Gordon Institute of Business Science
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The effect of digital maturity and entrepreneurial agility on firm performance in digital transformation of traditional organisations

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Abstract

Traditional organisations are under pressure to undergo digital transformations (DT) to manage the threat of disruption caused by the adoption of digital technologies. There is thus a need for businesses to understand how competitive advantage can be achieved through their DTs. However, their progress lags that of the technology industry as they have lower digital maturity scores, fewer benefits, and still largely traditional business models. This study drew on the resource based view (RBV) and dynamic capabilities framework (DCF) to understand the effect of entrepreneurial agility (EA) and digital maturity (DM) on competitive advantage, measured through firm performance in DTs. This was achieved through a quantitative research design with 60 online survey respondents, of whom the majority were in traditional organisations. This study extends the existing theory on entrepreneurial agility to DTs by showing a positive correlation with firm performance. Similarly, the moderating effects of digital maturity on the relationship between EA and firm performance were evaluated. The results showed much fewer moderating effects than were expected following a review of the digital maturity literature. These findings are discussed in the context of recent literature on organisational- and industry-related barriers for traditional organisations in DTs. A framework for traditional organisations is proposed based on how they can leverage EA and DM to achieve a competitive advantage through DTs.

Keywords

Digital maturity, Digital transformation, Entrepreneurial agility, Competitive advantage, Firm performance.

Declaration

The following declaration should appear on a separate page:

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 Business Administration 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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List of Abbreviations and symbols

AI: Artificial intelligence
AVE: Average variance explained
CEO: Chief executive officer
CFA: Confirmatory factor analysis
CRM: Customer relationship management
DBS: Digital business strategy
DCE: Digital culture embeddedness
DCF: Dynamic capabilities framework
DI: Digital insights
DM: Digital maturity
DOS: Digital organisational structure
DT: Digital transformation
DTE: Digital technology embeddedness
DTS: Digital technology strategy
DV: Dependant variable
EA: Entrepreneurial agility
EFA: Exploratory factor analysis
FP: Firm performance
HBR: Harvard Business Review
IS: Information systems
IT: Information technology
IoT: Internet of Things
IV: Independent variable
LS: Leadership support
MV: Moderator variable
OA: Organisational agility
PCA: Principal component analysis
RBV: Resource based view
ROI: Return on investment
SMACIT: Social, mobile, analytics, cloud and internet of things
VRIN: Valuable, rare, inimitable, non-substitutable
WEF: World economic forum

β: Moderation co-efficient
r: Correlation coefficient

Chapter 1: Introduction to the research problem

1.1 Context to the research problem

Digital transformation (DT) is concerned with the adoption of digital technologies and their impacts on customer behaviour and industry competitive responses (Chanias, Myers, & Hess, 2019; Ferreira, Fernandes, & Ferreira, 2019; Hess, Benlian, Matt, & Wiesböck, 2016; Matt, Hess, & Benlian, 2015; Remane, Andre, Florian, & Lutz, 2017; Sebastian, Ross, & Beath, 2017; Verhoef et al., 2019; Vial, 2019). The disintermediation of value chains caused by these technologies is transforming the way customers engage with firms (Verhoef et al., 2019; Vial, 2019), which is creating disruptive changes that can threaten the competitive advantage and business models of incumbent firms (Bughin & van Zeebroeck, 2017; Gill & Van Boskirk, 2016; Matzler, von den Eichen, Anschober, & Kohler, 2018). Traditional organisations are driven to adopt digital technologies to compete with changes in the environment, using a measure called digital maturity to gauge their progress (Anderson & Ellerby, 2018; Gill & VanBoskirk, 2016; Gurumurthy, Schatsky, & Camhi, 2020; Kane, Palmer, Phillips, Kiron, & Buckley, 2015; 2016; 2017), however their progress has been slow, with these firms still largely operating with their traditional business models (Hanelt, Piccinini, Gregory, Hildebrandt, & Lutz, 2015; Kane et al., 2015; WEF, 2017). Considering this changing environment and proactively sensing and responding to these changes through a capability called entrepreneurial agility (EA) may be important for firms to understand how they can achieve competitive advantage through the adoption of digital technologies (Chakravarty, Grewal, & Sambamurthy, 2013; Verhoef et al., 2019; Vial, 2019).

