities are necessary to actualize digital business strategy, which is relevant to create financial performance" (p. 4). The study by Leischnig et al. (2017) examined the impact of DBS to market performance and the findings, among other hypotheses, predicted a positive effect of a DBS on firms' market intelligence capability which illuminated "the causal process through which a digital business strategy transforms into market performance" (p. 11).

Pavlou et al. (2011), in their research on dynamic capabilities, postulated that managers lack the ability to use DC in turbulent environments as a result of "poor understanding of dynamic capabilities and the lack of a measurable model" (p.240). The authors concluded that these two factors are the main contributors to managers' inability to reconfigure both managerial capabilities and operational capabilities in turbulent environments which manifest in poor corporate decisions. Teece et al. (2016) found that an enhanced DC framework "can help guide managers with respect to when and how to manage under deep uncertainty" (p. 31) provided the DC framework is well understood and it becomes the "CEO's leitmotif, as it delineates pathways that allow escape from the agility/efficiency tradeoff" (p. 32).

4.4.2. Instrument scale

To determine the relationship between DBS dimensions and business performance, the researcher resolved to base the survey questionnaire on a five-point Likert scale as per table 4 below. A Likert scale format is preferred to measure the attitudes or opinions of respondents. Hair et al. (2019) maintain that "Likert scales often use a five-point scale to assess the strength of agreement or disagreement about a statement" (p. 245). However, it is not uncommon to use a seven-point Likert scale in order to be more precise in establishing the extent of agreement or disagreement with a statement. Bell & Waters (2018) argue that "Likert scales can be useful, as long as the wording is clear, there are no double questions, and no unjustified claims are made about the findings" (p. 146). To prepare the data for analysis, the responses were coded as per table 4 below.

Table 4: Likert scale format

Strongly agree	Agree	Neither agree not disagree	Disagree	Strongly Disagree
5	4	3	2	1

Source: Author's compilation

4.5. Ethical considerations
At the research planning stage, the researcher reflected on potential ethical issues that may arise during the course of the project and resolved to rely on the data that was collected from participants who completed the survey questionnaire. Saunders et al. (2009) argue that “the data collection stage is associated with a range of ethical issues” (p. 193). Thus, the decision to conduct research in a financial services organisation was influenced by time constraints related to the process of requesting permission to conduct research from multiple organisations.

Considering that the ethical clearance approval is a prerequisite for commencing with the data collection process, unforeseen delays in getting access to conduct research from multiple organisations was highlighted as a potential risk. Regarding ethical issues related to the survey, the researcher stipulated on the questionnaire that participation is voluntary and, as such, participants are free to withdraw any time without penalty. In addition, the survey was designed to be anonymous and only aggregated data was reported. The ethical clearance from GIBS Ethics Committee was received on 07 September 2023 (see appendix A).

4.6. Quality control

4.6.1. Research quality and rigour
Rigour is the cornerstone of good scientific research. Sekaran & Bougie (2016) argue that rigour “connotes carefulness, scrupulousness, and the degree of exactitude in research investigation” (p. 19). Thus, rigour implies that the research process is free from value judgement and bias which allows the researcher to interpret the data objectively thereby allowing other researchers to replicate the research process and findings thereof. To ensure that the results of this research project are undergirded and credible, the researcher conducted numerous quality control measures that are detailed below.

4.6.2. Reliability
In scientific research, reliability measures the extent to which a research instrument (questionnaire) or method produces consistent and repeatable results (Bell et al., 2022, Pallant, 2020 & Hair et al., 2019). Therefore, reliability is about achieving consistent research findings. Furthermore, a good research instrument produces consistent results regardless of multiple items (variables/ indicators) being measured (Hair at al., 2019). Although all types of research consider the extent to which the research instrument is

reliable, in quantitative research reliability is very important as the analysis of the data is conducted using statistical analysis to draw conclusions.

There are three ways to measure research instrument or method reliability. First, researchers can perform a *test-retest measure* which involves administering the same research instrument to the same participants on different occasions and then calculate "the correlation between the two scores" (Pallant, 2007, p, 6). In short, the test-retest measure is interested in measuring the strength and the direction of the relationship between variables. Second, researchers can perform an *interrater reliability test* wherein multiple independent raters assess the same data with the aim of determining the level agreement. The higher the level of agreement, the higher the instrument reliability.

Third, the commonly used reliability measure is *internal consistency measure*. Internal consistency "is used to assess a summated scale where several statements (items) are summed to form a total score for a construct" (Hair et al., 2019, p. 261). Accordingly, a reliable research instrument or method should have items that are all measuring the same attribute. Cronbach's Alpha is commonly used to measure internal consistency. The measure "provides an indication of the average correlation among all of the items that make up the scale. Values range from 0 to 1, with higher values indicating greater reliability" (Pallant, 2007, p. 6). Bell et al. (2019) argue that "the figure 0.8 is typically employed as a rule of thumb to denote acceptable level of internal reliability, though many writers accept a slightly lower figure" (p. 227). Table 5 below provides internal consistency guideline. The results of Cronbach's Alpha calculations are presented in Chapter 5.

Table 5: Cronbach's Alpha guideline

Cronbach's Alpha	**Internal consistency**
$\alpha \geq 0.9$	Excellent
$0.9 > \alpha \geq 0.8$	Good
$0.8 > \alpha \geq 0.7$	Acceptable
$0.7 > \alpha \geq 0.6$	Questionable
$0.6 > \alpha \geq 0.5$	Poor
$0.5 > \alpha$	Unacceptable

Source: adapted from Bell et al. (2019) and George & Mallery (2021)

4.6.3. Validity

Measuring validity is a critical part of conducting research. According to Bell et al. (2019), "validity has to do with whether or not a measure of a concept really measures that concept" (p. 228). There are two types of validity: external and internal validity. External validity refers "to the extent to which the results of a sample are transferable to a population" (Burns & Burns, 2008, p. 426). Testing external validity is important because, in general, researchers conduct research with the aim of generalising results beyond the sample data.

In contrast, internal validity has to do with the "degree to which the conditions within the experiment are controlled, so that any differences or relationships can be ascribed to the independent variable, and not [to] other factors" (Burns & Burns, 2008, p. 427). Several measures can be applied to test internal validity. Some of these measures are discussed below:

i) *Content validity* refers to "the extent to which the content of a measurement reflects the intended content to be investigated" (Burns & Burns, 2008, p. 427).
ii) *Face validity* involves asking people with experience or expertise in the relevant field to determine whether or not the measure, on the face of it, appears to measure the concept as expected (Bell et al., 2019). It should be noted that this approach is mostly intuitive.
iii) *Predictive validity* "seeks to determine the extent by which it is possible to predict future performance by some current measure" (Burns & Burns, 2008, p. 429). For example, targeted management development programme can serve as a predictor of future performance for the target group.
iv) *Concurrent validity* assesses the level of correlation between a new research instrument with an existing one. Low correction may suggest questionable validity which requires further investigation (Bell et al., 2019).
v) *Construct validity* "involves relating a theoretical concept to a specific measuring device or procedure. Does the measuring instrument tap the concept as theorized?" (Burns & Burns, 2008, p. 430)

To measure internal validity for this study, construct validity test was applied. In summary, reliability and validity are the hallmarks of conducting good research, particularly, in quantitative research. Although reliability and validity are two separate concepts they are related. Bell et al. (2019) argue that "validity presumes reliability. This means that if your measure is not reliable, it cannot be valid" (p. 229). In nutshell, reliability has to do with "stability, accuracy and dependability of data" (p. 435) whereas validity is interested in "whether the test measures what it claims to measure" (p. 436).

4.7. Data analysis approach

4.7.1. Overview

To analyse the data, the R-statistical software programme was used. However, the statistical analysis was conducted by a professional Statistician. The steps in table 6 below were followed to analyse the data collected from the survey instrument.

Table 6: Data analysis approach

Main headings	4.7. Data analysis approach	
	4.7.1. Overview	4.7.2. Factor analysis
		4.7.2.1. Exploratory factor analysis
		4.7.2.2. Confirmatory factor analysis
	4.7.3. Factor analysis suitability test	4.7.4. Normality tests
	4.7.3.1. Spearman correlation	4.7.4.1. Bar graph
	4.7.3.2. The Kaiser-Meyer-Olkin test	4.7.4.2. Q–Q plot
	4.7.3.3. Bartlett's test of Sphericity	4.5.4.3. Shapiro-Wilk normality test
	4.7.5. Statistical techniques	
	4.7.5.1. Regularised regression	4.7.5.2. Structural equation modelling
	4.8. Research limitations	

Source: Author's compilation

4.7.2. Factor analysis

To condense data into a manageable number of factors, the researcher resolved to conduct factor analysis. According to Burns & Burns (2008), factor analysis help to establish "if the observed variables can be explained largely or entirely in terms of a much smaller number of super-variables or underlying factors" (Burns & Burns, 2008, p. 440). As argued by Pallant (2007), the significance of conducting factor analysis lies in the ability "to reduce a large number of related variables to a more manageable number, prior to using them in other analyses such as multiple regression or multivariate analysis of variance" (p. 179). The two common approaches to factor analysis are: 1) exploratory factor analysis and confirmatory factor analysis.

4.7.2.1. Exploratory factor analysis

In general, exploratory factor analysis (EFA) approach is conducted "in the early stages of research to gather information about (explore) the interrelationships among a set of variables" (Pallant, 2007, p. 179). The purpose is "to summarize the information from a large number of variables into a much smaller number of variables or factors" (Hair et al., 2019, p. 395). As the process of analysing data can often be complex, the value of EFA is in the simplification of the data making it easy to understand.

4.7.2.2. Confirmatory factor analysis

Unlike the EFA which is conducted to explore the data much earlier in the research process, CFA is said to be "a complex and sophisticated set of techniques used later in the research process to test (confirm) specific hypotheses or theories concerning the structure underlying a set of variables" (Pallant, 2007, p. 179). Thus, the value of CFA is derived from "confirming that the factor structure or model obtained in an EFA study is robust and is not simply a consequence of one set of data" (Burns & Burns, 2008, p. 443). Thus, CFA can be applied to validate the EFA model results using a new set of data or to confirm predetermined factors. This study applied the CFA approach to establish the extent to which DBS dimensions influence business performance.

4.7.3. Factor analysis suitability test

To conduct factor analysis, the data must be assessed for suitability. According to Pallant (2007), there are two main considerations which are necessary to establish the suitability of factor analysis, "sample size and the strength of the relationship among the variables" (p. 180).

4.7.3.1. Spearman correlation

Spearman's rank correlation is a non-parametric measure which is often used when the assumptions of Pearson correlation are not met, for example, when the variables are not normally distributed. The measure is used to establish the strength of the relationship between two variables. "A positive correlation indicates that as one variable increases, so does the other. A negative correlation indicates that as one variable increases, the other decreases" (Pallant, 2007, p. 101). The Spearman's rank correlation coefficient is calculated by ranking the values of each variable from lowest to highest, and then calculating the correlation between the ranks. The correlation coefficient can range from -

1 to 1, with a value of -1 indicating a perfect negative correlation, a value of 0 indicating no correlation, and a value of 1 indicating a perfect positive correlation.

4.7.3.2. The Kaiser-Meyer-Olkin test

The Kaiser-Meyer-Olkin (KMO) test "measures the sampling adequacy, which should be greater than 0.5 for a satisfactory factor analysis to proceed" (Burns & Burns, 2008, p. 454). Pallant (2007) suggests a value of 0.6 as a threshold for a good factor analysis. Thus, a KMO value of 0.9 or higher is considered excellent, a value of 0.8 or higher is considered good, a value of 0.7 or higher is considered acceptable, and a value of 0.59 or lower is considered unacceptable.

4.7.3.3. Bartlett's test of Sphericity

Bartlett's test of sphericity is a form of identity matrix in which all the diagonal elements are 1 and all the off-diagonal elements are 0. In other words, an identity matrix indicates that there is no correlation between the variables. Therefore, the Bartlett's test of Sphericity is statistically significant if the p-value is less than 0.05 which is sufficient for the factor analysis to be considered appropriate (Pallant, 2007). The null hypothesis of Bartlett's test of Sphericity is that the correlation matrix is an identity matrix. The alternative hypothesis is that the correlation matrix is not an identity matrix, which means that there is at least some correlation between the variables.

4.7.4. Normality tests

Normal distribution suggests that the distributed of the data is arranged in normal curve or bell-shaped curve with most of the data points clustered around the mean and fewer data points occurring farther from the mean. When the data is normally distributed, "it provides the underlying basis for many of the inferences made by business researchers who collect data using sampling" (Hair et al., 2019, 342).

However, if the data is not normally distributed, the analysis based on assumptions that the data is normally distributed can produce inaccurate or misleading results. To overcome the problem of skewness of the data, the researcher can run the Q-Q plot and Shapiro-Wilk tests to determine the extent to which the distribution in the sample deviates from a normal distribution. If the tests show that the differences are not significant, the researcher can decide to continue with the analysis (Burns & Burns, 2008).

4.7.4.1. Bar graph
The bar graphs can be used to plot the distribution of the data. According to Burns & Burns, 2008), bar graphs are "useful for ordering data and presenting them in an easily interpreted form" (p. 147). However, to make bar graphs useful, researchers must assess the number of variables to include to avoid creating complexity. As demonstrated by Pallant (2007), "bar graph can show the number of cases in particular categories, or it can show the score on some continuous variable for different categories" (p. 67).

4.7.4.2. Q–Q plot
Quantile–quantile plot as known as Q-Q plot is a test which "shows how the obtained scores deviate from the normal distribution with the normal distribution shown as a straight line" (Burns & Burns, 2008, p. 163). As such, this test is shown in a graphical format depicting how well the quantiles of one distribution match up with the quantiles of another distribution.

4.7.4.3. Shapiro-Wilk normality test
The Shapiro-Wilk normality test is considered to be one of the measures that can provide an objective measure on certain aspects of normality by determining "whether the obtained distribution as a whole deviates from a normal deviation distribution with the same mean and standard deviation" (Burns & Burns, 2008, p. 163). If the p-value is smaller than 0.05, it is considered statistically significant, which means that the null hypothesis is rejected at the 5% level of significance.

4.7.5. Statistical techniques
In this study, two statistical techniques were conducted: 1) regularized regression and 2) SEM. Initially, regularised regression was conducted to address the multicollinearity model error as a result of shewed data. The test results indicated that a huge amount of data clean-up was required before the model can be stable. The researcher then resolved to use the SEM statistical technique as an alternative.

4.7.5.1. Regularised regression
This statistical technique is used to prevent overfitting in regression models. Overfitting occurs when a statistical model is too complex for the data it is trained on resulting in

unexpected results. The two main approaches of regularisation regression are lasso and ridge. These approaches are considered to be effective in dealing "with multicollinearity and display the ideal properties to minimize the numerical instability that may occur due to overfitting" (Pereira et al., 2016, 638). Lasso, also known as L1, adds a penalty to the sum of the absolute values of the model coefficients. According to Pereira et al. (2016), this "shrink parameter estimates towards zero and, in some cases, equate parameters to be exactly zero and thus allows the exclusion of some of the variables from the model" (p. 638). Ridge regression (L2) also adds a penalty but to the sum of the squares of the model coefficients. This shrink the coefficients towards zero, but it does not exclude any features from the model.

4.7.5.2. Structural equation model

The SEM statistical techniques were developed to address common limitations that multivariate data analysis techniques have, namely: "(1) the postulation of a simple model structure, (2) requiring that all variables can be considered observable, and (3) the assumption that all variables are measured without error" (Hair et al., 2021, p. 3). Unlike multivariate techniques, SEM is amenable to modelling and estimating complex relationships among multiple dependent and independent variables simultaneously. The ability to model in ambidextrous manner is important in situations where the "concepts under consideration are typically unobservable" (p. 4). Observed variables are the variables that are directly measured whereas latent variables are the variables that are not directly measured but are inferred from the observed variables.

4.8. Research limitations

The researcher identified the following limitations in this research. Although the survey questionnaire attempted to use the language that is familiar to most respondents, some might have interpreted the concepts linked to DBS based on their own understanding and experience leading to bias. Furthermore, due to time constraints, the data was collected using a cross-sectional approach and the research was conducted in a single organisation and, as such, the results might not be generalisable beyond the financial services organisation surveyed.

Additionally, the survey questionnaire was designed to measure responses based on a Likert scale which may have limited detailed responses and the survey applied a purposive sampling method (non-probability sampling) which "is a form of convenience sampling in which the researcher’s judgment is used to select the sample elements” (Hair et al., 2019, p. 193). Lastly, considering that the survey was conducted online, it is possible that there was self- selection bias, wherein some participants tend to be drawn to online surveys whilst others do not (Sekaran & Bougie, 2016).

5. RESULTS

5.1. Introduction and roadmap

In this chapter, statistical results based on the quantitative research methodology are presented. This chapter follows the research design structure as per table 7 below.

Table 7: Results roadmap

Main headings	5.1. Introduction and roadmap	
	5.2. Exploratory data analysis	
	5.2.1. Demographic data analysis	5.2.2. Survey responses distribution
	5.2.1.1. Age distribution	5.2.2.1. Responses distribution: managerial capabilities
	5.2.1.2. Gender distribution	5.2.2.2. Responses distribution: operational capabilities
	5.2.1.3. Level of seniority distribution	5.2.2.3. Responses distribution: managerial capabilities moderated by DC
	5.2.1.4. Functional area distribution	5.2.2.4. Responses distribution: operational capabilities moderated by DC
	5.2.1.5. Number of years in a role distribution	5.2.2.5. Responses distribution: business performance
	5.2.3. Descriptive statistics	
	5.2.3.1. Mean distribution: managerial capabilities	5.2.3.3. Mean distribution: managerial capabilities moderated by DC
	5.2.3.2. Mean distribution: operational capabilities	5.2.3.4. Mean distribution: operational capabilities moderated by DC
Main headings	5.3. Reliability of research instrument	
	5.3.1. Managerial capabilities Cronbach's Alpha	5.3.4. Operational capabilities moderated by DC Cronbach's Alpha
	5.3.2. Operational capabilities Cronbach's Alpha	5.3.5. Business performance Cronbach's Alpha
	5.3.3. Managerial capabilities moderated by DC Cronbach's Alpha	
	5.4. Construct validity tests	
	5.4.1. Parameter estimates	5.4.2. Model fit statistics
	5.5. Factor analysis suitability tests	
	5.5.1. Spearman correlation	5.5.3. Bartlett's test of Sphericity
	5.5.2. The Kaiser-Meyer-Olkin (KMO) Test	
	5.6. Normality tests	5.8. Structural Equation Model
	5.6.1. Q–Q plot	5.8.1. Statistical technique model fit
	5.6.2. Shapiro-Wilk normality test	5.8.2. Hypotheses testing
	5.7. Regularised regression	

Source: Author's compilation

5.2. Exploratory data analysis

An exploratory analysis examines the data from different angles to understand its characteristics. The process allows the researcher to identify patters in the data as well as uncovering useful insights (Tukey, 1977 & Morgenthaler, 2009). Overall, 201 responses were received out of a total targeted population of 878 which is 22,9% (see table 8 below). Considering that this was a cross-sectional survey, the researcher deemed the response rate to be acceptable. As such, the response rate was calculated to have a 6% margin of error at 95% confidence level (SurveyMonkey, 2023).

Table 8: Survey response rate

	Number	Percentage
Survey distribution	878	100%
Survey responses	201	22,9%

5.2.1. Demographic data analysis

5.2.1.1. Age distribution

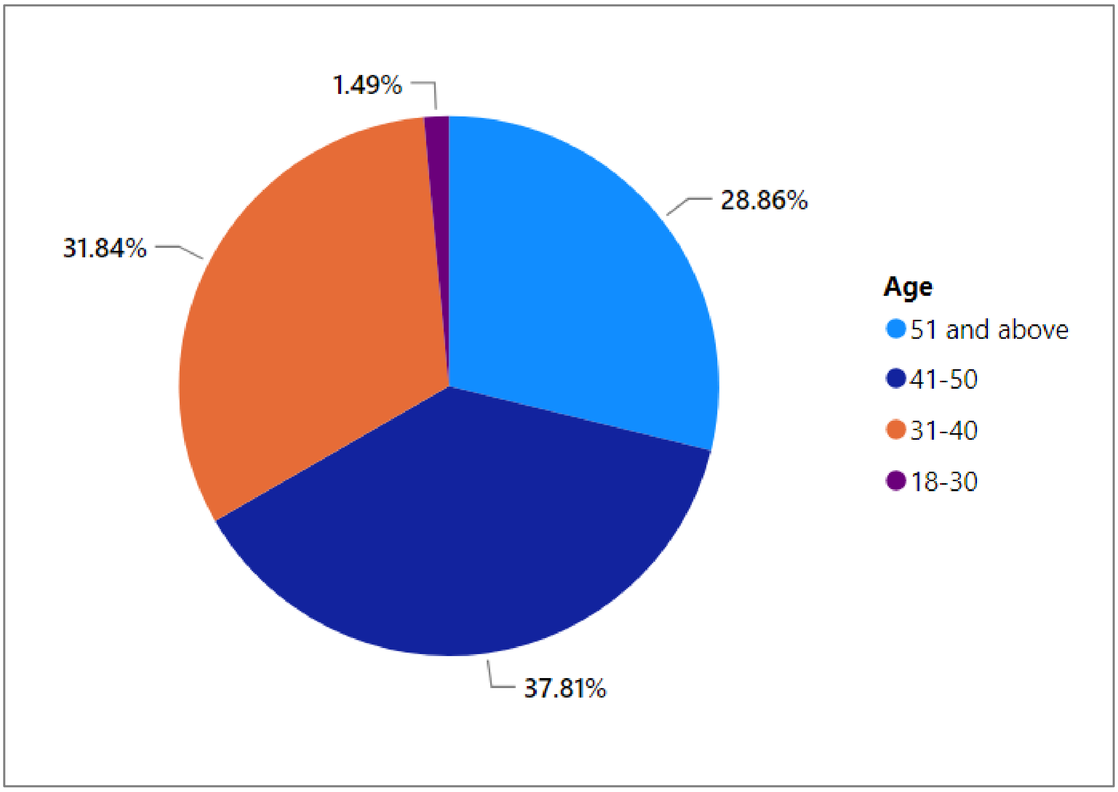


Figure 5: Age distribution

Majority of respondents are between the age range of 41-50 followed by 31-40 which is to be expected given average age in the organisation which is estimated to be around 42 years of age. The lowest percentage of respondents is that of employees between the age range of 18-30. Majority of employees in this age range tend to be below the management bands.

5.2.1.2. Gender distribution

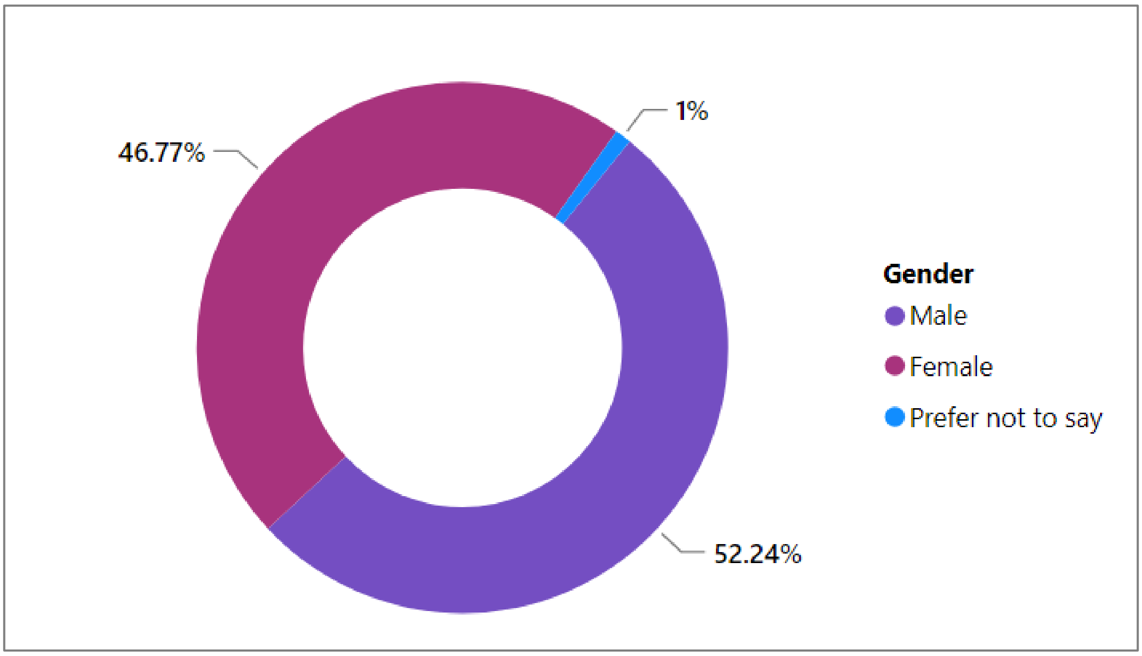


Figure 6: Gender distribution

Given the gender split in the organisation at managerial levels, the responses are consistent with the gender representation profile of the organisation. The option not to disclose gender was included to accommodate respondents who might be transitioning from one gender to the other.

5.2.1.3. Level of seniority distribution

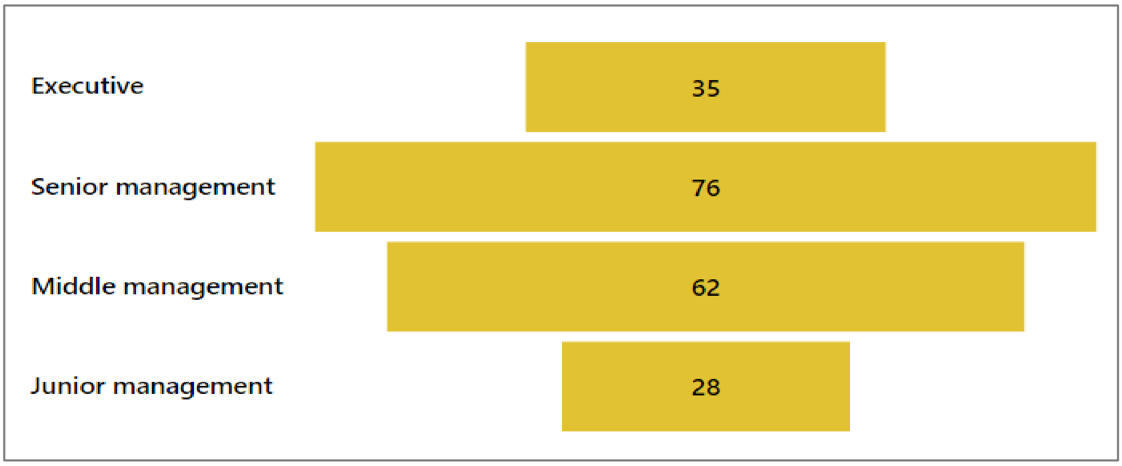


Figure 7: Level of seniority distribution

The shape of responses by level of seniority represents a diamond which is consistent with the profile of the organisation. This is also consistent with the researcher's expectation regarding the depth and knowledge of the digital journey that the organisation is currently undertaking.

5.2.1.4. Functional area distribution

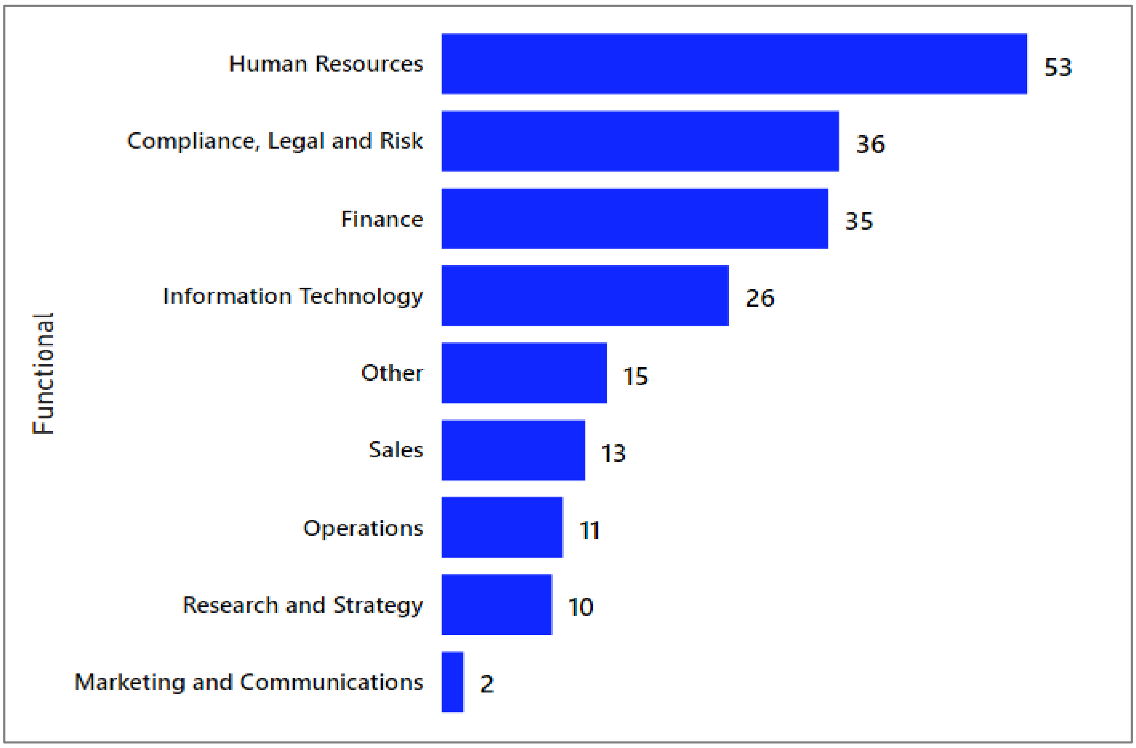


Figure 8: Functional area distribution

Majority of responses were received from employees who perform Human Resources related jobs followed by Compliance, Legal and Risk functional area. The lowest responses by functional area were received from respondents who perform Marketing and Communications related jobs.

5.2.1.5. Number of years in a role distribution

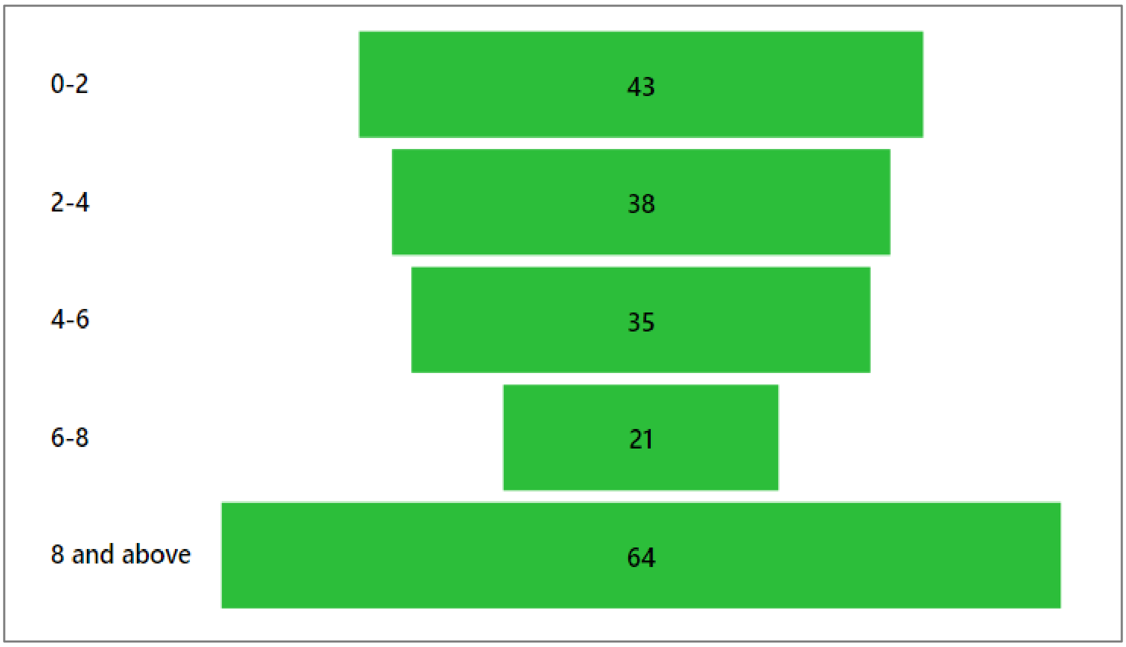


Figure 9: Number of years in a role distribution

Majority of responses were received from employees who have been in their current roles for eights and above followed by a tenure range of 0-2 years. The tenure distribution is not surprising given the seniority of majority of respondents who are at senior and middle management levels.

5.2.2. Survey responses distribution

5.2.2.1. Responses distribution: managerial capabilities

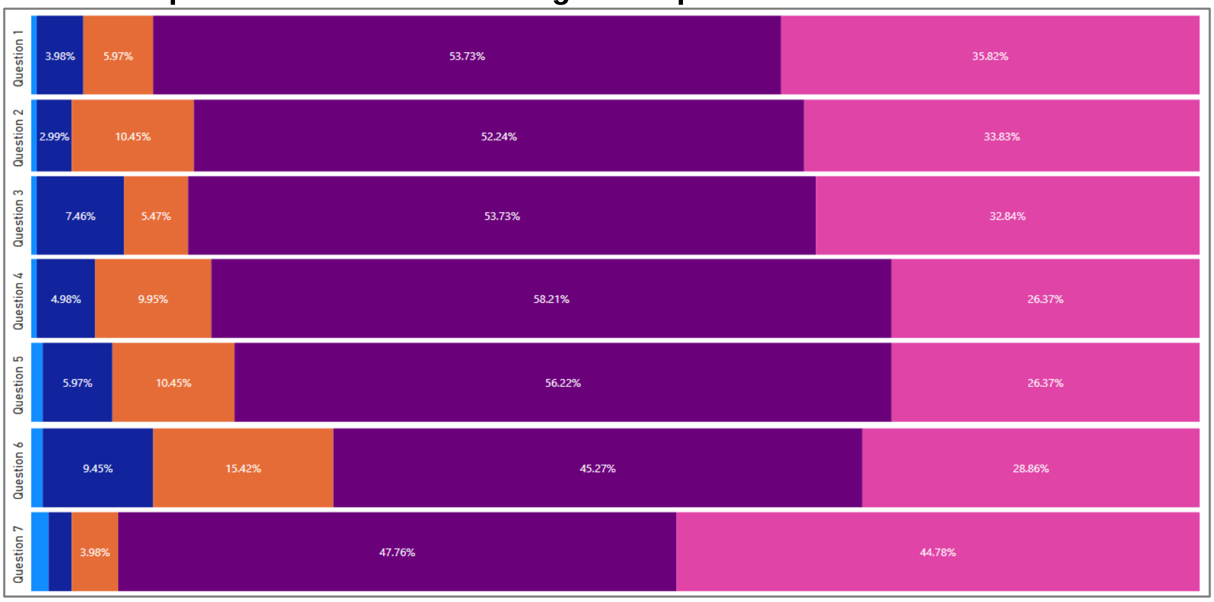


Figure 10: Responses distribution: managerial capabilities

Majority of respondents have rated statements related to managerial capabilities agree or strongly agree which may be indicative of familiarity with the organisational digital journey and a sense of ownership by managers in driving digitality.

5.2.2.2. Responses distribution: operational capabilities

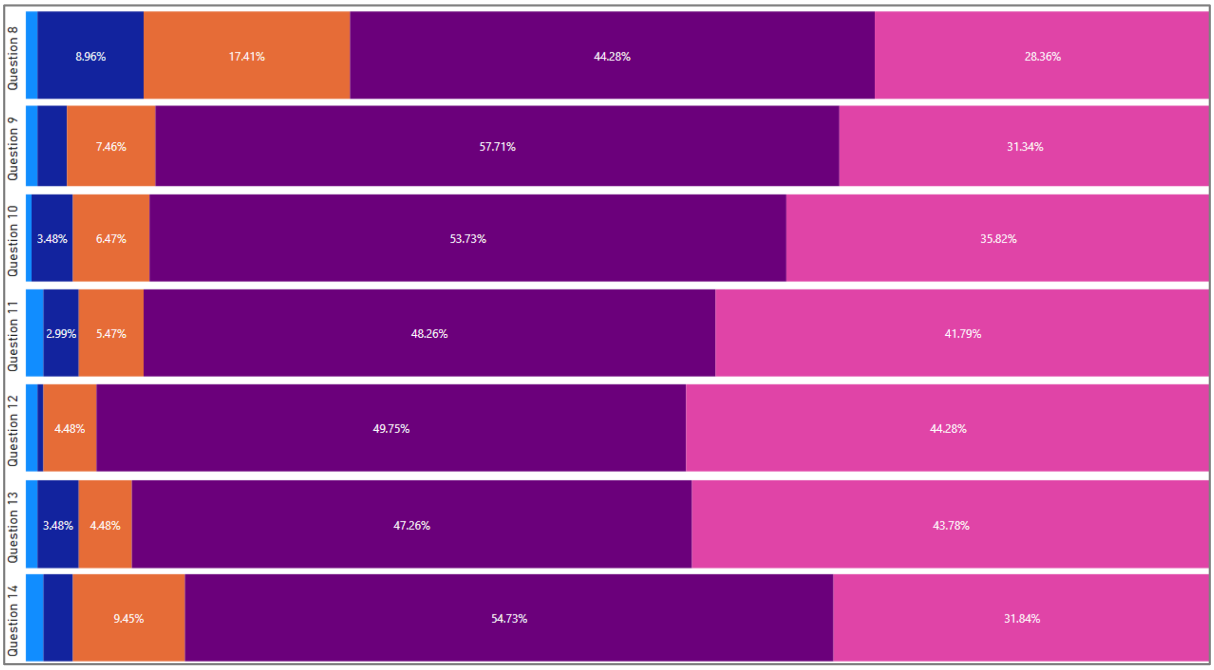


Figure 11: Responses distribution: operational capabilities

Majority of respondents have rated statements related to operational capabilities agree or strongly agree which may be indicative of familiarity with the organisational digital journey and a sense of inclusion in decision making related to the adoption of digital resources.