The purpose of this research is to understand what the relationship between entrepreneurial agility and digital maturity is with regard to competitive advantage and firm performance for traditional firms that have embarked on digital transformations.

Digital transformation is a complex phenomenon because it occurs at multiple levels, i.e. the firm, industry and society (Matt et al., 2015; Matzler et al., 2018; Remane, et al., 2017). At the society level, the adoption of digital technologies is changing customers' behaviours and expectations of firms, as they prefer the use of online and omni-channel purchasing (multiple channels) and expect more efficient and customer centric service (Parise, Guinan, & Kafka, 2016). This is being enabled by the likes of social media, which has increased the level of connectivity between people in society and between customers and firms (Mhlungu, Chen, & Alkema, 2019; Vial, 2019; Westerman, Bonnet, & Mcafee, 2014). For example, a negative social media post describing the bad quality of a firm can lead to a widespread boycotting of their products.

At the industry level, digital companies are leveraging customers' affinity for digital products and services by developing business models that disrupt existing value chains through disintermediation (Teece, 2018; Verhoef et al., 2019; Warner & Wäger, 2019). An example of this is the disruption of the hotel industry by Airbnb, where customers opt to stay in another individual's personal home which provides them with a cheaper alternative than a hotel, and that individual's home becomes a source of revenue for them. This business model is thus able to capture value for customers and suppliers are created. Similarly, the car sharing service, Zipcar, is disrupting the ownership model of existing car manufacturers, where an individual's unused vehicle becomes a source of income for one person and provides a cost efficient service to others. Digital technologies enable these transactions to be facilitated with ease and efficiency (Verhoef et al., 2019).

At the firm level, incumbent firms are finding themselves under pressure to adapt to these changing market trends; not having the digital capabilities to compete in this environment puts them at a competitive disadvantage, where new, small digital firms can threaten to steal their market share because they have stronger digital capabilities (Bughin & van Zeebroeck, 2017; Karimi, 2015; Verhoef et al., 2019; Vial, 2019). This inability to compete forces traditional firms to be reactive rather than proactive, thus firms need to develop digital capabilities through a process called digital transformation. Digital transformation is defined as the process of adopting digital technologies across an organisation, fundamentally transforming business strategies, business models, business processes, firm capabilities, products and services with the purpose of achieving competitive advantage (Bhadradwaj, El Sawy, Pavlou, & Venkatraman, 2013; Matt et al., 2015; Vial, 2019).

Digital technologies, according to Bhadradwaj, El Sawy, Pavlou and Venkatraman (2013, p. 471), are viewed as "combinations of information, computing, communication, and connectivity technologies". These digital technologies go by the acronym SMACIT which includes social, mobile, analytics, cloud and internet of things. In last few years, the rapid development and pervasiveness of these digital technologies have changed the strategic approaches of firms, whereby in the past a firm's organisational or business strategy had an information technology (IT) functional strategy which supported the business strategy (Kahre, Hoffmann, & Ahlemann, 2017). IT enabled capabilities in firms to better interact with customers, e.g. through customer relationship management; helped streamline internal processes; and improved strategies through computing technologies (Kahre et al., 2017; Mithas, Krishnan, & Fornell, 2016), which had benefits for companies in terms of improved firm performance (Tallon, Queiroz, Coltman, & Sharma, 2019). However, in recent years, the strategic role of digital technologies has shifted to being integrated with the organisational strategy, called the digital business strategy (Bhadradwaj et al., 2013).

Bhadradwaj et al. (2013, p. 41) defined a digital business strategy (DBS) as an "organisational strategy formulated and executed by leveraging digital resources to create differential value". The key difference here is the overlap and integration into an organisation's operational strategy (processes, products, markets) and functional strategies (IT, finance, human resource etc.) (Hess et al., 2016; Matt et al., 2015). The DBS senses digital trends in the environment, assesses an organisation's existing capabilities in terms of being able to compete, defines what the digital capabilities required are, and assesses how firms should compete in the changing digital environment (Bhadradwaj et al., 2013; Sebastian et al., 2017). DT creates the digital resources and capabilities firms need to compete as defined by the DBS, which are managed and coordinated through the DT strategy (Chanias et al., 2019; Hess et al., 2016; Matt et al., 2015).