5.2.2.3. Responses distribution: managerial capabilities moderated by DC

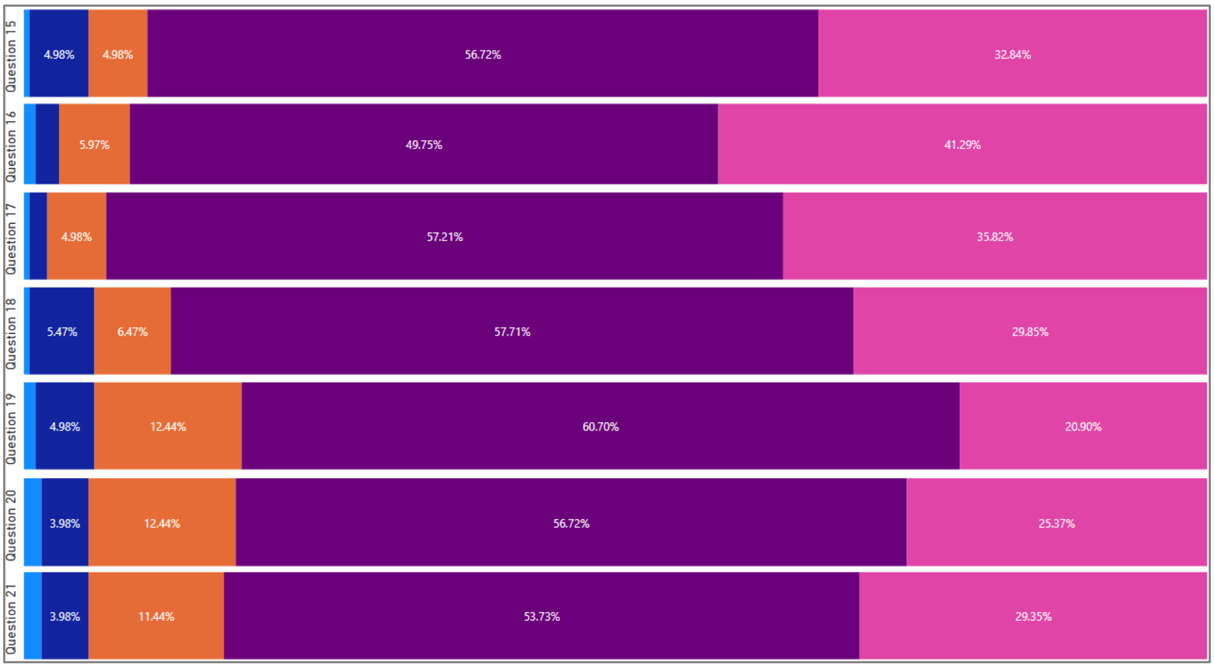


Figure 12: Responses distribution: managerial capabilities moderated by DC

Although majority of respondents have rated statements related to managerial capabilities moderated by dynamic capabilities in a similar manner as managerial capabilities, the agree rating slightly increased. Considering that responses to statements in this category have to do with managers being responsive to the changing environment necessitated by the digital transformation journey, the responses may be indicative of the level of maturity in terms of digital adoption by managers and the relevant skills required to respond to digital changes in an agile manner.

5.2.2.4. Responses distribution: operational capabilities moderated by DC

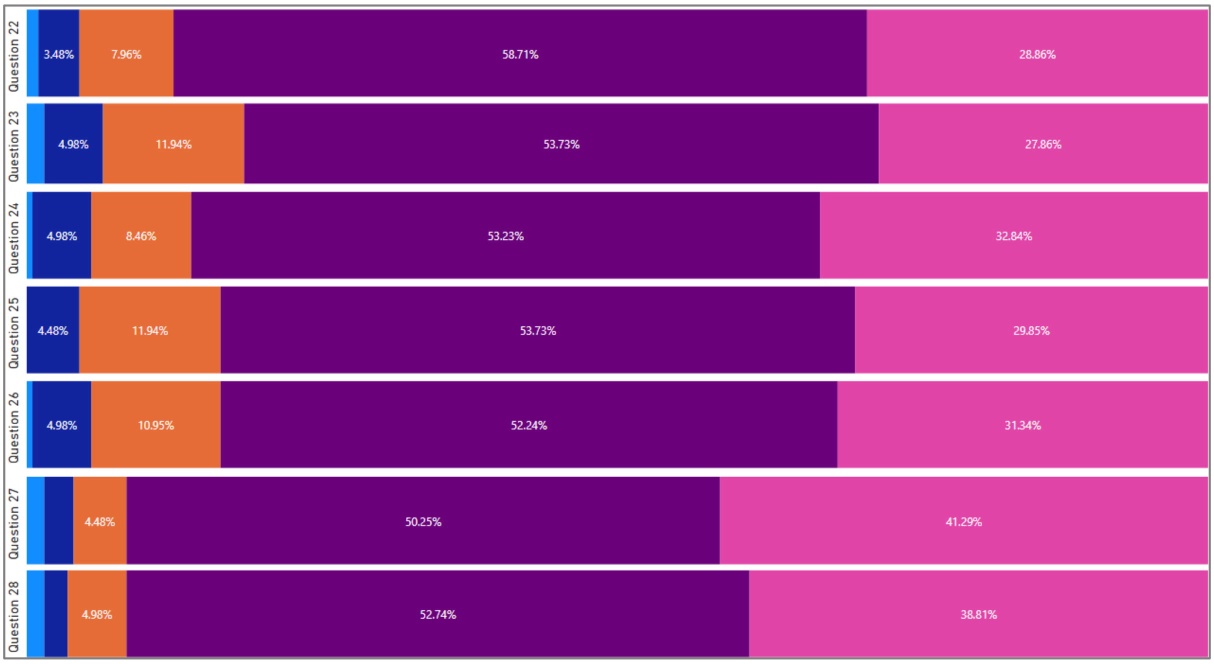


Figure 13: Responses distribution: operational capabilities moderated by DC

Although majority of respondents have rated the statements related to operational capabilities moderated by dynamic capabilities in a similar manner as operational capabilities, the agree rating also slightly increased. Considering that responses to statements in this category have to do with digital operational adoption, responses may be indicative of the speed of digital adoption and the ability of the organisation to respond to the changing environment in an agile manner.

5.2.2.5. Responses distribution: business performance

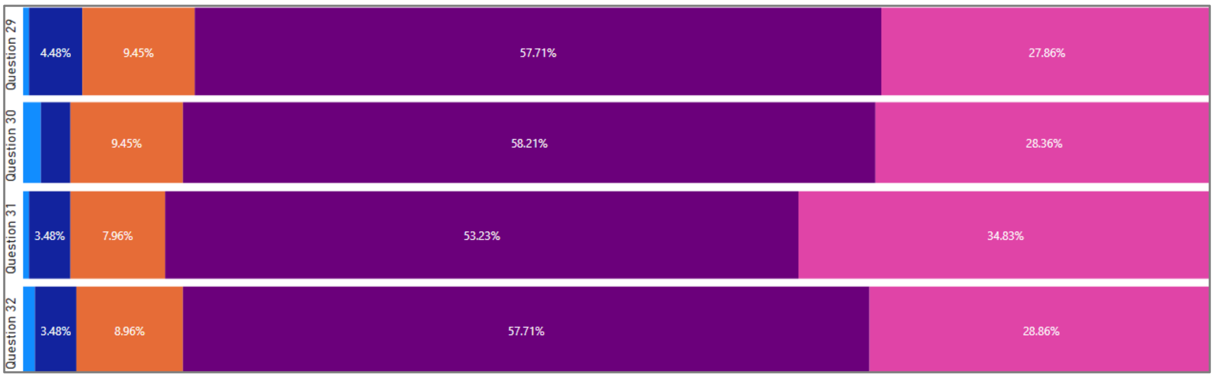


Figure 14: Responses distribution: business performance

Majority of respondents have rated statements related to business performance agree or strongly agree which may be indicative of improved business results as a result of digitality.

5.2.3. Descriptive statistics

5.2.3.1. Mean distribution: managerial capabilities

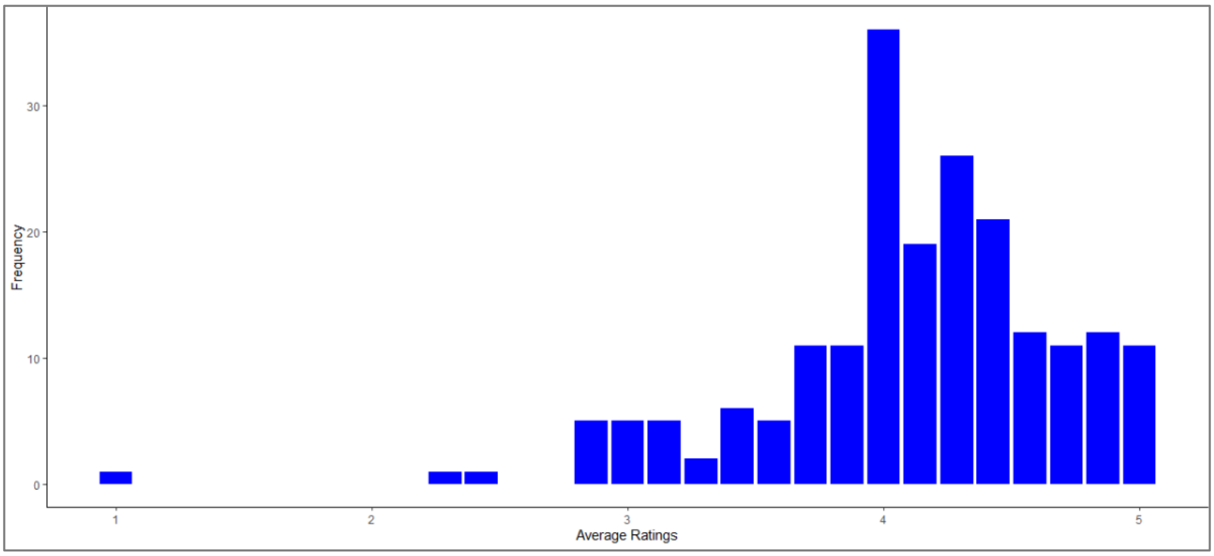


Figure 15: Mean distribution: managerial capabilities

The responses related to statements on managerial capabilities are skewed to the right indicating that majority of respondents rated the statements agree or strongly agree. This confirms that the data for this factor is not normally distributed.

5.2.3.2. Mean distribution: operational capabilities

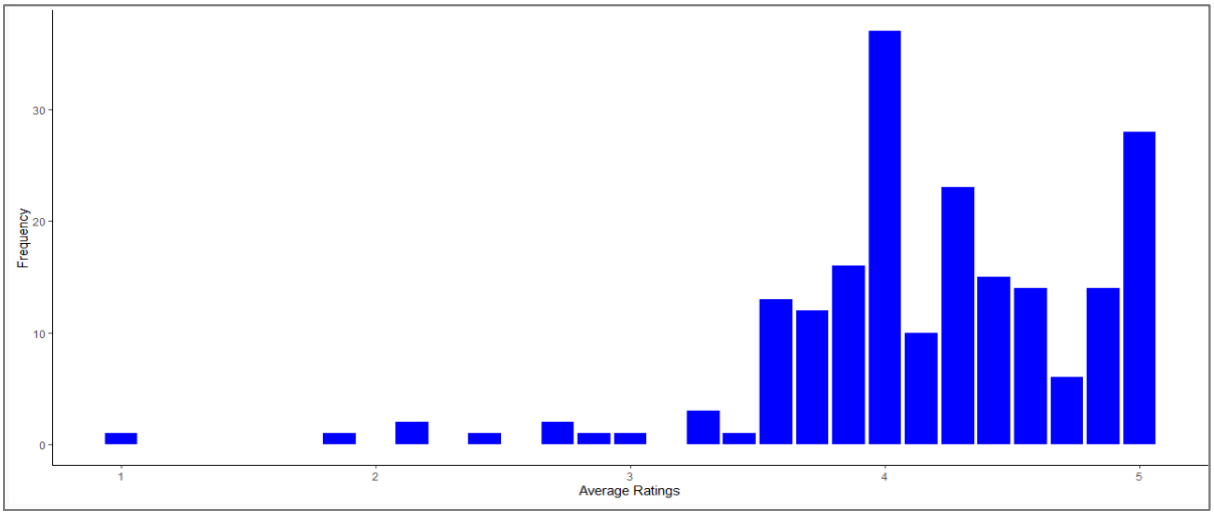


Figure 16: Mean distribution: operational capabilities

The responses related to statements on operational capabilities are skewed to the right indicating that majority of respondents rated the statements agree or strongly agree. This confirms that the data for this factor is also not normally distributed.

5.2.3.3. Mean distribution: managerial capabilities moderated by DC

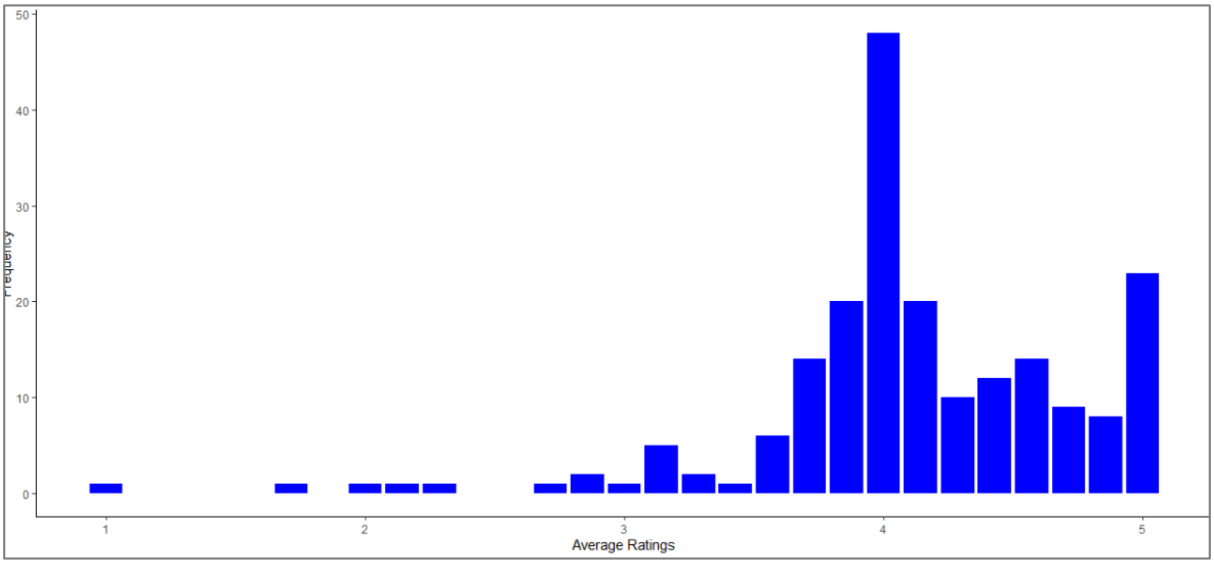


Figure 17: Mean distribution: managerial capabilities moderated by DC

The responses related to statements on managerial capabilities moderated by dynamic capabilities are skewed to the right indicating that majority of respondents rated the statements agree or strongly agree. This confirms that the data for this factor is equally not normally distributed.

5.2.3.4. Mean distribution: operational capabilities moderated by DC

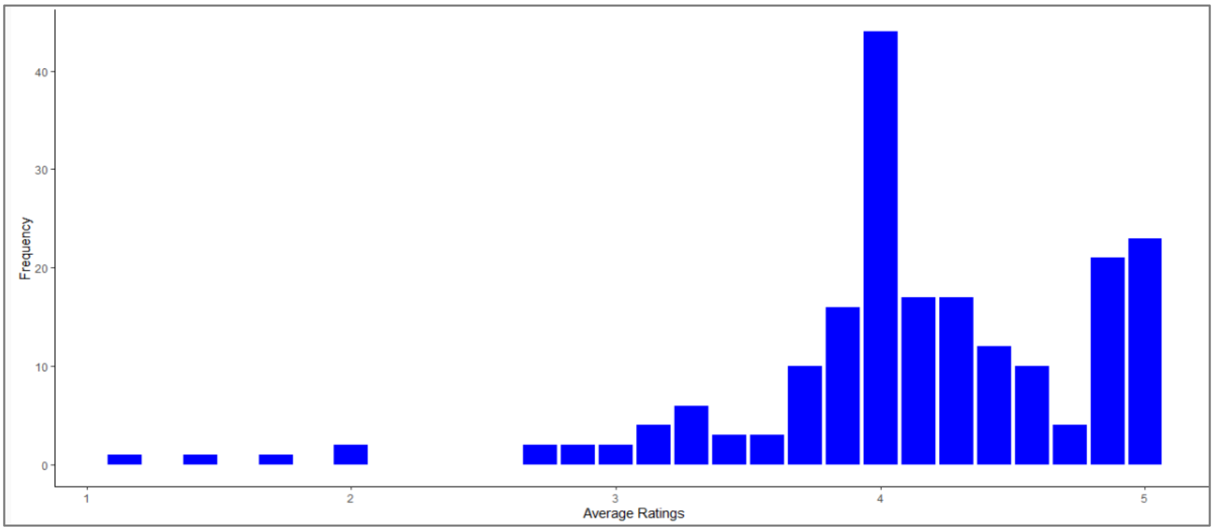


Figure 18: Mean distribution: operational capabilities moderated by DC

The responses related to statements on operational capabilities moderated by dynamic capabilities are skewed to the right indicating that majority of respondents rated the statements agree or strongly agree. This, once again, confirms that the data for this factor is not normally distributed.

5.3. Reliability of research instrument

Cronbach's Alpha was conducted to measures the extent to which the survey questionnaire produces consistent and repeatable results (Bell et al., 2022, Pallant, 2020 & Hair et al., 2019). The Cronbach's Alpha values demonstrate that the survey questionnaire has good internal consistency. According Bell et al. (2019), "the figure 0.8 is typically employed as a rule of thumb to denote acceptable level of internal reliability, though many writers accept a slightly lower figure" (p. 227). The outcome of Cronbach's Alpha calculations per factor is shown below (see table 9 – 13).

5.3.1. Managerial capabilities Cronbach's Alpha

The statements related to digital leadership acumen were designed to measure managerial capabilities as one of DBS dimensions. Thus, the following statement was included to preface managerial capabilities section of the questionnaire, "digital leadership acumen, as a dimension of digital business strategy included items related to managers' knowledge of and skills in digital tools, managers' clear vision for utilizing digitality, and managers' support for digitality". Overall, the Cronbach's Alpha value of 0.837 was achieved which shows that internal consistency is good.

Table 9: Managerial capabilities Cronbach's Alpha

```
      Alpha reliability =  0.837
Standardized alpha =  0.8381

Reliability deleting each item in turn:
     Alpha Std.Alpha r(item, total)
Q_1 0.8270    0.8284         0.5050
Q_2 0.8029    0.8031         0.6702
Q_3 0.8087    0.8105         0.6255
Q_4 0.8004    0.8007         0.6839
Q_5 0.8017    0.8031         0.6688
Q_6 0.8192    0.8188         0.5730
Q_7 0.8405    0.8437         0.4099
```

5.3.2. Operational capabilities Cronbach's Alpha

Similar to managerial capabilities, statements related to digital operational backbone were designed to measure operational capabilities. As such, the following statement was included to preface operational capabilities section of the questionnaire, “the ability of an organisation to be proficient in deploying digital solutions without disrupting business operations is an integral part of embedding operational capabilities in the implementation of a digital business strategy.” Cronbach’s Alpha value of 0.8966 was achieved which demonstrates that internal consistency is also good for this factor.

Table 10: Operational capabilities Cronbach’s Alpha

```
      Alpha reliability =  0.8966
Standardized alpha =  0.8989

Reliability deleting each item in turn:
      Alpha Std.Alpha r(item, total)
Q_8  0.8889    0.8887          0.6600
Q_9  0.8777    0.8814          0.7335
Q_10 0.8691    0.8716          0.8089
Q_11 0.8816    0.8841          0.6963
Q_12 0.8915    0.8951          0.6055
Q_13 0.8768    0.8797          0.7368
Q_14 0.8832    0.8861          0.6828
```

5.3.3. Managerial capabilities moderated by DC Cronbach’s Alpha

To establish the effects of managerial capabilities in a rapidly changing environment, the study moderated managerial capabilities with dynamic capabilities. The statements related to digital leadership agility were, therefore, designed to measure managerial capabilities moderated by DC. Thus, the following statement was included to preface this section of the questionnaire, “to navigate the complexity of fusing IT strategy and business strategy, managers are required to demonstrate the ability to orchestrate organisational capabilities to lead in a dynamic business environment.” Cronbach’s Alpha value of 0.9025 was achieved which indicates that internal consistency is excellent.

Table 11: Managerial capabilities moderated by DC Cronbach’s Alpha

```
      Alpha reliability =  0.9025
Standardized alpha =  0.9033

Reliability deleting each item in turn:
      Alpha Std.Alpha r(item, total)
Q_15 0.9009    0.9016          0.5947
Q_16 0.8938    0.8945          0.6582
Q_17 0.8871    0.8866          0.7316
Q_18 0.8831    0.8842          0.7538
Q_19 0.8788    0.8806          0.7908
Q_20 0.8838    0.8854          0.7481
Q_21 0.8876    0.8889          0.7177
```

5.3.4. Operational capabilities moderated by DC Cronbach's Alpha

To establish the effects of operational capabilities in a rapidly changing environment, the study moderated operational capabilities with dynamic capabilities. The statements related to digital operational agility were, therefore, designed to measure operational capabilities moderated by DC. Thus, the following statement was included to preface this section of the questionnaire, "technologically driven disruptions cause changes on a continuous basis. This requires companies to be agile in their adaptations within the context of developing and implementing a digital business strategy." Cronbach's Alpha value of 0.9283 was achieved which indicates that internal consistency is equally excellent.

Table 12: Operational capabilities moderated by DC Cronbach's Alpha

```
      Alpha reliability =  0.9283
Standardized alpha =  0.9285

Reliability deleting each item in turn:
      Alpha Std.Alpha r(item, total)
Q_22 0.9171    0.9174         0.7742
Q_23 0.9147    0.9148         0.7992
Q_24 0.9113    0.9117         0.8319
Q_25 0.9184    0.9188         0.7607
Q_26 0.9215    0.9216         0.7296
Q_27 0.9206    0.9208         0.7367
Q_28 0.9171    0.9173         0.7739
```

5.3.5. Business performance Cronbach's Alpha

Lastly, four statements linked to each of the four factors above were included to establish their effects to business performance. These statements were: 1) our team's adoption of digital strategies has contributed to improved overall business performance, 2) the integration of market-leading digital solutions into our operations has positively impacted our overall business performance, 3) I believe that our proficiency in data analytics, combined with dynamic leadership approaches, improves our business performance, and 4) our combination of dynamic operational efficiencies and digital strategies has contributed to notable improvements in our overall business performance. As a result, the Cronbach's Alpha value of 0.8881 was achieved which indicates that these statements have a good internal consistency (see table 13 below).

Table 13: Business performance Cronbach's Alpha

```
      Alpha reliability =  0.8881
Standardized alpha =  0.8878

Reliability deleting each item in turn:
      Alpha Std.Alpha r(item, total)
Q_29 0.8504    0.8501         0.7698
Q_30 0.8265    0.8263         0.8306
Q_31 0.8947    0.8946         0.6488
Q_32 0.8487    0.8483         0.7740
```

5.4. Construct validity tests

To test validity, this study followed a construct validity approach which "involves relating a theoretical concept to a specific measuring device or procedure" (Burns & Burns, 2008, p. 430) to measure internal validity. As discussed in the methodology section, "validity has to do with whether or not a measure of a concept really measures that concept" (Bell et al., 2019, p. 228).

5.4.1. Parameter estimates

A hypothesis test for the parameter estimates in the output is a statistical procedure that evaluates whether the estimated factor loadings, factor variances, factor covariances, and residual variances are significantly different from zero. Therefore, the null hypotheses is:

$$H_0: Parameter\ estimates\ are\ equal\ to\ 0$$

$$H_a: Parameter\ estimates\ are\ not\ equal\ to\ 0$$

$$\alpha = 0.05$$

Considering that the p-values from the *parameter estimates* section in the construct validity test output (see appendix E) are all below the value α=0.05 for each factor, the null hypothesis for all factors was rejected and the conclusion is that the observed variables are statistically significant at a 5% level.

5.4.2. Model fit statistics

Although the comparative fit index (CFI) and the Tucker-Lewis index (TLI) are below 0.95, with statistics of 0.85 and 0,84 respectively, they are close enough to indicate that the model is better than the baseline (uncorrelated) model (see appendix H). Similarly, the Root Mean Square Error of Approximation (RMSEA) value of 0.09 is above the value of 0.06 which suggests that the model has a moderate fit (Xia & Yang, 2019). It was, therefore, concluded that construct validity has been achieved.

5.5. Factor analysis suitability tests

To test the data for factor analysis suitability, three tests were conducted, namely: Spearman correlation, The Kaiser-Meyer-Olkin (KMO) test and Bartlett's test of Sphericity. The results of the tests are presented below.

5.5.1. Spearman correlation

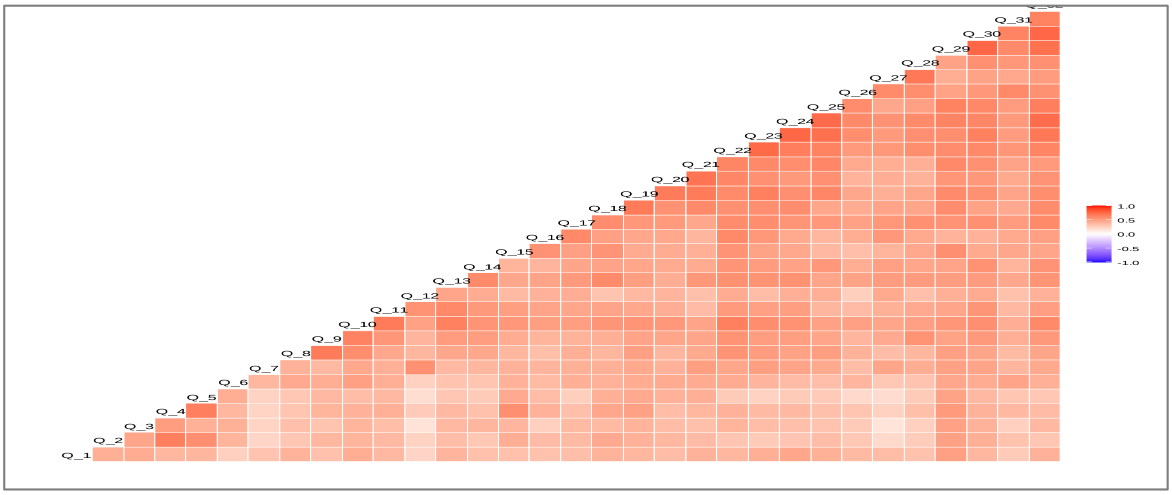
This test is used to establish the strength of the relationship between two variables. As shown in figure 19, the Spearman correlation test indicates that all observed variables have a positive correlation. This is further confirmed by the heatmap in figure 20 which shows that all values are positive.

Figure 19: Spearman correlation

	Q_1	Q_2	Q_3	Q_4	Q_5	Q_6	Q_7	Q_8	Q_9	Q_10	Q_11	Q_12	Q_13	Q_14
Q_2	0.414													
Q_3	0.429	0.464												
Q_4	0.372	0.646	0.504											
Q_5	0.378	0.572	0.407	0.647										
Q_6	0.248	0.389	0.407	0.372	0.422									
Q_7	0.314	0.218	0.223	0.224	0.231	0.374								
Q_8	0.395	0.298	0.334	0.303	0.292	0.438	0.400							
Q_9	0.325	0.377	0.308	0.390	0.370	0.427	0.363	0.666						
Q_10	0.426	0.389	0.389	0.403	0.346	0.489	0.449	0.580	0.629					
Q_11	0.370	0.364	0.339	0.409	0.366	0.416	0.411	0.450	0.541	0.668				
Q_12	0.223	0.236	0.152	0.274	0.173	0.243	0.562	0.378	0.387	0.485	0.555			
Q_13	0.385	0.343	0.366	0.365	0.297	0.315	0.365	0.456	0.509	0.639	0.602	0.466		
Q_14	0.324	0.287	0.381	0.325	0.272	0.303	0.375	0.452	0.504	0.547	0.524	0.431	0.593	
Q_15	0.326	0.419	0.382	0.571	0.439	0.402	0.401	0.372	0.428	0.530	0.496	0.358	0.454	0.389
Q_16	0.321	0.352	0.244	0.403	0.342	0.356	0.384	0.336	0.391	0.497	0.468	0.403	0.469	0.384
Q_17	0.337	0.358	0.361	0.331	0.251	0.412	0.404	0.416	0.395	0.502	0.458	0.418	0.519	0.465
Q_18	0.393	0.438	0.360	0.460	0.410	0.402	0.409	0.377	0.415	0.541	0.470	0.310	0.593	0.474
Q_19	0.372	0.402	0.393	0.486	0.439	0.429	0.445	0.495	0.470	0.547	0.450	0.368	0.496	0.462
Q_20	0.344	0.373	0.342	0.347	0.403	0.435	0.404	0.379	0.466	0.530	0.423	0.387	0.422	0.435
Q_21	0.397	0.352	0.329	0.372	0.413	0.433	0.496	0.445	0.462	0.470	0.352	0.327	0.533	0.437
Q_22	0.374	0.301	0.389	0.402	0.272	0.433	0.460	0.551	0.553	0.644	0.519	0.429	0.561	0.547
Q_23	0.413	0.271	0.345	0.359	0.238	0.386	0.495	0.511	0.503	0.580	0.489	0.344	0.550	0.515
Q_24	0.459	0.302	0.334	0.363	0.272	0.355	0.472	0.481	0.499	0.558	0.500	0.412	0.558	0.480
Q_25	0.406	0.350	0.310	0.330	0.275	0.337	0.443	0.502	0.467	0.487	0.381	0.414	0.465	0.529
Q_26	0.359	0.287	0.271	0.305	0.196	0.382	0.350	0.399	0.382	0.488	0.352	0.252	0.475	0.421
Q_27	0.345	0.200	0.143	0.242	0.185	0.290	0.467	0.348	0.439	0.466	0.405	0.445	0.515	0.490
Q_28	0.320	0.270	0.248	0.336	0.273	0.315	0.421	0.372	0.549	0.494	0.440	0.334	0.512	0.461
Q_29	0.493	0.485	0.487	0.519	0.475	0.454	0.483	0.492	0.476	0.539	0.463	0.410	0.506	0.470
Q_30	0.372	0.416	0.400	0.397	0.369	0.431	0.470	0.463	0.526	0.573	0.544	0.434	0.511	0.558
Q_31	0.273	0.320	0.249	0.367	0.299	0.468	0.378	0.357	0.417	0.418	0.363	0.324	0.452	0.389
Q_32	0.404	0.298	0.371	0.353	0.294	0.412	0.447	0.464	0.525	0.597	0.498	0.400	0.544	0.552

	Q_15	Q_16	Q_17	Q_18	Q_19	Q_20	Q_21	Q_22	Q_23	Q_24	Q_25	Q_26	Q_27	Q_28	Q_29	Q_30	Q_31
Q_16	0.556																
Q_17	0.488	0.603															
Q_18	0.553	0.490	0.587														
Q_19	0.433	0.457	0.530	0.665													
Q_20	0.430	0.448	0.520	0.559	0.665												
Q_21	0.411	0.378	0.456	0.598	0.663	0.697											
Q_22	0.552	0.597	0.586	0.565	0.593	0.608	0.617										
Q_23	0.476	0.533	0.581	0.571	0.643	0.570	0.603	0.738									
Q_24	0.452	0.441	0.545	0.580	0.572	0.526	0.578	0.653	0.750								
Q_25	0.362	0.373	0.528	0.460	0.615	0.570	0.613	0.636	0.713	0.735							
Q_26	0.338	0.427	0.483	0.432	0.455	0.394	0.445	0.520	0.581	0.597	0.585						
Q_27	0.388	0.528	0.534	0.468	0.417	0.418	0.427	0.534	0.518	0.557	0.457	0.593					
Q_28	0.451	0.446	0.569	0.464	0.460	0.399	0.413	0.579	0.571	0.593	0.494	0.576	0.680				
Q_29	0.572	0.397	0.553	0.582	0.589	0.538	0.601	0.584	0.579	0.626	0.636	0.482	0.422	0.479			
Q_30	0.447	0.401	0.564	0.480	0.561	0.527	0.566	0.602	0.639	0.608	0.607	0.529	0.475	0.570	0.751		
Q_31	0.454	0.442	0.513	0.440	0.470	0.447	0.473	0.539	0.511	0.525	0.515	0.596	0.451	0.527	0.597	0.625	
Q_32	0.465	0.488	0.597	0.584	0.579	0.552	0.519	0.618	0.678	0.726	0.654	0.561	0.514	0.563	0.712	0.750	0.635

Figure 20: Spearman correlation heatmap



5.5.2. The Kaiser-Meyer-Olkin (KMO) test

A KMO value closer to 1 indicates that the data is suitable for factor analysis. The collected data yielded a value of 0,94 (see table 14) indicating that the data is suitable for factor analysis.

Table 14: The Kaiser-Meyer-Olkin test

```
Kaiser-Meyer-Olkin factor adequacy
Call: KMO(r = mymat)
Overall MSA =  0.94
MSA for each item =
 Q_1  Q_2  Q_3  Q_4  Q_5  Q_6  Q_7  Q_8  Q_9 Q_10 Q_11 Q_12 Q_13 Q_14 Q_15
0.96 0.91 0.93 0.87 0.92 0.94 0.94 0.94 0.93 0.96 0.95 0.91 0.95 0.97 0.95
Q_16 Q_17 Q_18 Q_19 Q_20 Q_21 Q_22 Q_23 Q_24 Q_25 Q_26 Q_27 Q_28 Q_29 Q_30
0.95 0.96 0.94 0.95 0.95 0.95 0.96 0.95 0.96 0.96 0.94 0.94 0.95 0.95 0.94
Q_31 Q_32
0.94 0.95
```

5.5.3. Bartlett's test of Sphericity

Bartlett's test of sphericity is a form of identity matrix in which all the diagonal elements are 1 and all the off-diagonal elements are 0. The null hypothesis therefore is:

$$H_0: The \text{ correlation matrix is an identity matrix}$$

$$H_a: The \text{ correlation matrix is not an identity matrix}$$

$$\alpha = 0.05$$

Bartlett's test of sphericity test has returned a p-value of zero (see table 15), which is less than 0.05. Therefore, the null hypothesis was rejected and the conclusion is that the variables are correlated enough to perform factor analysis.

Table 15: Bartlett's test of Sphericity

```
$chisq
[1] 5104.83

$p.value
[1] 0

$df
[1] 496
```

5.6. Normality tests

To avoid running the data based on the assumption that the data is normally distributed which can lead to inaccurate conclusions, two tests were conducted, that is, the Q-Q plot and Shapiro-Wilk normality test. The tests demonstrated that the data is not normally distributed.

5.6.1. Q–Q plot

The Q-Q plots of each factor deviates from the plotted line indicating that the data is not normally distributed (see appendices F1 – F5).

5.6.2. Shapiro-Wilk normality test

The Shapiro-Wilk normality test also support the above observations. The null hypothesis therefore is:

$$H_0\text{: } The\ Data\ is\ Normal$$

$$H_a\text{: } The\ Data\ is\ not\ Normal$$

Given that the p-values for all the factors are below 0.05 (see appendices F1 – F5), the null hypothesis was rejected and the conclusion is the data is not normally distributed.

5.7. Regularised regression

This statistical technique was conducted to address the multicollinearity model error as a result of shewed data. The test results indicated that a huge amount of data clean-up was required before the model fit to the data. As shown by the results below (see table 16 below), the best elastic net RMSE model achieved a value of 0.118 which is higher than what is considered to be an acceptable value of below 0.08. Therefore, the conclusion was the model is not a good fit to the data.

Table 16: Elastic Net RMSEs for different values of Alpha

```
   alpha       mse   fit.name
1    0.0 0.1181089    Alpha 0
2    0.1 0.1180416 Alpha 0.1
3    0.2 0.1237370 Alpha 0.2
4    0.3 0.1218829 Alpha 0.3
5    0.4 0.1200011 Alpha 0.4
6    0.5 0.1285956 Alpha 0.5
7    0.6 0.1322823 Alpha 0.6
8    0.7 0.1327655 Alpha 0.7
9    0.8 0.1299351 Alpha 0.8
10   0.9 0.1395663 Alpha 0.9
11   1.0 0.1280410    Alpha 1
```

5.8. Structural Equation Model

Ex post applying regularised regression, the researcher resolved to use the SEM statistical technique given its properties to model in situations where the “concepts under consideration are typically unobservable” (Hair et al., 2021, p. 4). Therefore, applying SEM enabled the researcher to measure latent variables.

5.8.1. Statistical technique model fit

The construct validity test results indicated that an acceptable model fit with the data was achieved even though CFI and TLI are below 0.95. Although the values of 0.85 and 0.84 respectively, the CFI and TLI are relatively close to indicate that the SEM model is better than the baseline (uncorrelated) model. As shown below in table 17, an RMSEA value of 0.09 is above the value of 0.06 which suggests that the model has an overall moderate but acceptable fit (Xia & Yang, 2019).

Table 17: Structural Equation Model fit

```
lavaan 0.6.16 ended normally after 90 iterations

  Estimator                                         ML
  Optimization method                           NLMINB
  Number of model parameters                        74

  Number of observations                           201

Model Test User Model:

  Test statistic                              1195.842
  Degrees of freedom                               454
  P-value (Chi-square)                           0.000

Model Test Baseline Model:

  Test statistic                              5443.346
  Degrees of freedom                               496
  P-value                                        0.000

User Model versus Baseline Model:

  Comparative Fit Index (CFI)                    0.850
  Tucker-Lewis Index (TLI)                       0.836

Loglikelihood and Information Criteria:

  Loglikelihood user model (H0)              -5467.567
  Loglikelihood unrestricted model (H1)      -4869.646

  Akaike (AIC)                               11083.133
  Bayesian (BIC)                             11327.578
  Sample-size adjusted Bayesian (SABIC)      11093.135

Root Mean Square Error of Approximation:

  RMSEA                                          0.090
  90 Percent confidence interval - lower         0.084
  90 Percent confidence interval - upper         0.096
  P-value H_0: RMSEA <= 0.050                    0.000
  P-value H_0: RMSEA >= 0.080                    0.996

Standardized Root Mean Square Residual:

  SRMR                                           0.078
```

```
Parameter Estimates:

  Standard errors                             Standard
  Information                                 Expected
  Information saturated (h1) model          Structured
```

5.8.2. Hypotheses testing

The hypotheses were tested using the SEM statistical technique and R-statistical software programme. The modelling results are presented below in table 18.