Management consultants and practice based literature (Anderson & Ellerby, 2018; Chanias & Hess, 2016; Gill & VanBoskirk, 2016; Gurumurthy et al., 2020; Kane et al., 2015; Remane, et al., 2017; Valdez-de-Leon, 2016) have developed digital maturity models to help firms manage their digital transformations. These instruments are based on literature analysis, expert interviews and quantitative analysis (Remane, Hanelt, Wiesboeck, & Lutz, 2017), which compares firms against a defined normative best practice standard. DM is described as the status or progress made in a firm's digital transformation (Chanias & Hess, 2016). The results from these global executive surveys and analyses indicate that there is a positive correlation between DM and a firm's performance, however these typically compare traditional firms in industries such as finance, manufacturing, automotive, mining etc. with technology firms on the same scale.

As expected, technology firms outperform traditional firms (Kane et al., 2015), thus this may not be a realistic comparison because of the industry and organisational specific challenges that firms may face (Gao, Hakanen, Töytäri, & Rajala, 2019; Vogelsang, Liere-netheler, & Packmohr, 2019; Warner & Wäger, 2019). Comparing all these firms with the same yardstick may thus be an over-simplification of their digital maturities (Remane et al., 2017). Furthermore, these digital maturities tell traditional firms what their capabilities should be, but do not describe how these digital resources and capabilities can be used to achieve competitive advantage. Developing these digital resources and capabilities may thus not be enough for competitive advantage, as many firms have invested in DT initiatives but few have seen the benefits (Sutcliff, Narsalay, & Sen, 2019; Westerman & Davenport, 2018).

Considering the changing environments created by DT, this research will also aim to understand whether there is a relationship between proactive and rapid responses to market changes and competitive advantage through entrepreneurial agility. Furthermore, it will also aim to understand whether the digital resources and capabilities developed in at DT, as measured by digital maturity, can enhance the relationship between entrepreneurial agility and firm performance in traditional firms. The next section will discuss the theoretical need based on the above argument.

1.2 Theoretical need for the research

The phenomenon of DT at the level of the organisation is dynamic in that both the external environment is driving change within the organisation, as well as the internal environment itself through the adoption of digital technologies (Vial, 2019). The external environment changes are being monitored by the firm through the DBS (Bhadradwaj et al., 2013), and internal changes by being managed by the DTS (Hess et al., 2016; Matt et al., 2015). The DT process creates digital capabilities for firms that they need in order to support the DBS to achieve the firm's competitive strategies. Hence, in order to understand this phenomenon, the resource based view (RBV) of the firm was used where if a firm's resources are VRIN (valuable, rare, inimitable, non-substitutable) (Barney, 1991), these .can lead to competitive advantage. Similarly, the dynamic capabilities framework (DCF) which extends from the RBV, helps to understand how competitive advantage can be achieved in dynamic environments through the use of dynamic capabilities (Teece & Pisano, 1994). Teece and Pisano (1994, p. 6) described dynamic capabilities as, "the subset of the competences/capabilities which allow the firm to create new products and processes, and respond to changing market circumstances".

Whilst the context for digital technologies is new, the adoption of IT in organisations is not new in information science (IS) research. Over the last two decades, several studies have been conducted on the impact of IT on competitive advantage and firm performance through the concept of organisational agility (Sambamurthy, Bharadwaj, & Grover, 2003; Overby, Bharadwaj & Sambamurty, 2006; Sambamurthy, Lim, Lee, Lee, & Lim, 2007; Lu & Ramamurthy, 2011; Chakravarty et al., 2013; Chen et al., 2014; Tallon et al., 2019). Organisational agility (OA) is defined as the ability of firms to sense competitive market opportunities, and the use of its resources to seize these opportunities (Goldman, Nagel & Preiss, 1995).

Organisational agility is seen in literature as a multi-dimensional construct, which is largely described as having a proactive and reactive component (Chakravarty et al., 2013; Felipe, Roldán, & Leal-Rodríguez, 2016; Overby, Bharadwaj, & Sambamurthy, 2006; Sambamurthy, Bharadwaj, & Grover, 2003; Sambamurthy et al., 2007). These are called entrepreneurial agility (EA) and adaptive agility (AA) respectively. EA anticipates changes in the environment and responds by conducting strategic experiments with new business models and approaches, in order to capitalise on first mover advantage through radical changes (Sambamurthy et al., 2007). This has been found to correlate with improved competitive advantage in firms, particularly in changing environments (Chakravarty et al., 2013; Sambamurthy et al., 2007), AA is more reactive and is based on institutionalising best practices in firms to recover from disruption, which leaves them vulnerable to disruption from digital firms (Chakravarty et al., 2013; Sambamurthy et al., 2007). For these reasons, EA is more suitable to the current environment created by DT.