Table 18: Structural Equation Model results

```
Regressions:
                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
  BP ~
    DLA               0.399    0.140    2.857    0.004    0.265    0.265
    DOB               0.047    0.121    0.391    0.696    0.049    0.049
    DLAg              0.264    0.191    1.384    0.166    0.202    0.202
    DOAg              0.490    0.138    3.556    0.000    0.483    0.483
```

To establish the relationship between DBS and business performance, the study tested the following four hypotheses: 1) H1: managerial capabilities are positively related to business performance, 2) H2: operational capabilities are positively related to business performance, 3) H3: dynamic capabilities positively moderates the relationship between managerial capabilities and business performance, and 4) H4: dynamic capabilities positively moderates the relationship between operational capabilities and business performance.

H1 (DLA) predicts a positive effect of DBS on business performance. As table 18 above shows, the relationship between managerial capabilities and business performance is statistically significant with a p-value of 0.004. In the same vein, the model shows that H4 (DOAg) results are statistically significant with a p-value of zero. Thus, managerial capabilities (H1) and operational capabilities moderated by dynamic capabilities (H4), as DBS dimensions, are supported to have effect on business performance.

Inversely, H2 (DOB) and H3 (DLAg) predict not to have a positive effect on business performance. As shown in table 18, H2 has a p-value of 0.696 indicating that the relationship is not statistically significant. Similarly, H3 has a p-value of 0.166 also indicating that the relationship is not statistically significant. Therefore, H2 and H3 are not supported to have effect on business performance.

6. DISCUSSION

6.1. Introduction and roadmap

To reiterate, the aim of this study was to investigate the relationship between digital business strategy and business performance in a South African financial services organisation. Table 19 below provides the chapter structure.

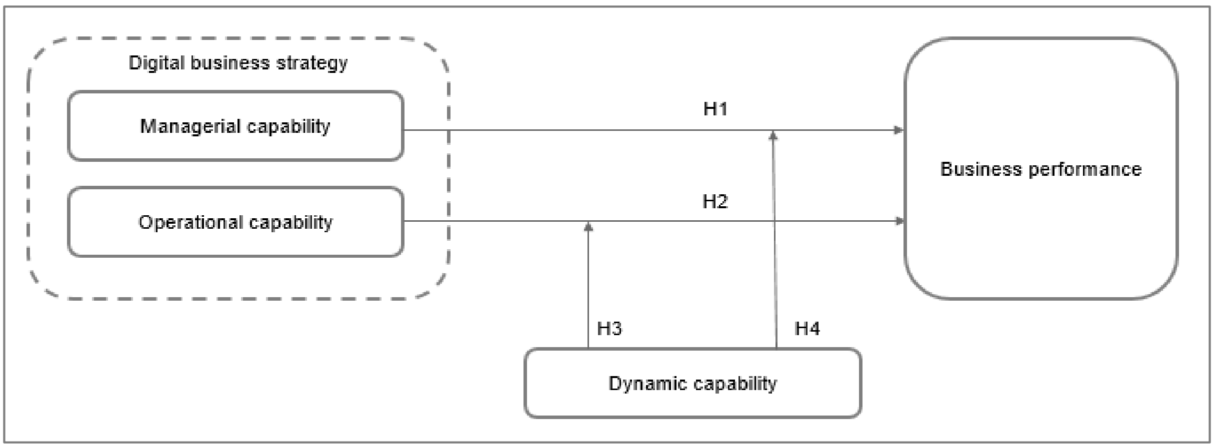
Table 19: Discussion roadmap

Main headings	6.1. Introduction and roadmap	
	6.2. Digital business strategy and business performance studies	
	6.3. Research question 1	6.4. Research question 2
	6.3.1. Managerial capabilities	6.4.1. Managerial capabilities moderated by DC
	6.3.2. Conclusion	6.4.2. Conclusion
	6.3.3. Operational capabilities	6.4.3. Operational capabilities moderated by DC
	6.3.4. Conclusion	6.4.3.1. Sensing operational capabilities
		6.4.3.2. Learning operational capabilities
		6.4.3.3. Integrating operational capabilities
		6.4.3.4. Co-ordinating operational capabilities
		6.4.4. Conclusion
	6.5. Summary	

Source: Author's compilation

This chapter discuss the results presented in Chapter 5 in relation to the literature review insights presented in Chapter 2. The chapter follows the structure of the research questions (RQ1 and RQ 2) and the conceptual framework. Flowing from Chapter 5, the four hypotheses are discussed below to re-affirm the conceptual framework (see figure 21 below).

Figure 21: Conceptual framework



Source: Adapted from Ukko et al. (2019).

6.2. Digital business strategy and business performance studies

Despite the evolving literature discussion in digital business strategy, the researcher reviewed research studies below (table 20) and established some relationship with this study which offered useful insights at the study design phase. Thus, table 20 below shows the following information: authors including the year of publication, research findings, the measure used (statistical technique) and whether the main findings confirmed a positive, neutral or negative relationship between independent and dependent variables.

Table 20: Literature related to digital business strategy and business performance

Authors	Research findings	Measurement	Relationship
Adner & Helfat (2003)	Time-varying corporate effects associated with corporate-level managerial decisions	Anova analogous to a hierarchical OLS regression	Positive
Wilden et al. (2013)	Organic organisational structures facilitate the impact of dynamic capabilities on organizational performance	SEM (PLS)	Positive
Setia & Patel (2013).	Digital design is an antecedent to two customer service capabilities: customer orientation capability and customer response capability which enhances customer service performance	Smart PLS with bootstrap	Positive
Chi et al. (2016)	1. Digital business strategy is the enabler to create and appropriate value in the digital setting	SEM (PLS)	Positive
	2. E-collaboration capability is the full mediator between digital business strategy and firm performance		Neutral

Leischnig et al. (2017)	Effect of Digital Business Strategy to Market Performance	SEM	Positive
Rantala et al. (2019)	Value creation through service process and product related elements constitute higher company performance	Regression analyses	Positive
Ukko et al. (2019)	Managerial capabilities nor operational capabilities are statistically significantly related to financial performance	Regression analysis	Neutral
	Sustainability strategy enhances the effect of managerial capabilities on financial performance		Positive
	Sustainability strategy suppresses the effect of operational capabilities on financial performance		Negative
Bitencourt et al.(2020)	Effect of resources, knowledge management & learning, alliances, and environmental dynamism on DC	SEM	Positive
Park & Mithas (2020)	IT-enabled information analytics capability alone is neither necessary nor sufficient in any configuration for high performance.	Configurational perspective and fuzzy-set qualitative comparative analysis (fsQCA)	Neutral
	Few parsimonious configurations have an isomorphic structure that produces both high financial performance and high		Positive

	customer performance simultaneously.		
	The structures of configurations for high performance differ from those of not-high performance		Positive

6.3. Research question 1
The first part of the study examined the effects of a digital business strategy to business performance in a moderately changing environment which implies that the industry is relatively stable and change is evolutionary. To examine the causal relationship between DBS and business performance the study identified two main dimensions of digital business strategy, managerial capabilities and operational capabilities. Ukko, et al. (2019) argue that digital business strategy is about "the transformation in the business process, company capabilities and operational routines and their integration with the corporate strategy" (p. 1). As such, managerial capabilities and operational capabilities were identified as main components that underpin the framing and execution of DBS.

6.3.1. Managerial capabilities
This findings of the study showed that managerial capabilities have a positive effect on business performance **(H1)** which demonstrate that managers play a crucial role in shaping the process of digital transformation. Therefore, hypothesis H1 is supported. However, Ukko's et al. (2019) research concluded that managerial capabilities, as a dimension of digital business strategy, had a neutral effect on financial performance. El Sawy et al. (2016) & Ukko et al. (2019) argue that the ability of managers to operate with digitality is one of the key drivers of the digital transformation process. The ability to operate with digitality is related to these statements in the survey: "I believe that my digital leadership skills contribute to better decision-making" & "I consider my digital leadership skills to be a contributing factor in achieving our performance targets". Based on the responses from the study, it is clear that, ultimately, it is the ability of managers to leverage digital technologies that shapes the organisation's DBS. According to El Sawy et al. (2016), the transition to digitality "require a different mindset at all levels of the

organization" (p. 142). This mindset cultivates a salubrious environment "to experiment and innovate while occasionally failing" (p. 143) across all levels of an organisation.

Thus, to transform the organisation towards digital adoption at scale, there is a need to understand the role of digital leadership. Hence the statement "our leaders provide strategic direction to leverage digitality with clear business objectives" was included. Digital leadership is defined as "doing the right things for the strategic success of digitalization for the enterprise and its business ecosystem" (p. 142). The authors juxtapose the difference between leadership and management by arguing that "leadership is about doing the right thing for the success of the organization [whereas] management is about doing the thing right" (p. 142). In essence, leading an organisation in the digital era requires different set of leadership skills beyond the traditional practice. This is because digitality by its very nature tend to dismantle traditional parameters of organisations and industries alike thereby morphing parameters into business ecosystems due to high level of interconnectedness.

However, the shift towards digital should be supported by a conducive digital leadership and culture. This implies that top leadership teams must be equipped to give strategic direction to managers to develop and implement digital strategies. Key to this process is assessing managers' mental models. Adner & Helfat (2003) argue that managerial cognition constitutes "managerial beliefs and mental models that serve as a basis for decision making (p. 1021). These are set of beliefs, mental models and processes enable managers to perceive, interpret and respond to information (Helfat & Martin, 2015). Therefore, managers' mental models must be congruent with the shift to operate with digitality.

Given the significance of leveraging managerial resources to execute DBS, it is critical that managers have the ability to deploy talent where it is most needed. Possessing co-ordination capabilities enable managers to allocate resources and assign tasks to the relevant people in an agile manner to create new operational capabilities (Wilden et al., 2016) or core competencies (Prahalad & Hamel, 2003). This level of co-ordination enables the organisation to fully exploit the benefits of the relevant digital resources. As defined by Pavlou & El Sawy (2011), co-ordination capability is "the ability to orchestrate and deploy tasks, resources, and activities in the new operational capabilities" (p. 246). Teece et al. (1997) argue that "capability is embedded in distinct ways of coordinating" (p. 519).

Invariably, companies that master co-ordination exploit resources more optimally than those that do not. In a classical sense, this is the role of strategic leaders who give strategic direction to the organisation.

Adner & Helfat (2003) identified human capital and social capital as critical drivers of managerial capabilities. Human capital is defined as “learned skills that require some investment in education, training, or learning more generally” (Adner & Helfat, 2003, p. 1020). Heterogeneity in human capital is believed to be the main driver of performance differences between organisations (Adner & Helfat, 2003). Therefore, access to scarce and critical skilled talent is seen as a necessary condition to operate with digitality. In support of this view, Park & Mithas (2020) argue that human capital is a critical capability as it “pertains to the ability of an organization to create a conducive workforce environment, accomplish an organization’s work, and provide a supportive and secure work climate” (p. 90). However, to build effective teams proficient in digitality, organisations must leverage managerial social capital which involves cultivating networks and relationships that managers have both internally and externally.

6.3.2. Conclusion

It is pleasing that this study showed that managerial capabilities have a positive effect on business performance which demonstrate that DBS require digital managers to be executed. By contrast, Ukko’s at al. (2019) research indicated that managerial capabilities have a neutral effect on financial performance.

6.3.3. Operational capabilities

The study showed that operational capabilities have a neutral effect on business performance **(H2)**. Therefore, hypothesis H2 is not supported. Ukko’s et al. (2019) research arrived at a similar conclusion regarding the relationship between operational capabilities and financial performance. Although the results of this study are consistent with the conclusion reached by these authors, this does not suggest that operational capabilities are not essential, particularly, given that operational capabilities are said to increase the ability for an organisation to be proficient in deploying digital solutions without disrupting business operations (Sebastian et al., 2017). According to Ukko et al. (2019) operational capabilities include “digitality in internal processes, the integration of digitality across the whole business, and the existence of digitality in all business functions” (p. 5).

In this study, to establish the extent to which the organisation under review leverage operational capabilities, respondents were asked to rate the following statement, “my organisation's effective use of digital tools such as artificial intelligence (AI), machine learning and leveraging data positively impacts our operational efficiencies and productivity”. This statement is supported by Wu’s et al. (2010) view that operational capabilities are ‘secret ingredient’ that serve as a source of competitive advantage.

This research also tested the extent to which operational capabilities enable the organisation to leverage digital resources to create unique value propositions in a manner that leverage operational capabilities. Thus, the survey asked respondents to rate the following two statements, “our proficiency in digital platforms enhances our ability to deliver high-quality products and services which leads to value creation” & “I consider our digital technological optimisation to be a contributing factor in achieving our operational efficiencies and value creation”. Based on the overwhelming number of respondents who agreed with these statements, the creation of unique value propositions is, therefore, perceived to stem “from a digital strategy that is focused on either a set of digitized, integrated offerings or a relationship that engages customers in ways that competitors can’t match” (Ross et al., 2017, p. 9). Furthermore, the opinions of respondents related to leveraging operational capabilities to gain competitive advantage was tested by asking respondents to rate the following statement, “I am confident that our digital operational approaches contribute to our ability to innovate and stay competitive”.

6.3.4. Conclusion

The results on operational capabilities confirm Ukko’s at al. (2019) findings that operational capabilities have a neutral effect on financial performance. However, considering that operational capabilities are critical in the implementation of DBS, further research that include other financial services organisations is required. In addition, many financial services organisations continue to invest in what Ross et al. (2017) & Sebastian et al. (2017) refer to as the operational backbone to accelerate their rate of digital transformation.

6.4. Research question 2

The second part of the study examined the effects of digital business strategy on business performance when managerial capabilities and operational capabilities are moderated by dynamic capabilities.

6.4.1. Managerial capabilities moderated by DC

The study established that managerial capabilities moderated by DC have a neutral effect on business performance **(H3)**. Therefore, hypothesis H3 is not supported. In contrast, Ukko’s et al. (2019) research revealed that sustainability strategy enhances the effect of managerial capabilities on financial performance. Similarly, Leischnig’s et al. (2016) research that was anchored on the adoption of dynamic capabilities indicated that “digital business strategy leads to superior market performance through market intelligence capability and value creation and value capture routes” (p. 11). Therefore, the researcher is of the view that further research is required with the aim of extending the data collection to other financial services organisations to establish the effects of DBS on business performance ex post adopting dynamic capabilities perspective to managerial capabilities.

As discussed in Chapter 2, the concept of managerial capabilities presumes that managers possess ordinary managerial capabilities that enable them to make decisions in stable environments. By adopting dynamic capabilities, the organisation achieve a multiplier effect that enable the organisation to achieve superior performance and stay competitive in rapidly changing environments (Teece, 2018a). This view is supported by Adner & Helfat (2003) who view dynamic capabilities as a key differentiator to performance across companies. This is because dynamic capabilities enable managers to “integrate, build, and reconfigure internal and external competences to address rapidly changing environments” (Teece et al.,1997, p. 516). Thus, the survey had the following statements, “my proficiency in utilising digital tools positively influences my ability to lead and adapt to changing market conditions” & “our digital leadership skills have a direct impact on our ability to respond proactively to emerging trends”, to establish the extent to which managers respond in dynamic market environments. To that end, the study revealed that in dynamic conditions, managers are expected to “draw on a set of underlying managerial resources, namely, managerial cognition, managerial social capital, and managerial human capital” (Helfat & Martin, 2015, p. 1285). Adner & Helfat (2003) view the underlying managerial resources as key drivers of dynamic managerial capabilities.

Human capital is defined as “learned skills that require some investment in education, training, or learning more generally” (Adner & Helfat, 2003, p. 1020). As a result, the study included this statement “our digital leadership practices enhance our ability to monitor team performance and make agile adjustments”. This is because possession of idiosyncratic skills is seen as the main driver of superior performance which invariably leads to profits above the industry average. Therefore, access to scarce and critical skilled talent is seen as a necessary condition to increase the propensity of an organisation to sense, seize and reconfigure opportunities in a rapidly changing environment (Helfat & Martin, 2015).

Furthermore, the interpersonal relationships and networks possessed by manages such as social ties that facilitate the flow of information within the organisation is essential in reconfiguring routines. Therefore, in a rapidly changing environment, access to information is critical. Consequently, the statement that canvassed the opinions of respondents was “our digital leadership practices contribute to cross-functional collaboration and enhanced capacity for quicker responses”. Similarly, the statement, “I believe that our digital leadership practices enhance employee engagement and morale in a fast moving and competitive environment”, is also relevant.

Critically, to execute DBS in a fast moving environment, the organisation should be in a position to identify cultural aspects that lead to success. Therefore, the study had this statement, “our digital leadership practices enhance our ability to monitor team performance and make agile adjustments”, was included to gauge the sentiments of respondents regarding the organisation’s ability to manage change related to behaviours that inhibit effective implementation of a digital strategy. Consequently, by applying dynamic managerial capabilities, organisations can position themselves to understand the extent to which certain behaviours impact business decisions and performance in rapidly changing environments.

6.4.2. Conclusion

The results show that managerial capabilities moderated by DC have a neutral effect on business performance. This is in contrast to Ukko’s et al. (2019) research which showed that sustainability strategy enhances the effect of managerial capabilities on financial performance. In the same vein, Leischnig’s et al. (2016) research revealed that the adoption of dynamic capabilities has a moderating effect to DBS.

6.4.3. Operational capabilities moderated by DC

The study established that operational capabilities moderated by DC have a positive effect on business performance **(H4).** Therefore, hypothesis H4 is supported**.** Inversely, Ukko’s et al. (2019) research revealed that “the interaction of a sustainability strategy and operational capabilities for digitality shows a negative and statistically significant beta value" (p. 6). As a result, the hypothesis was not supported. In a nutshell, the results show a suppressing effect as a consequence of the sustainability relationship. Nevertheless, this study joins other researchers such as Leischnig et al. (2016) who demonstrated that the adoption of dynamic capabilities indicated that "digital business strategy leads to superior market performance through market intelligence capability and value creation and value capture routes" (p. 11).

Considering that operational capabilities are a critical component of organisational resource base, to respond to digital threats, organisations must reconfigure their operational capabilities to gain competitive advantage in a rapidly changing environment. Thus, the survey included the following statements, "our proficiency in digital operational optimisation positively impacts our ability to adapt our processes and resources to changing market conditions" & "our digital operational approaches enable us to respond proactively to emerging trends and disruptions". According to Pavlou & El Sawy (2011), operational capabilities can be reconfigured to become dynamic by applying the following DC tools: sensing; learning, integration, and coordination.

6.4.3.1. Sensing operational capabilities

Now that it is apparent that operational capabilities have a positive effect on business performance, there is a need to invest more resources to reconfigure these capabilities as part of executing DBS. As such, there is a need to constantly scan the environment for trends likely to influence the industry and, invariably, the company. Pavlou & El Sawy (2011) define sensing capability "as the ability to spot, interpret, and pursue opportunities in the environment" (pp. 243-244). The argument is possessing the sensing ability allows the company to reconfigure its existing operational capabilities to be more responsive to customer needs, identify new market opportunities or develop new products through innovative processes and design (Leischnig et al., 2017).

6.4.3.2. Learning operational capabilities

Reconfiguring routines is a critical part of exploiting dynamic capabilities. Thus, to create new products and services at the right time, organisations need to keep up with trends by levering data (Bharadwaj et al., 2013). The learning capability gives the organisation the "ability to revamp existing operational capabilities with new knowledge" (Pavlou & El Sawy, 2011, p. 244) which ultimately result in developing innovative solutions that create and capture value to meet customer needs.

6.4.3.3. Integrating operational capabilities

It is clear that learning is an integral part of the reconfiguration process, however, new knowledge is often dispersed across the organisation. To maximise the contribution of each manager, there is a need to embed new knowledge into collective processes, routines, integration through knowledge management and learning reinforcement has to take place (Setia & Patel, 2013 and Bitencourt et al., 2020). According to Teece (2007), DC only become effective when new knowledge is integrated into collective activities and sense-making through socialisation across the organisation. As such, to improve business performance, knowledge management is critical (Setia & Patel, 2013 & Bitencourt et al., 2020).

6.4.3.4. Co-ordinating operational capabilities

Implementing DBS under dynamic market conditions require that managers allocate resources and assign tasks to the relevant people in an agile manner to reconfigure and create new operational capabilities (Wilden et al., 2016). This precise level of co-ordination enables the organisation to fully exploit the benefits presented by new opportunities. As defined by Pavlou & El Sawy (2011), co-ordination capability is “the ability to orchestrate and deploy tasks, resources, and activities in the new operational capabilities” (p. 246). Teece et al. (1997) argue that “capability is embedded in distinct ways of coordinating” (p. 519). Considering the positive relationship between operational capabilities and business performance, leveraging co-ordination becomes a critical part of DBS execution layer.

Invariably, the process of revamping operational capabilities involves transforming basic routines such as increasing the speed and quality of gathering market intelligence (Leischnig et al., 2017) to deliberate exploitation and assimilation of new knowledge in a manner that positions the organisation to be competitive (Wilden et al., 2013). To that end, this statement was included in the survey, “I am confident that our dynamic digital operational approaches contribute to staying competitive”. In summary, competitive advantage is achieved when companies offer unique value propositions to its customers that cannot be replaced or imitated. In the era of digital, unique value proposition “stems from a digital strategy that is focused on either a set of digitized, integrated offerings or a relationship that engages customers in ways that competitors can't match" (Ross et al., 2017, p. 9). As a result, the following statement was included in the survey, "the integration of market-leading digital solutions into our operational practices positively affects our efficiency, agility and business performance". As illustrated by Wu et al. (2010), to create value from dynamic capabilities, operational capabilities have to be reconfigured into dynamic operational capabilities. In essence, this is value of possessing dynamic capabilities.

6.4.4. Conclusion

It is pleasing that the results of this study established a positive relationship between business performance and operational capabilities moderated by DC. By contrast, Ukko's et al. (2019) research showed that sustainability strategy suppresses the effect of operational capabilities on financial performance. Interestingly, this study confirms Leischnig's et al. (2016) research which revealed that the adoption of dynamic capabilities has moderating effects to DBS.

6.5. Summary

On research question 1, the study demonstrated that managerial capabilities have a positive effect on business performance which demonstrate that DBS require digital managers to be executed. Interestingly, Ukko's at al. (2019) research indicated that managerial capabilities have a neutral effect on financial performance. By contrast, the results on operational capabilities confirm Ukko's at al. (2019) findings that operational capabilities have a neutral effect on financial performance. Given that many financial services organisations continue to invest in what Ross et al. (2017) & Sebastian et al. (2017) refer to as the operational backbone to accelerate their rate of digital transformation, the researcher is of the view that future research should be dedicated to include other financial services organisations.

On research question 2, the study showed that managerial capabilities moderated by DC have a neutral effect on business performance. Inversely, Ukko's et al. (2019) research showed that sustainability strategy enhances the effect of managerial capabilities on financial performance. In the same vein, Leischnig's et al. (2016) research revealed that the adoption of dynamic capabilities has a moderating effect to DBS. Lastly, the study established that there is a positive relationship between business performance and operational capabilities moderated by DC. On the other hand, Ukko's et al. (2019) research showed that sustainability strategy suppresses the effect of operational capabilities on financial performance. Considering that the data for this study was collected from a single organisation, caution must be exercised when interpreting the results to avoid over-generalisations beyond the surveyed organisation. Notwithstanding the sample limitations, the researcher is of the view that the study's contribution has laid a solid foundation to include other financial services organisations in future research.

7. CONCLUSION

7.1. Introduction

As organisations increasingly endeavour to identify opportunities offered by digital capabilities, they are turning to DBS to address the challenge of driving digitality. Bharadwaj et al. (2013) term the formation of business strategy and IT strategy a digital business strategy which is defined as “organizational strategy formulated and executed by leveraging digital resources to create differential value” (p. 472). The DBS definition is said to transcend the traditional view of business strategy that is in general disentangled from organisational functional areas strategies such as IT strategy (Bharadwaj et al., 2013 & Chi et al., 2016). In this regard, DBS elevates digital resources beyond the IT functional area thereby treating them as part of strategic resources that can be deployed in line with the resource based view of competitive advantage (Barney, 1991) and dynamic capabilities (Teece at al., 1997).

It has been observed that, notwithstanding the evolutionary nature of DBS and its infancy as a research field, empirical research has been on the rise since 2015. Based on a systematic literature review on DBS conducted by Uhlig & Remané (2022), there are “key components that must be defined when developing and executing a DBS” (p. 6). These components include the following: “digitalization of products and processes, business model execution, IT governance and principles, IT investment and prioritization, digital resources, ecosystem compatibility, capabilities, leadership and culture” (p. 6). This shift demonstrate that DBS is growing as a research field since Bharadwaj et al. (2013) developed the concept a decade ago anchored on four themes: scope, scale, speed and sources of value creation and capture after realising that digital technologies were “fundamentally transforming business strategies, business processes, firm capabilities, products and services, and key interfirm relationships in extended business networks” (p. 471).

Due to the disruptive nature of digital technologies, the concept of DC was integrated with DBS. The rationale was dynamic capabilities are viewed as critical moderators of performance in turbulent business environments because “they allow organizations to systematically generate and modify their organizational capabilities to gain long-term competitive advantages” (Konopik et al., 2022, p. 2). In a classical sense, dynamic capabilities are about “two important aspects of achieving competitive advantage: dynamics and capabilities” (Bitencourt et al., 2020, p. 109). The term ‘dynamic’ is related to the execution of innovation when the organisation requires it whereas the term ‘capabilities’ is related to agile adaptability in a changing business environment (Teece et al., 1997).

Invariably, DC denote the ability to innovate and adapt in a rapidly changing environment. This is the moderating effect that is required to enhance both managerial and operational capabilities as dimensions of DBS. El Sawy & Pavlou (2008) defines operational capabilities as “planned ability to effectively execute substantive day-to-day activities, such as manufacturing, logistics, and sales” (p. 140). In relation to managerial capabilities, the DC framework provides key insights to DBS based on its ability to enable managers to sense unknown futures, mobilise resources to capture value (seizing) and transform/ reconfigure the business environment for maximum adaptability (Teece et al., 2016).

7.2. Principal conclusions

This study was interested in answering two research questions: RQ 1 “to what extent does adopting a digital business strategy improve business performance in a moderately changing environment” and RQ 2 “to what extent does adopting a digital business strategy improve business performance in a rapidly changing environment”. **On research question 1**, the study investigated the relationship between business performance and DBS dimensions, managerial capabilities and operational capabilities. The findings demonstrated that the relationship between managerial capabilities and business performance is statistically significant and, therefore, positive which implies that an increase in managerial capabilities result in an increase in business performance. However, this finding is not corroborated by Ukko’s et al. (2019) study which demonstrated that the relationship between managerial capabilities and financial performance is neutral. Considering that business performance can be represented by two variables, financial performance and / or customer performance, it is probable that future research will validate the results of this study. Interestingly, Ukko’s et al. (2019) study corroborated this study’s findings on operational capabilities wherein the relationship with business performance was also neutral.

On research question 2, the study investigated the relationship between business performance and DBS dimensions moderated by dynamic capabilities. The findings demonstrated that the relationship between managerial capabilities moderated by dynamic capabilities and business performance is statistically not significant. Although

Ukko's et al. (2019) study focused on sustainability strategy, as a moderator of managerial capabilities, their findings showed a positive relationship with financial performance. In the same vein, this study showed a positive relationship between operational capabilities moderated by dynamic capabilities and business performance whereas Ukko's et al. (2019) study demonstrated that the relationship is negative which implies that sustainability strategy suppresses the effect of operational capabilities on financial performance. However, Leischnig's et al. (2016) study revealed that the adoption of dynamic capabilities has a moderating effect to DBS.

7.3. Research contribution

This paper reviewed several studies on DBS and the closest two studies to this study were Leischnig's et al. (2016) and Ukko's et al. (2019). However, both studies were conducted in developed countries. To that end, the findings of this study contributes to DBS research from a developing country perspective. Given that research in DBS is relatively new, the research also contributes towards a growing empirical body of knowledge in DBS. In addition, the paper demonstrated that DBS require DC to be effective in rapidly changing environment. Thus, the discussion on integrating DC with systems theory is viewed as a necessary step towards strengthening DBS. The application of systems theory is useful in understanding how organisations work. To co-ordinate the organisation effectively, Teece (2018b) argues that combining systems theory with DC provides a suitable framework given that organisations are "social systems made up of sub-units that must inter-relate in a harmonious (congruent) manner for the organisation to be effective" (p. 360).

7.4. Management implications

The findings of this study provide guidance for organisations, particularly in financial services industry, to re-focus their digital strategies to drive business performance in an environment where inefficiencies continue to drive high costs. This research has showed that to achieve better business performance, organisations need to recognise the pivotal role played by managers to operate with digitality. Focusing on managerial capabilities, as a dimension of DBS, will help organisations to improve their mangers' knowledge and skills to operate with digitality enabling them to develop a clear vision to contextualise key components that must be reviewed when developing DBS such as business model execution, ecosystem compatibility, capabilities, leadership, culture, etc. to better formulate and execute DBS. However, the study also showed that there is a neutral relationship between dynamic managerial capabilities and business performance which suggests that wholesale revamping of managerial capabilities may not be congruent with improving business performance. Therefore, organisations must balance their investments by being more deliberate, measured and targeted in building and pacing dynamic managerial capabilities.

Regarding operational capabilities, the study demonstrated that developing robust operational backbone is key but more importantly organisations need to adopt dynamic capabilities to sense, seize and reconfigure routines to improve operational efficiencies. Therefore, adopting dynamic operational capabilities is the solution to gain competitive advantage and stay on a path for economic success. Thus, instead of focusing on incremental improvements of operational practices, organisations must focus on revamping their operational capabilities to make them more responsive in dynamic market conditions to realise the benefits of digitality.

7.5. Limitation and further research

Few limitations have been identified in this study. The study was conducted in a single financial services organisation at a point in time (cross-sectional) thereby confining the sample to the surveyed organisation which might lead to generalisability concerns. As expressed by the researcher in the previous section, these limitations offer other researchers the opportunity to conduct future research with a broader research scope that include other financial services organisations in South Africa and beyond. A broader scope may also make it viable to collect research data over a long period making the study longitudinal.

Although the survey questionnaire attempted to explain technical concepts and used the language that is familiar to most respondents, some might have interpreted the concepts based on their own understanding and experience leading to bias. In addition, the survey instrument was designed to measure responses based on a Likert scale which may have limited detailed responses. Furthermore, the survey used purposive sampling method (non-probability sampling), a form of convenience sampling wherein the researcher’s discretion is used to select the sample participants. Another limitation was that the survey was distributed online which opens up the possibility of self- selection bias, wherein some participants tend to be drawn to online surveys whilst others do not.

In conclusion, although this study offers compelling insights into the relationship between digital business strategy and business performance, undoubtedly further research is still required to enrich the evolving literature in digital business strategy whilst providing guidance to managers on how to formulate and execute digital business strategies.

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APPENDICES

A. Ethical clearance

Gordon Institute of Business Science
University of Pretoria

Ethical Clearance Approved

Dear Ntungufhadzeni Masindi,

Please be advised that your application for Ethical Clearance has been approved.
You are therefore allowed to continue collecting your data.
We wish you everything of the best for the rest of the project.

Ethical Clearance Form

Kind Regards

This email has been sent from an unmonitored email account. If you have any comments or concerns, please contact the GIBS Research Admin team.

B. Survey questionnaire

Gordon Institute
of Business Science
University of Pretoria

Digital business strategy and business performance survey

Dear Participant,

I am conducting research to "*investigate the relationship between digital business strategy and business performance in a financial services organisation*". To that end, you are asked to complete a survey relating to my topic. The survey is estimated to take you 7 minutes. Your participation is voluntary and you can withdraw at any time without penalty. Your participation is anonymous and only aggregated data will be reported. By completing the survey, you indicate that you voluntarily participate in this research. The final research report will be submitted to GIBS in partial fulfilment of the requirements for the degree of Master of Philosophy in Corporate Strategy. If you have any concerns, please feel free to contact me or my supervisor. Our details are provided below.

Researcher name: Ntungu Masindi

Email: ntungum@nedbank.co.za

Phone: 0768638229

Research supervisor name: Prof. Manoj Chiba

Email: ChibaM@gibs.co.za

Phone: 0827845769

Digital leadership acumen

In this context, digital leadership acumen as a dimension of digital business strategy included items related to managers' knowledge of and skills in digital tools, managers' clear vision for utilizing digitality, and managers' support for digitality.

1. Our leaders provide strategic direction to leverage digitality with clear business objectives *

	Strongly agree	Agree	Neither agree nor disagree	Disagree	Strongly disagree
To what extent do you agree with this statement?	◯	◯	◯	◯	◯

2. I believe that my digital leadership skills contribute to better decision-making *

	Strongly agree	Agree	Neither agree nor disagree	Disagree	Strongly disagree
To what extent do you agree with this statement?	◯	◯	◯	◯	◯

3. Our team's proficiency in digital collaboration tools positively influences our ability to deliver high-quality results *

	Strongly agree	Agree	Neither agree nor disagree	Disagree	Strongly disagree
To what extent do you agree with this statement?	◯	◯	◯	◯	◯

4. I consider my digital leadership skills to be a contributing factor in achieving our performance targets *

	Strongly agree	Agree	Neither agree nor disagree	Disagree	Strongly disagree
To what extent do you agree with this statement?	◯	◯	◯	◯	◯

5. I believe that my digital leadership skills contribute to my team's continuous learning, improved engagement and morale *

	Strongly agree	Agree	Neither agree nor disagree	Disagree	Strongly disagree
To what extent do you agree with this statement?	◯	◯	◯	◯	◯

6. I consider my team's proficiency in data analytics to have a direct impact in improving our business performance metrics *

	Strongly agree	Agree	Neither agree nor disagree	Disagree	Strongly disagree
To what extent do you agree with this statement?	○	○	○	○	○

7. Our adoption of digital communication channels positively improves our overall clients experience
*

	Strongly agree	Agree	Neither agree nor disagree	Disagree	Strongly disagree
To what extent do you agree with this statement?	○	○	○	○	○

Digital operational backbone

The ability of an organisation to be proficient in deploying digital solutions without disrupting business operations is an integral part of embedding operational capabilities in the implemention of a digital business strategy.

8. My organisation's effective use of digital tools such as artificial intelligence (AI), machine learning and leveraging data positively impacts our operational efficiencies and productivity *

	Strongly agree	Agree	Neither agree nor disagree	Disagree	Strongly disagree
To what extent do you agree with this statement?	○	○	○	○	○

9. I believe that our digital operational efficiencies contribute to better decision-making *

	Strongly agree	Agree	Neither agree nor disagree	Disagree	Strongly disagree
To what extent do you agree with this statement?	○	○	○	○	○

10. Our proficiency in digital platforms enhances our ability to deliver high-quality products and services which leads to value creation *

	Strongly agree	Agree	Neither agree nor disagree	Disagree	Strongly disagree
To what extent do you agree with this statement?	○	○	○	○	○

11. I consider our digital technological optimisation to be a contributing factor in achieving our operational efficiencies and value creation *

	Strongly agree	Agree	Neither agree nor disagree	Disagree	Strongly disagree
To what extent do you agree with this statement?	○	○	○	○	○

12. Our adoption of digital technologies for clients interactions positively improves our clients' experience *

	Strongly agree	Agree	Neither agree nor disagree	Disagree	Strongly disagree
To what extent do you agree with this statement?	○	○	○	○	○

13. I am confident that our digital operational approaches contribute to our ability to innovate and stay competitive
*

	Strongly agree	Agree	Neither agree nor disagree	Disagree	Strongly disagree
To what extent do you agree with this statement?	○	○	○	○	○

14. The use of digital platforms for monitoring operational performance has led to more accurate and actionable insights *

	Strongly agree	Agree	Neither agree nor disagree	Disagree	Strongly disagree
To what extent do you agree with this statement?	○	○	○	○	○

Digital leadership agility

To navigate the complexity of fusing IT strategy and business strategy, managers are required to demonstrate the ability to orchestrate organisational capabilities to lead in a dynamic business environment.

15. My proficiency in utilising digital tools positively influences my ability to lead and adapt to changing market conditions *

	Strongly agree	Agree	Neither agree nor disagree	Disagree	Strongly disagree
To what extent do you agree with this statement?	○	○	○	○	○

16. Our digital leadership skills have a direct impact on our ability to respond proactively to emerging trends *

	Strongly agree	Agree	Neither agree nor disagree	Disagree	Strongly disagree
To what extent do you agree with this statement?	○	○	○	○	○

17. The integration of digital tools enhances our team's innovation capabilities, leading to better business performance *

	Strongly agree	Agree	Neither agree nor disagree	Disagree	Strongly disagree
To what extent do you agree with this statement?	○	○	○	○	○

18. I am confident that our digital leadership practices have made us more agile which contributes to staying competitive *

	Strongly agree	Agree	Neither agree nor disagree	Disagree	Strongly disagree
To what extent do you agree with this statement?	○	○	○	○	○

19. Our digital leadership practices enhance our ability to monitor team performance and make agile adjustments *

	Strongly agree	Agree	Neither agree nor disagree	Disagree	Strongly disagree
To what extent do you agree with this statement?	○	○	○	○	○

20. I believe that our digital leadership practices enhance employee engagement and morale in a fast moving and competitive environment *

	Strongly agree	Agree	Neither agree nor disagree	Disagree	Strongly disagree
To what extent do you agree with this statement?	◯	◯	◯	◯	◯

21. Our digital leadership practices contribute to cross-functional collaboration and enhanced capacity for quicker responses *

	Strongly agree	Agree	Neither agree nor disagree	Disagree	Strongly disagree
To what extent do you agree with this statement?	◯	◯	◯	◯	◯

Digital operational agility

Technologically driven disruptions causes changes on a continuous basis. This requires companies to be agile in their adaptations within the context of developing and implementing a digital business strategy.