Given that the strategic role of digital technologies have changed significantly, particularly for DTs, this means that they have a much broader impact across the organisation in not just supporting the business strategy of firms, but in defining the strategy for firms. This illustrates the need for literature to understand what the relationship between EA and FP is in the DT context. Several authors have indicated the value of organisational agility in digital transformations (Verhoef et al., 2019; Vial, 2019; Warner & Wäger, 2019), but to the researcher's knowledge there has not been an empirical assessment of this relationship .

The DM construct has been largely used by practice based literature and management consultants. Chanias et al. (2016) defined DM as progress made in a DT. While this correlates with improved FP, it is not clear what the relationships between the digital resources and capabilities developed in a DT are on enabling competitive advantage in firms. While the effects of DM on EA and firm performance have not been studied widely in literature, Chakravarty et al. (2013) showed that IT competencies can have a moderating effect between entrepreneurial agility and firm performance. This study was conducted on DT, however, and there has not been any literature measuring the moderating effects of the broader capabilities associated with DM on EA and firm performance (Vial, 2019). Researchers have highlighted the relevance some of interactive relationships between aspects of digital organisational structure and culture on enhancing agility in DT, but these have not been tested empirically (Verhoef et al., 2019; Warner & Wäger, 2019). Hence this research provides an empirical assessment of the moderating effects based on the current definitions of DM in literature. This will help to validate some of the concerns raised by Remane et al. (2017) on the construct validity of DM, which may be oversimplified in practice by assuming all industries follow the same linear path.

1.3 Business need for the research

According to global executive surveys conducted by MIT's Sloan Management Review and Deloitte, the majority of senior leaders believe their organisations will be disrupted by digital technologies, but few believe they are adequately prepared for it (Anderson & Ellerby, 2018; Kane et al., 2016). There has been significant investment globally in DT initiatives; a global executive survey by Accenture showed that between 2016 and 2018, 1,350 firms globally spent over $100 billion on digital transformation, but very few have seen the returns expected on their investment (Sutcliff et al., 2019). The implementation of digital transformations in practice thus do not always deliver the expected benefits for firms (Westerman & Davenport, 2018). This has seen the rise of C-suite executive positions such as Chief Digital Officers, as well as CEOs themselves leading the digital transformation agenda (Siebel, 2020; Singh & Hess, 2017; Westerman & Davenport, 2018).

This research aimed to provide strategic insights to traditional firms undergoing digital transformations. The first was to understand whether proactive and rapid strategic responses through EA correlate with improved competitive advantage and firm performance in DT. This may provide business leaders with insights as to whether they should adjust their DBS to incorporate these strategic approaches, for example through prospector/analyser strategies.

The second is to help understand the relationships between the digital resources and capabilities developed in a DT, measured through the use of the concept digital maturity, and the competitive advantage of traditional firms. This will provide insights to business leaders on the use of digital maturity as a lever for competitive advantage.

1.4 Scope of research

The objective of this research is to understand: what is the effect of EA and DM on firm performance for traditional firms undergoing digital transformations. The scope of the research was limited to the definitions below for the purpose of this study:

Digital transformation: the process of the adoption of digital technologies across an organisation which fundamentally transforms business strategies, business models, business processes, firm capabilities, products and services, with the purpose of achieving competitive advantage (Bhadradwaj, El Sawy, Pavlou, & Venkatraman, 2013; Matt et al., 2015; Vial, 2019).

Digital maturity: the firm's progress in developing digital resources and capabilities in a digital transformation, as an outcome of the digital transformation strategy (Chanias & Hess, 2016).

EA: a dynamic capability in a digital transformation that enables a firm to proactively sense opportunities and reconfigure its internal resources and capabilities, which can include assets, structure, strategy and resources, to bring about fundamental changes in the firm to capitalise on those opportunities (Chakravarty et al., 2013; Lu & Ramamurthy, 2011; Sambamurthy et al., 2003).

Digital technologies: are "combinations of information, computing, communication, and connectivity technologies" (Bhadradwaj, El Sawy, Pavlou, & Venkatraman, 2013, p. 471).

Chapter 2: Literature review

2.1 Introduction

This literature review presents a discussion on the complex nature of digital transformations and provides a definition of this phenomenon at the level of the organisation (Verhoef et al., 2019; Vial, 2019; Warner & Wäger, 2019). The literature review discusses the impact of digital transformation at the level of the organisation with regard to its ability to create new digital resources and capabilities through the adoption of digital technologies. This process is managed through the digital transformation strategy (Hess et al., 2016; Matt et al., 2015), which is guided by the digital business strategy of the firm (Bhadradwaj et al., 2013).

The competitive advantages that adopting digital technologies may bring to firms are discussed and their links to firm performance. Two theoretical lenses, i.e. the resource based view and dynamic capabilities, were used in this study to understand the relationships between digital maturity, entrepreneurial agility and firm performance, as well as the effects of digital maturity on the relationship between entrepreneurial agility and firm performance. The purpose of the research was to understand how these constructs can improve the competitive advantage of traditional firms undergoing digital transformations.

The literature review further explores the applicability of organisational agility for digital transformations, as well as what elements of it are most applicable to enable firms to achieve a competitive advantage in digital transformations. The proactive construct of entrepreneurial agility is then explored, as are its effects on firm performance in a digital transformation. The construct digital maturity is discussed and a definition is provided for the context of this study. The literature review goes on to explore the concept of digital maturity and its relationship with improved firm performance. Lastly, it explores the effects of digital maturity on the relationship between entrepreneurial agility and firm performance.

The next section begins with a description and definition of the phenomenon under study, namely digital transformation.

2.2 Digital Transformation

2.2.1 Description and definition of the digital transformation phenomenon

Digital transformation (DT) is concerned with the adoption and impacts of digital technologies on firms, industry and society (Chanias et al., 2019; Majchrzak, Markus, & Wareham, 2016; Matt et al., 2015; Vial, 2019), i.e. it is a multiple-level, complex phenomenon. Vial (2019) performed a literature review on digital transformation across a total of 282 papers from journals and conferences in order to describe the phenomenon of DT. Vial (2019) proposed a framework based on the literature findings, which still needs to be validated empirically.

The framework describes the adoption of digital technologies at both the industry and society levels fuels disruptions in the market place through changes in customer behaviours and expectations (Vial, 2019), which triggers competitive changes in industry and the availability of data these technologies provide (Porter & Heppelmann, 2015; Verhoef et al., 2019; Vial, 2019). The complexity of DT thus lies in that it causes changes in both the external environment through changing customer behaviours and industry responses (Matzler, von den Eichen, Anschober, & Kohler, 2018), as well as changes within the firm as it adopts digital technologies. This requires strategic alignment between the firm and the environment, which is achieved through a digital business strategy (Bhadradwaj et al., 2013) and digital transformation strategy (Matt et al., 2015). These are dependent on the adoption of digital technologies within the organisation (Bhadradwaj et al., 2013; Hess et al., 2016). At the firm level, the adoption of digital technologies enable changes in value creation paths, which are affected by structural changes (organisational culture, company structure, leadership, employee roles and responsibilities) and organisational barriers (inertia and resistance to change) (Singh & Hess, 2017; Warner & Wäger, 2019). This generates either positive effects which translate into firm performance (Westerman & Bonnet, 2015; Westerman & Mcafee, 2012), or negative effects due to security and privacy concerns (Majchrzak et al., 2016). This research focuses on digital transformation at the level of the organisation.

There is lack of consensus and clarity on the definition of DT in literature, particularly around the different impacts of adopting digital technologies across multiple units of analysis, i.e. the firm, society and industry levels (Vial, 2019; Warner & Wäger, 2019). In a literature review on the phenomenon DT, Vial (2019) reviewed definitions from 28 sources, which contained 23 definitions of DT in literature at multiple levels (society, industry and organisational). The common themes across these definitions included the use or adoption of digital technologies, the unit of analysis (society, industry or organisation), the area of transformational change, and the purpose of the change.