22. Our proficiency in digital operational optimisation positively impacts our ability to adapt our processes and resources to changing market conditions *

	Strongly agree	Agree	Neither agree nor disagree	Disagree	Strongly disagree
To what extent do you agree with this statement?	◯	◯	◯	◯	◯

23. Our digital operational approaches enable us to respond proactively to emerging trends and disruptions *

	Strongly agree	Agree	Neither agree nor disagree	Disagree	Strongly disagree
To what extent do you agree with this statement?	○	○	○	○	○

24. I am confident that our dynamic digital operational approaches contribute to staying competitive *

	Strongly agree	Agree	Neither agree nor disagree	Disagree	Strongly disagree
To what extent do you agree with this statement?	○	○	○	○	○

25. Our digital operational approaches enhance our ability to monitor performance metrics and make agile adjustments *

	Strongly agree	Agree	Neither agree nor disagree	Disagree	Strongly disagree
To what extent do you agree with this statement?	○	○	○	○	○

26. I believe that our proficiency in data analytics, combined with dynamic operational approaches, improves our financial performance *

	Strongly agree	Agree	Neither agree nor disagree	Disagree	Strongly disagree
To what extent do you agree with this statement?	○	○	○	○	○

27. The use of our digital platforms in fast moving and competitive environment lead to quicker responses to clients' needs *

	Stronly agree	Agree	Neither agree nor disagree	Disagree	Strongly disagree
To what extent do you agree with this statement?	○	○	○	○	○

28. The integration of market-leading digital solutions into our operational practices positively affects our efficiency, agility and business performance
*

	Strongly agree	Agree	Neither agree nor disagree	Disagree	Strongly disagree
To what extent do you agree with this statement?	○	○	○	○	○

Business performance

Digitality is perceived as an an important ingridient to conceive of and implement business strategies that improve business performance.

29. Our team's adoption of digital strategies has contributed to improved overall business performance *

	Strongly agree	Agree	Neither agree nor disagree	Disagree	Strongly disagree
To what extent do you agree with this statement?	○	○	○	○	○

30. The integration of market-leading digital solutions into our operations has positively impacted our overall business performance *

	Strongly agree	Agree	Neither agree nor disagree	Disagree	Strongly disagree
To what extent do you agree with this statement?	○	○	○	○	○

31. I believe that our proficiency in data analytics, combined with dynamic leadership approaches, improves our business performance *

	Strongly agree	Agree	Neither agree nor disagree	Disagree	Strongly disagree
To what extent do you agree with this statement?	○	○	○	○	○

32. Our combination of dynamic operational efficiencies and digital strategies has contributed to notable improvements in our overall business performance *

	Strongly agree	Agree	Neither agree nor disagree	Disagree	Strongly disagree
To what extent do you agree with this statement?	○	○	○	○	○

Demographic information

33. Please select your age *

- ◯ 18-30
- ◯ 31-40
- ◯ 41-50
- ◯ 51 and above

34. Please select your gender *

- ◯ Male
- ◯ Female
- ◯ Prefer not to say

35. How would you classify your primary functional area? *

- ◯ Compliance, Legal and Risk
- ◯ Finance
- ◯ Human Resources
- ◯ Information Technology
- ◯ Marketing and Communications
- ◯ Sales
- ◯ Research and Strategy
- ◯ Operations
- ◯ Other

36. Please select your level of seniority *

- ◯ Executive
- ◯ Senior management
- ◯ Middle management
- ◯ Junior management

37. Please select indicate the number of years you have been at your current role *

- ◯ 0-2
- ◯ 2-4
- ◯ 4-6
- ◯ 6-8
- ◯ 8 and above

C. Python code: data transformation

```
#Importing the Pandas package to transform the data

import pandas as pd

#Reading the data from excel and setting the ID column as the index
data = pd.read_excel("Working File 2.xlsx")
data = data.set_index("ID")


#Renaming the columns Q_1 to Q_37
names = [f"Q_{x}" for x in range(1,len(data.columns)+1)]
data.columns = names


#Converting the Likert Scale responses to numeric values with 1 (Strongly
disagree) being the lowest value and 5 (Strongly agree) being the highest
value
data.replace(to_replace=["Strongly disagree","Disagree","Neither agree nor
disagree","Agree","Strongly agree","Stronly agree"]
             ,value=[1,2,3,4,5,5],inplace=True)

#Grouping the column names per section as constructed in the survey
digital_leadership_acumen = data.columns[:7]
digital_operational_backbone = data.columns[7:14]
digital_leadership_agility = data.columns[14:21]
digital_operational_agility = data.columns[21:28]
business_performance = data.columns[28:32]


#Calculating the row mean for each question and adding it to the overall data
frame
data['digital_leadership_acumen_mean'] =
data[digital_leadership_acumen].mean(axis=1)
data['digital_operational_backbone_mean'] =
data[digital_operational_backbone].mean(axis=1)
data['digital_leadership_agility_mean'] =
data[digital_leadership_agility].mean(axis=1)
data['digital_operational_agility_mean'] =
data[digital_operational_agility].mean(axis=1)
data['business_performance_mean'] = data[business_performance].mean(axis=1)
#Exporting the “Mean” columns to Excel
data[['digital_leadership_acumen_mean','digital_operational_backbone_mean','di
gital_leadership_agility_mean','digital_operational_agility_mean','business_pe
rformance_mean']].to_excel("Mean Working File.xlsx")

#Exporting the data frame to Excel
Data.to_excel("Working File.xlsx")
```

D. R Code

D.1. Cronbach's Alpha

```
#Loading the required libraries to load the data on R and calculate
Cronbach's Alpha
library(readxl)
library(umx)

#Reading the data and coverting to a data frame
data <- read_excel("Working File.xlsx")
df <- as.data.frame(data)

#Slicing the data to the different sections and calculating the alphas
mymat <- data.matrix(df[2:33])
reliability(cov(mymat))
DLA_mat <- data.matrix(df[2:8])
reliability(cov(DLA_mat))
DOB_mat <- data.matrix(df[9:15])
reliability(cov(DOB_mat))
DLAg_mat <- data.matrix(df[16:22])
reliability(cov(DLAg_mat))
DOAg_mat <- data.matrix(df[23:29])
reliability(cov(DOAg_mat))
BP_mat <- data.matrix(df[30:33])
reliability(cov(BP_mat))
```

D.2. Suitability tests

```
#Required libraries
library(psych)
library("Hmisc")
library(GGally)

#KMO Test
KMO(mymat)

#Bartlett's test of Sphericity
cortest.bartlett(cor(mymat), n = nrow(mymat))

#Correlation Test

as.dist(round(cor(mymat,method="spearman"),3)) #Spearman Rank
ggcorr(mymat,
    method = c("all.obs", "spearman"),
    #nbreaks = 5,
    low = "blue",
    mid = "white",
    high = "red")
```

D.3. Construct validity

```
#loading the required package
library(lavaan)

#defining and fitting the construct model
model <- '
DLA =~Q_1 + Q_2 + Q_3 + Q_4 + Q_5 + Q_6 + Q_7
DOB =~Q_8 + Q_9 + Q_10 + Q_11 + Q_12 + Q_13 + Q_14
DLAg=~ Q_15 + Q_16 + Q_17 + Q_18 + Q_19 + Q_20 + Q_21
DOAg=~ Q_22 + Q_23 + Q_24 + Q_25 + Q_26 + Q_27 + Q_28
BP =~ Q_29 + Q_30 + Q_31 + Q_32'

fit <- cfa(model,data=df)
summary(fit,fit.measures=TRUE,standardized=TRUE)
```

D.4. Exploratory data analysis – bar charts

```
library(ggplot2)

ggplot(data=df2,aes(digital_leadership_acumen_mean))+geom_bar(fill="blue")+
labs(title = "Mean Distribution: Managerial Capabilities", x = "Average
Ratings",y = "Frequency")+ theme_classic() +
theme(plot.title=element_text(hjust=0.5))

ggplot(data=df2,aes(digital_operational_backbone_mean
))+geom_bar(fill="blue")+labs(title = "Mean Distribution: Operational
Capabilities", x = "Average Ratings",y = "Frequency")+ theme_classic() +
theme(plot.title=element_text(hjust=0.5))

ggplot(data=df2,aes(digital_leadership_agility_mean
))+geom_bar(fill="blue")+labs(title = "Mean Distribution: Managerial
Capabilities Moderated by DC", x = "Average Ratings",y = "Frequency")+
theme_classic() + theme(plot.title=element_text(hjust=0.5))

ggplot(data=df2,aes(digital_operational_agility_mean
))+geom_bar(fill="blue")+labs(title = "Mean Distribution: Operational
Capabilities Moderated by DC", x = "Average Ratings",y = "Frequency")+
theme_classic() + theme(plot.title=element_text(hjust=0.5))

ggplot(data=df2,aes(business_performance_mean))+geom_bar(fill="blue")+labs(
title = "Mean Distribution: Business Performance", x = "Average Ratings",y
= "Frequency")+ theme_classic() + theme(plot.title=element_text(hjust=0.5))
```

D.5. Tests for normality

```
#Test for Normality
"Managerial Capabilities Means Q-Q Plot"
qqnorm(df2$business_performance_mean)
qqline(df2$business_performance_mean)
shapiro.test(df2$business_performance_mean)


qqnorm(df2$digital_operational_backbone_mean)
qqline(df2$digital_operational_backbone_mean)
shapiro.test(df2$digital_operational_backbone_mean)

qqnorm(df2$digital_leadership_agility_mean)
```

```
qqline(df2$digital_leadership_agility_mean)
shapiro.test(df2$digital_leadership_agility_mean)


qqnorm(df2$digital_operational_agility_mean)
qqline(df2$digital_operational_agility_mean)
shapiro.test(df2$digital_operational_agility_mean)


qqnorm(df2$digital_leadership_acumen_mean)
qqline(df2$digital_leadership_acumen_mean)
shapiro.test(df2$digital_leadership_acumen_mean)
```

D.6. Regularized regression

```
#Required library
library(glmnet)

#setting the seed
set.seed(1)

# Splitting the data in a training (80%) and test (20%) sets

train = sample(1:nrow(df),.8*nrow(df))
x_train =as.matrix(df2[train,2:5])
x_test = as.matrix(df2[-train,2:5])
y_train = as.matrix(df2[train,6])
y_test = as.matrix(df2[-train,6])

#Trying Different Alphas and fitting an Elasticnet model

list_of_fits <- list()

for(i in 0:10){
fit_name <- paste("Alpha",i/10)

list_of_fits[[fit_name]] <-
cv.glmnet(x_train,y_train,type.measure="mse",alpha=i/10,family="gaussian")

}

results <- data.frame()

for(i in 0:10){

fit_name <-paste("Alpha",i/10)

predicted <- predict(list_of_fits[[fit_name]],
s=list_of_fits[[fit_name]]$lambda.1se,newx=x_test)

mse <- mean((y_test - predicted)^2)

temp <- data.frame(alpha=i/10,mse=mse,fit.name=fit_name)
results <- rbind(results,temp)
}
#Fitting the best model
e_fit <-
cv.glmnet(x_train,y_train,type.measure="mse",alpha=0.1,family="gaussian")
coef(e_fit)
```

D.7. Structural Equation Model

```
model <- '
#Measurement model

DLA =~ Q_1 + Q_2 + Q_3 + Q_4 + Q_5 + Q_6 + Q_7
DOB =~ Q_8 + Q_9 + Q_10 + Q_11 + Q_12 + Q_13 + Q_14
DLAg=~ Q_15 + Q_16 + Q_17 + Q_18 + Q_19 + Q_20 + Q_21
DOAg=~ Q_22 + Q_23 + Q_24 + Q_25 + Q_26 + Q_27 + Q_28
BP =~  Q_29 + Q_30 + Q_31 + Q_32

#Regressions
BP ~ DLA + DOB + DLAg + DOAg
'

#Fitting a Structural Equation Model

fit <- sem(model,data=df)

summary(fit,fit.measures=TRUE,standardized=TRUE)
```

E. Construct validity test

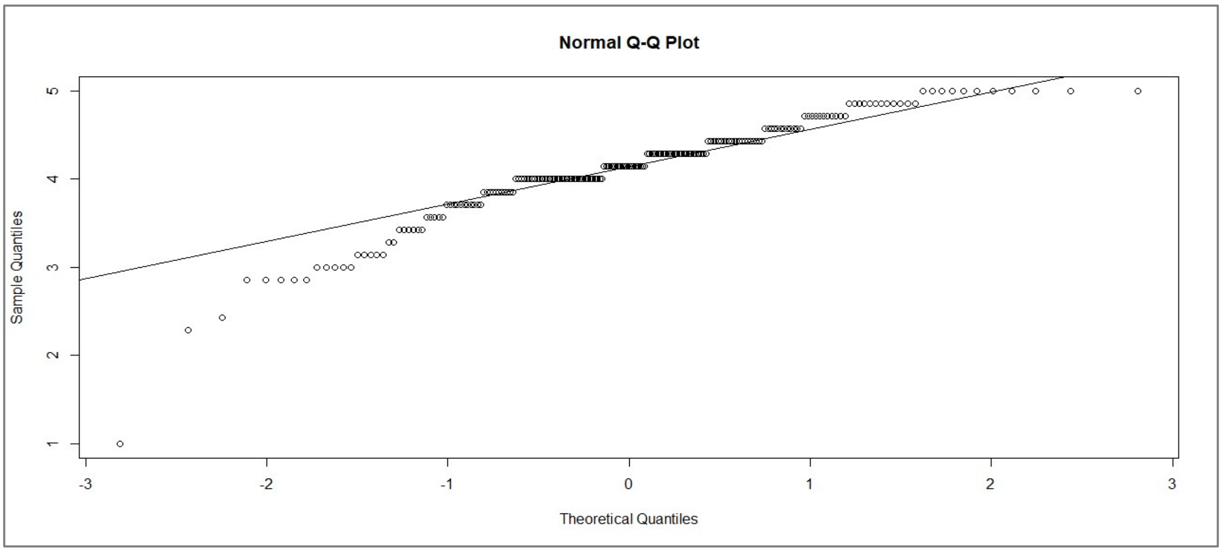
```
lavaan 0.6.16 ended normally after 98 iterations

  Estimator                                         ML
  Optimization method                           NLMINB
  Number of model parameters                        74

  Number of observations                           201

Model Test User Model:

  Test statistic                              1195.842
  Degrees of freedom                               454
  P-value (Chi-square)                           0.000

Model Test Baseline Model:

  Test statistic                              5443.346
  Degrees of freedom                               496
  P-value                                        0.000

User Model versus Baseline Model:

  Comparative Fit Index (CFI)                    0.850
  Tucker-Lewis Index (TLI)                       0.836
Loglikelihood and Information Criteria:

  Loglikelihood user model (H0)              -5467.567
  Loglikelihood unrestricted model (H1)      -4869.646

  Akaike (AIC)                               11083.133
  Bayesian (BIC)                             11327.578
  Sample-size adjusted Bayesian (SABIC)      11093.135

Root Mean Square Error of Approximation:

  RMSEA                                          0.090
```

```
  90 Percent confidence interval - lower         0.084
  90 Percent confidence interval - upper         0.096
  P-value H_0: RMSEA <= 0.050                    0.000
  P-value H_0: RMSEA >= 0.080                    0.996

Standardized Root Mean Square Residual:

  SRMR                                           0.078

Parameter Estimates:

  Standard errors                             Standard
  Information                                 Expected
  Information saturated (h1) model          Structured

Latent Variables:
                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
  DLA =~
    Q_1               1.000                               0.428    0.562
    Q_2               1.330    0.173    7.670    0.000    0.569    0.747
    Q_3               1.341    0.185    7.240    0.000    0.574    0.679
    Q_4               1.379    0.178    7.745    0.000    0.590    0.759
    Q_5               1.450    0.189    7.654    0.000    0.621    0.744
    Q_6               1.437    0.205    7.021    0.000    0.615    0.647
    Q_7               0.886    0.154    5.758    0.000    0.379    0.491
  DOB =~
    Q_8               1.000                               0.663    0.701
    Q_9               0.861    0.083   10.339    0.000    0.571    0.768
    Q_10              0.968    0.085   11.454    0.000    0.642    0.856
    Q_11              0.915    0.091   10.063    0.000    0.607    0.747
    Q_12              0.665    0.076    8.720    0.000    0.441    0.644
    Q_13              0.943    0.089   10.624    0.000    0.625    0.790
    Q_14              0.887    0.089    9.989    0.000    0.588    0.741
  DLAg =~
    Q_15              1.000                               0.492    0.639
    Q_16              1.063    0.123    8.655    0.000    0.523    0.699
    Q_17              1.037    0.111    9.331    0.000    0.511    0.768
    Q_18              1.254    0.132    9.520    0.000    0.618    0.788
    Q_19              1.345    0.134   10.005    0.000    0.662    0.841
    Q_20              1.308    0.138    9.505    0.000    0.644    0.786
    Q_21              1.333    0.140    9.498    0.000    0.656    0.785
  DOAg =~
    Q_22              1.000                               0.636    0.831
    Q_23              1.145    0.076   15.052    0.000    0.728    0.851
    Q_24              1.092    0.070   15.525    0.000    0.694    0.868
    Q_25              0.968    0.071   13.694    0.000    0.615    0.802
    Q_26              0.938    0.078   12.053    0.000    0.596    0.735
    Q_27              0.925    0.075   12.380    0.000    0.588    0.749
    Q_28              0.959    0.071   13.537    0.000    0.610    0.796
  BP =~
    Q_29              1.000                               0.646    0.840
    Q_30              1.059    0.067   15.892    0.000    0.684    0.881
    Q_31              0.824    0.073   11.220    0.000    0.532    0.699
    Q_32              1.023    0.068   15.135    0.000    0.660    0.855

Covariances:
                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
  DLA ~~
    DOB               0.209    0.038    5.491    0.000    0.737    0.737
    DLAg              0.162    0.030    5.398    0.000    0.770    0.770
    DOAg              0.169    0.031    5.385    0.000    0.621    0.621
```

```
    BP                 0.209    0.036    5.839    0.000    0.755    0.755
  DOB ~~
    DLAg               0.283    0.045    6.291    0.000    0.866    0.866
    DOAg               0.367    0.052    7.108    0.000    0.870    0.870
    BP                 0.359    0.051    7.004    0.000    0.838    0.838
  DLAg ~~
    DOAg               0.275    0.041    6.772    0.000    0.877    0.877
    BP                 0.277    0.041    6.759    0.000    0.871    0.871
  DOAg ~~
    BP                 0.355    0.046    7.769    0.000    0.866    0.866

Variances:
                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
   .Q_1                0.397    0.042    9.438    0.000    0.397    0.684
   .Q_2                0.257    0.031    8.406    0.000    0.257    0.442
   .Q_3                0.385    0.043    8.931    0.000    0.385    0.539
   .Q_4                0.256    0.031    8.272    0.000    0.256    0.423
   .Q_5                0.311    0.037    8.433    0.000    0.311    0.447
   .Q_6                0.525    0.058    9.104    0.000    0.525    0.581
   .Q_7                0.453    0.047    9.622    0.000    0.453    0.759
   .Q_8                0.456    0.049    9.327    0.000    0.456    0.509
   .Q_9                0.226    0.025    8.978    0.000    0.226    0.410
   .Q_10               0.151    0.019    8.018    0.000    0.151    0.268
   .Q_11               0.292    0.032    9.109    0.000    0.292    0.442
   .Q_12               0.274    0.029    9.512    0.000    0.274    0.585
   .Q_13               0.235    0.027    8.813    0.000    0.235    0.375
   .Q_14               0.284    0.031    9.140    0.000    0.284    0.451
   .Q_15               0.352    0.037    9.575    0.000    0.352    0.592
   .Q_16               0.287    0.031    9.400    0.000    0.287    0.512
   .Q_17               0.182    0.020    9.080    0.000    0.182    0.411
   .Q_18               0.233    0.026    8.945    0.000    0.233    0.379
   .Q_19               0.181    0.022    8.413    0.000    0.181    0.292
   .Q_20               0.257    0.029    8.957    0.000    0.257    0.382
   .Q_21               0.268    0.030    8.963    0.000    0.268    0.383
   .Q_22               0.181    0.021    8.793    0.000    0.181    0.309
   .Q_23               0.201    0.023    8.570    0.000    0.201    0.275
   .Q_24               0.158    0.019    8.340    0.000    0.158    0.247
   .Q_25               0.210    0.023    9.035    0.000    0.210    0.357
   .Q_26               0.303    0.032    9.382    0.000    0.303    0.460
   .Q_27               0.271    0.029    9.326    0.000    0.271    0.439
   .Q_28               0.215    0.024    9.077    0.000    0.215    0.367
   .Q_29               0.174    0.021    8.214    0.000    0.174    0.294
   .Q_30               0.135    0.018    7.382    0.000    0.135    0.224
   .Q_31               0.295    0.032    9.315    0.000    0.295    0.511
   .Q_32               0.161    0.020    7.966    0.000    0.161    0.269
    DLA                0.183    0.045    4.114    0.000    1.000    1.000
    DOB                0.440    0.079    5.568    0.000    1.000    1.000
    DLAg               0.243    0.049    4.946    0.000    1.000    1.000
    DOAg               0.404    0.056    7.172    0.000    1.000    1.000
    BP                 0.417    0.058    7.235    0.000    1.000    1.000
```