Vial (2019, p. 121) provided a general conceptual definition of DT, i.e. it is “a process that aims to improve an entity by triggering significant changes to its properties through combinations of information, computing, communication, and connectivity technologies”. Organisational level DT literature describes the outcomes as being fundamental changes to a firm’s strategy, processes, capabilities, products and services, which may even result in changes to the business model in order for the firm to be competitive in the environment it operates in (Bhadradwaj et al., 2013; Hess, Benlian, Matt, & Wiesböck, 2016; Matt et al., 2015; Vial, 2019). The following definition of the DT phenomenon at the level of the organisation was used in this study: the process of the adoption of digital technologies across an organisation, which fundamentally transforms business strategies, business models, business processes, firm capabilities, products and services, with the purpose of achieving competitive advantage.

2.2.2 Digital business strategy and digital transformation strategy

Bhadradwaj et al. (2013, p. 41) defined digital business strategy (DBS) as an “organisational strategy formulated and executed by leveraging digital resources to create differential value”. This has a much broader fundamental impact for the entire organisation, since it integrates across the operational and functional components of the organisation, and is based on how an organisation can create differentiated value from the adoption of digital technologies (Bhadradwaj et al., 2013). The digital business strategy detects digital trends in the external environment from the development and adoption of digital technologies in the external environment, and also assesses the organisational shifts required to create value from them. These organisational shifts are be created through the DT process. DT may require fundamentally transforming business strategies, business models, business processes, firm capabilities, products and services to create the differentiated value (Bhadradwaj et al., 2013; Hess, Benlian, Matt, & Wiesböck, 2016; Matt et al., 2015; Vial, 2019).

In order to help organisations manage this DT process, DT strategies (Hess et al., 2016; Matt et al., 2015) and digital maturity models (DMM) (Anderson & Ellerby, 2018; Gill & VanBoskirk, 2016; Kane et al., 2016; 2017) have been developed. Matt et al. (2015) and Hess, Benlian, Matt and Wiesböck (2016) developed a DT strategy to help co-ordinate the widespread changes and activities, as well as to manage the development of the firm capabilities required by the organisation's DBS. The elements of the DT strategy comprise the use of digital technologies, changes in value creation, structural changes and financial aspects (Chanias & Hess, 2016). The progress a firm makes through its DT has been described by the concept called digital maturity (DM) (Kane & Kiron, 2015; Kane et al., 2017). DM has been used as measure of progress in DT in terms of creating digital resources and digital capabilities(Anderson & Ellerby, 2018; Gurumurthy et al., 2020; Kane et al., 2017; Westerman & Mcafee, 2012).

Digital technologies, according to Bhadradwaj, El Sawy, Pavlou and Venkatraman (2013, p. 471), are viewed as "combinations of information, computing, communication, and connectivity technologies". Based on this definition, research into the adoption of digital technologies into organisations is not new, with the role of information technology (IT) being a part of information systems literature (Bhadradwaj et al., 2013; Henderson & Venkatraman, 1993; Mithas, Krishnan, & Fornell, 2016; Ngai, Chau, & Chan, 2011; Nwankpa & Roumani, 2016; Overby et al., 2006; Ravichandran, 2018; Sabherwal & Jeyaraj, 2015) Focussing on the alignment of IT strategy and business strategy, as well as the strategic role of IT in organisations. The research by Chakravarty et al. (2013) and Sambamurthy et al. (2007) identified the role of IT in enabling the concept, entrepreneurial agility (EA), which was found to positively relate to firm performance by enabling firms to proactively and rapidly respond to the changing environment. In recent years, however, the rapid development and the pervasiveness of digital technologies (e.g. social media, data analytics, internet of things, digital platforms, block chain, artificial intelligence, machine learning) has caused a shift in the strategic role of IT, from aligning and being subordinate to the business strategy, to an integrated strategy of both IT and business strategy, i.e. a digital business strategy (Bhadradwaj et al., 2013; Kahre, Hoffmann, & Ahlemann, 2017). This research thus aims to understand the relationship between EA, DM and firm performance in DTs.

2.2.3 The need for digital transformation of traditional organisations

The adoption of digital technologies is creating both existential threats and opportunities for organisations, particularly those that are still largely traditional (Sebastian et al., 2017), due to customer behavioural changes, the resultant industry responses and the threats to their existing business models. These organisations need to accelerate the adoption of these digital technologies in order to better compete in the growing digital landscape or risk being digitally disrupted (Karimi, 2015; Matzler et al., 2018; Shrivastava, 2017; Westerman & Bonnet, 2015; Westerman & Mcafee, 2012). The potential benefits are broad, including an increase in sales and productivity, creating innovative ways of creating value, and improving interactions with customers (Dremel, Herterich, Wulf, Waizmann, & Brenner, 2017;Fitzgerald, 2015; 2016a; 2016b; Gurumurthy, Schatsky, & Camhi, 2020). The widespread impacts of DT can cause a company's entire business model to change (Chanias et al., 2019; Hess et al., 2016; Matt et al., 2015; Verhoef et al., 2019), thus firms need to understand how they sense, respond to and capitalise on opportunities through EA, and how developing digital capabilities through DM affects these fundamental changes.

Digital disruption poses a major risk for incumbent firms in traditional industries (Bughin & van Zeebroeck, 2017; Matzler et al., 2018; Verhoef et al., 2019; Vial, 2019), for example the impact of online retailers like Amazon and Alibaba, which resulted in the bankruptcy of Toys"R"Us, and the disruption by Booking.com and Airbnb on the hotel industry. These digital organisations leverage digital technologies to disintermediate existing organisation's traditional products and value chains (Warner & Wäger, 2019). This is where consumers use digital technologies to access products and services directly from the suppliers without having the need to go through any traditional intermediaries like wholesalers and retailers, for example. An example is Amazon, where consumers buy their products through the platform that Amazon provides directly from the supplier, without using the traditional physical wholesale and retail stores. Another example is the car sharing market – digital companies like Zipcar can supply consumers with cars that they do not own, bypassing the traditional ownership model between consumers and car manufacturers, where the car in this model is a commodity that is shared and not owned (Hanelt, Piccinini, Gregory, Hildebrandt, & Lutz, 2015). BMW and Daimler have had to respond by developing their own digital capabilities to provide a car sharing service in this market because of consumer demand, as well as the threat by this new market to their existing business models. This disintermediation can also enable small digital firms to disrupt large traditional firms by leveraging digital technologies (Bughin & van Zeebroeck, 2017; Vial, 2019). DM and EA are therefore important for understanding the level of digital capabilities that a firm requires, as well as how to proactively respond to the disruptive environment that digital technologies are creating.

Global executive surveys conducted by MIT's Sloan Management Review and Deloitte (Kane et al., 2016) indicate that nearly 90% of executives and managers believe that their industries will be disrupted by digital technologies, but only 44% believe they are adequately prepared for it. There has thus been a significant investment globally in DT initiatives; a global executive survey by Accenture showed that between 2016 and 2018, 1,350 firms spent over $100 billion on DT, but few have reported achieving the expected benefits (Sutcliff et al., 2019). The risks of digital disruption are thus major drivers of DT in firms (Matzler et al., 2018; Vial, 2019), but companies need to understand how to gain a competitive advantage through DT (Westerman & Davenport, 2018). This research is thus relevant to help provide insights into how firms can gain these expected benefits in performance through digital transformation, by understanding the role of DM and EA.

A popular example of a successful DT vs. a company that did not digitally transform is Blockbuster and Netflix. Both these firms were once competing in the same industry, however Blockbuster failed to adopt digital technologies with the emergence of the internet and changes in customer preferences. Netflix, on the other hand, was proactive at developing its digital capabilities through DT, and reconfigured its business model. Netflix has continued to experience rapid growth and is now disrupting the TV broadcasting and film industries (Verhoef et al., 2019), while Blockbuster went bankrupt.

In summary, DT is a process that involves the adoption of digital technologies across an organisation, and as a result brings about fundamental changes within that organisation as well as the products and services it provides (Bhadradwaj et al., 2013; Hess, Benlian, Matt, & Wiesböck, 2016; Matt et al., 2015; Vial, 2019). DT creates capabilities which are leveraged by the DBS to achieve a competitive advantage for the firm (Bhadradwaj et al., 2013; Vial, 2019). The DT strategy co-ordinates and manages the development of the digital capabilities, and is guided by an organisation's DBS (Bhadradwaj et al., 2013; Matt et al., 2015). DM measures the progress an organisation makes through a DT. The purpose of this study is to understand the effects of DM and EA, which should help firms to proactively respond to the environment to manage threats of disruption and create a competitive advantage.