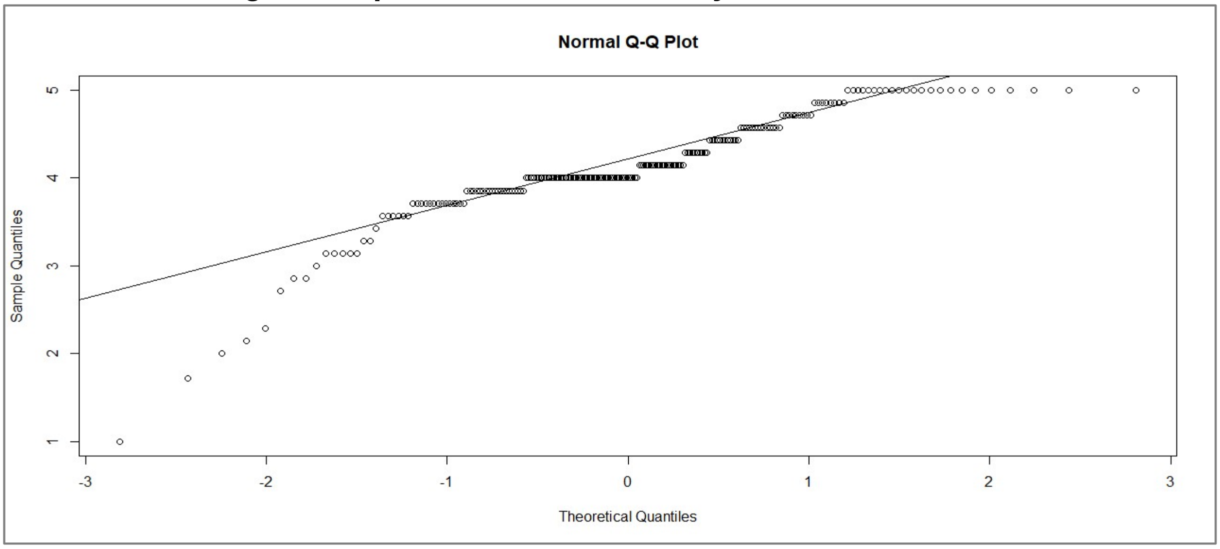
F. Normality tests

F.1. Managerial capabilities



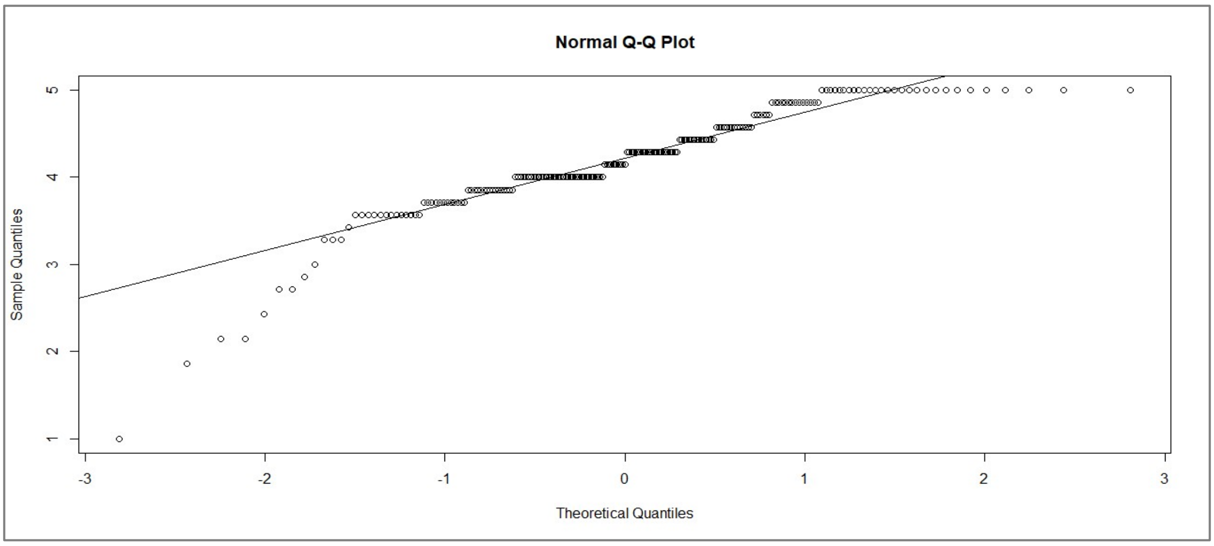

```
        Shapiro-Wilk normality test

data:  df2$digital_leadership_acumen_mean
W = 0.91825, p-value = 4.057e-09
```

F.2. Managerial capabilities moderated by DC



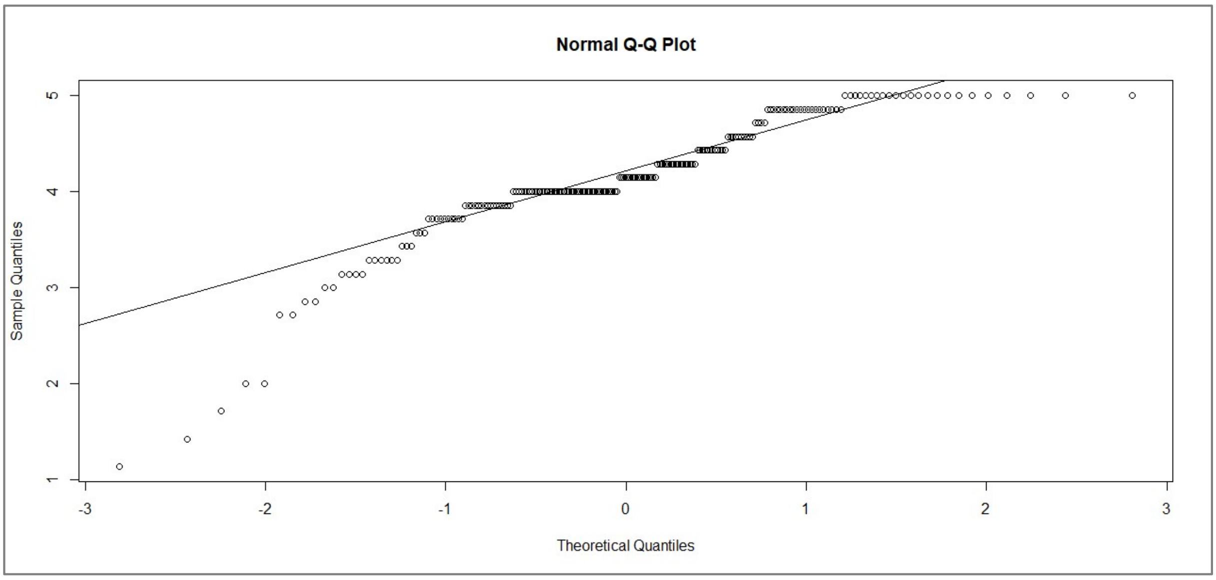

```
        Shapiro-Wilk normality test

data:  df2$digital_leadership_agility_mean
W = 0.88411, p-value = 2.529e-11
```

F.3. Operational capabilities



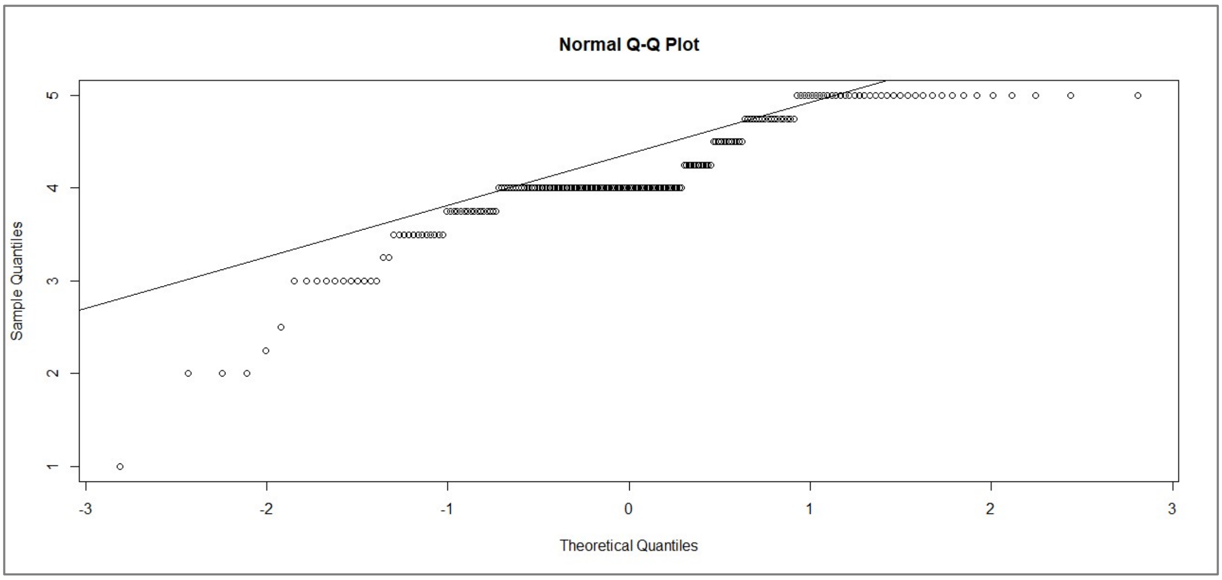

```
        Shapiro-Wilk normality test

data:  df2$digital_operational_backbone_mean
W = 0.89051, p-value = 6.034e-11
```

F.4. Operational capabilities moderated by DC




```
        Shapiro-Wilk normality test

data:  df2$digital_operational_agility_mean
W = 0.88333, p-value = 2.279e-11
```

F.5. Business performance




```
        Shapiro-Wilk normality test

data:  df2$business_performance_mean
W = 0.87932, p-value = 1.346e-11
```

G. Regularized regression model

G.1. Elastic Net RMSEs for different values of Alpha

```
   alpha       mse   fit.name
1    0.0 0.1181089    Alpha 0
2    0.1 0.1180416 Alpha 0.1
3    0.2 0.1237370 Alpha 0.2
4    0.3 0.1218829 Alpha 0.3
5    0.4 0.1200011 Alpha 0.4
6    0.5 0.1285956 Alpha 0.5
7    0.6 0.1322823 Alpha 0.6
8    0.7 0.1327655 Alpha 0.7
9    0.8 0.1299351 Alpha 0.8
10   0.9 0.1395663 Alpha 0.9
11   1.0 0.1280410    Alpha 1
```

G.2. Elastic Net with Alpha

```
5 x 1 sparse Matrix of class "dgCMatrix"
                                         s1
(Intercept)                       0.8019874
digital_leadership_acumen_mean    0.1895430
digital_operational_backbone_mean 0.1478764
digital_leadership_agility_mean   0.2229473
digital_operational_agility_mean  0.236571
```

H. Structural Equation Model

```
lavaan 0.6.16 ended normally after 90 iterations

  Estimator                                         ML
  Optimization method                           NLMINB
  Number of model parameters                        74

  Number of observations                           201

Model Test User Model:

  Test statistic                              1195.842
  Degrees of freedom                               454
  P-value (Chi-square)                           0.000

Model Test Baseline Model:

  Test statistic                              5443.346
  Degrees of freedom                               496
  P-value                                        0.000

User Model versus Baseline Model:

  Comparative Fit Index (CFI)                    0.850
  Tucker-Lewis Index (TLI)                       0.836

Loglikelihood and Information Criteria:

  Loglikelihood user model (H0)              -5467.567
  Loglikelihood unrestricted model (H1)      -4869.646

  Akaike (AIC)                               11083.133
  Bayesian (BIC)                             11327.578
  Sample-size adjusted Bayesian (SABIC)      11093.135

Root Mean Square Error of Approximation:

  RMSEA                                          0.090
  90 Percent confidence interval - lower         0.084
  90 Percent confidence interval - upper         0.096
  P-value H_0: RMSEA <= 0.050                    0.000
  P-value H_0: RMSEA >= 0.080                    0.996

Standardized Root Mean Square Residual:

  SRMR                                           0.078
```

```
Parameter Estimates:

  Standard errors                             Standard
  Information                                 Expected
  Information saturated (h1) model          Structured

Latent Variables:
                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
  DLA =~
    Q_1               1.000                               0.428    0.562
    Q_2               1.330    0.173    7.670    0.000    0.569    0.747
    Q_3               1.341    0.185    7.240    0.000    0.574    0.679
    Q_4               1.380    0.178    7.745    0.000    0.590    0.759
    Q_5               1.450    0.189    7.654    0.000    0.621    0.744
    Q_6               1.437    0.205    7.021    0.000    0.615    0.647
    Q_7               0.886    0.154    5.758    0.000    0.379    0.491
  DOB =~
    Q_8               1.000                               0.663    0.701
    Q_9               0.861    0.083   10.339    0.000    0.571    0.768
    Q_10              0.968    0.085   11.454    0.000    0.642    0.856
    Q_11              0.915    0.091   10.063    0.000    0.607    0.747
    Q_12              0.665    0.076    8.721    0.000    0.441    0.644
    Q_13              0.943    0.089   10.624    0.000    0.625    0.790
    Q_14              0.887    0.089    9.989    0.000    0.588    0.741
  DLAg =~
    Q_15              1.000                               0.493    0.639
    Q_16              1.063    0.123    8.655    0.000    0.523    0.699
    Q_17              1.037    0.111    9.332    0.000    0.511    0.768
    Q_18              1.254    0.132    9.521    0.000    0.618    0.788
    Q_19              1.345    0.134   10.005    0.000    0.662    0.841
    Q_20              1.308    0.138    9.505    0.000    0.644    0.786
    Q_21              1.333    0.140    9.498    0.000    0.656    0.785
  DOAg =~
    Q_22              1.000                               0.636    0.831
    Q_23              1.145    0.076   15.052    0.000    0.728    0.851
    Q_24              1.092    0.070   15.526    0.000    0.694    0.868
    Q_25              0.968    0.071   13.694    0.000    0.615    0.802
    Q_26              0.938    0.078   12.053    0.000    0.596    0.735
    Q_27              0.925    0.075   12.380    0.000    0.588    0.749
    Q_28              0.959    0.071   13.537    0.000    0.610    0.796
  BP =~
    Q_29              1.000                               0.646    0.840
    Q_30              1.059    0.067   15.892    0.000    0.684    0.881
    Q_31              0.824    0.073   11.220    0.000    0.532    0.699
    Q_32              1.023    0.068   15.135    0.000    0.660    0.855
Regressions:
                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
  BP ~
    DLA               0.399    0.140    2.857    0.004    0.265    0.265
    DOB               0.047    0.121    0.391    0.696    0.049    0.049
    DLAg              0.264    0.191    1.384    0.166    0.202    0.202
    DOAg              0.490    0.138    3.556    0.000    0.483    0.483

Covariances:
                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
  DLA ~~
    DOB               0.209    0.038    5.491    0.000    0.737    0.737
    DLAg              0.162    0.030    5.398    0.000    0.770    0.770
    DOAg              0.169    0.031    5.385    0.000    0.621    0.621
  DOB ~~
    DLAg              0.283    0.045    6.291    0.000    0.866    0.866
```

```
    DOAg             0.367    0.052    7.108    0.000    0.870    0.870
  DLAg ~~
    DOAg             0.275    0.041    6.772    0.000    0.877    0.877

Variances:
                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
   .Q_1              0.397    0.042    9.438    0.000    0.397    0.684
   .Q_2              0.257    0.031    8.406    0.000    0.257    0.442
   .Q_3              0.385    0.043    8.931    0.000    0.385    0.539
   .Q_4              0.256    0.031    8.272    0.000    0.256    0.423
   .Q_5              0.311    0.037    8.433    0.000    0.311    0.447
   .Q_6              0.525    0.058    9.104    0.000    0.525    0.581
   .Q_7              0.453    0.047    9.622    0.000    0.453    0.759
   .Q_8              0.456    0.049    9.327    0.000    0.456    0.509
   .Q_9              0.226    0.025    8.978    0.000    0.226    0.410
   .Q_10             0.151    0.019    8.018    0.000    0.151    0.268
   .Q_11             0.292    0.032    9.109    0.000    0.292    0.442
   .Q_12             0.274    0.029    9.512    0.000    0.274    0.585
   .Q_13             0.235    0.027    8.813    0.000    0.235    0.375
   .Q_14             0.284    0.031    9.140    0.000    0.284    0.451
   .Q_15             0.352    0.037    9.575    0.000    0.352    0.592
   .Q_16             0.287    0.031    9.400    0.000    0.287    0.512
   .Q_17             0.182    0.020    9.080    0.000    0.182    0.411
   .Q_18             0.233    0.026    8.945    0.000    0.233    0.379
   .Q_19             0.181    0.022    8.413    0.000    0.181    0.292
   .Q_20             0.257    0.029    8.957    0.000    0.257    0.382
   .Q_21             0.268    0.030    8.963    0.000    0.268    0.383
   .Q_22             0.181    0.021    8.793    0.000    0.181    0.309
   .Q_23             0.201    0.023    8.570    0.000    0.201    0.275
   .Q_24             0.158    0.019    8.340    0.000    0.158    0.247
   .Q_25             0.210    0.023    9.035    0.000    0.210    0.357
   .Q_26             0.303    0.032    9.382    0.000    0.303    0.460
   .Q_27             0.271    0.029    9.326    0.000    0.271    0.439
   .Q_28             0.215    0.024    9.077    0.000    0.215    0.367
   .Q_29             0.174    0.021    8.214    0.000    0.174    0.294
   .Q_30             0.135    0.018    7.382    0.000    0.135    0.224
   .Q_31             0.295    0.032    9.315    0.000    0.295    0.511
   .Q_32             0.161    0.020    7.966    0.000    0.161    0.269
    DLA              0.183    0.045    4.114    0.000    1.000    1.000
    DOB              0.440    0.079    5.568    0.000    1.000    1.000
    DLAg             0.243    0.049    4.946    0.000    1.000    1.000
    DOAg             0.404    0.056    7.172    0.000    1.000    1.000
   .BP               0.069    0.014    4.899    0.000    0.166    0.166
```