2.3 Firm performance and competitive advantage

Barney (1991) described competitive advantage as the outcome of a strategy that is not yet implemented by other firms, which provides a reduction in costs, the exploitation of market opportunities, and the neutralisation of competitive threats. This is viewed through the economic lens, with a firm being able to generate more economic value by the difference in perceived value and the economic costs to produce, when compared to competitors (Peteraf & Barney, 2003). Newbert (2008) described this advantage as being able to produce higher benefits for customers for the same costs as competitors, which implies a differentiation competitive advantage. Similarly, being able to produce similar benefits for lower costs implies an efficiency competitive advantage (Newbert, 2008). It is expected that these competitive advantages would translate into improved financial performance for a company, which was validated empirically by Newbert (2008) and Lin and Wu (2014). In this way, a firm's financial performance can be a measure of its competitive advantage. The purpose of DT would thus be to enable firms to achieve competitive advantage measured by improved firm performance through the adoption of digital technologies, as guided by the DBS (Bhadradwaj et al., 2013). This study aimed to understand the effect of DM and EA on achieving competitive advantage measured through firm performance in DTs.

2.3.1 Firm performance and digital transformation

Firm performance has been measured through the use of financial measures by several authors in information science literature (Chakravarty et al., 2013; Y. Chen et al., 2014; Ferreira, Fernandes, & Ferreira, 2019; Mithas et al., 2016; Sambamurthy et al., 2007; Wamba et al., 2017). These financial measures have included sales, market share, profit and return on investment (ROI). Firm financial performance will be referred to as firm performance going forward. Fitzgerald et al. (2013) indicated that firms capture value and a competitive advantage by adopting digital technologies, enhancing customer experience or engagement, streamlining their operations, generating new lines of business, and developing new business models. Developing new business models is observed less frequently in traditional companies, however (HBR Analytic Services, 2014; Fitzgerald et al., 2013).

2.3.2 Firm performance in terms of sales

The most common use of digital technologies is for customer engagement and interaction (Sebastian et al., 2017; Fitzgerald et al., 2013). This can be done through the use of social media, apps or tools, such as those for customer relationship management (CRM), which can improve customer satisfaction by increasing the level of interaction between a firm and its customers (Mithas et al., 2016; Sebastian et al., 2017), including managing queries (Gurumurthy et al., 2020; Mithas et al., 2016; Sebastian et al., 2017). Otto, Szymanski and Varadarajan (2020) indicated that customer satisfaction can lead to improved customer loyalty, positive word of mouth and an increased share of the customers' wallet, which are sources of competitive advantage that can lead to improved sales.

Firms may also use social media and internet search engines for their marketing and sales channels (Vial, 2019), which can use the data generated through advanced analytics to supply products and services based on customer needs (Bughin & van Zeebroeck, 2017). Facebook and Google, for example, use data algorithms to suggest products and services to customers on behalf of firms based on search patterns on their platforms, as well as through search engine optimisation. These technologies can give firms a competitive advantage, as customers and companies can be quickly connected through these channels. Similarly, online sales platforms can allow customers to purchase items online, which supports the customer behaviour change towards omni-channel purchases (multiple channel, physical and online) for different products and services (Bughin & van Zeebroeck, 2017; Parise, Guinan, & Kafka, 2016; Vial, 2019). This will broaden the firm's access to wider customer buying channels, which can enhance sales (Otto et al., 2020).

2.3.3 Firm performance in terms of market share

According to Edeling and Himme (2018), market share is an organisation's share of the total market, either monetary or volume. An organisation can increase its percentage of sales, but still have a lower market share than its competitors. Sales and market share are typically driven by similar factors, such as customer satisfaction (Edeling & Himme, 2018; Otto et al., 2020). Market share can also indicate an increase in competitive advantage due to higher economies of scale, market power and quality (Edeling & Himme, 2018). More advanced digital technologies include remote experts and digital assistants, which can provide real-time support to customers to improve their experience (Parise et al., 2016). This, in turn, can increase customer satisfaction and improve market share. Similarly, technologies like big data can provide firms with insights about customer trends and buying patterns, giving them superior knowledge of new products or lines of business that can help improve their market share (Wamba et al., 2017).

2.3.4 Firm performance in terms of profit

Profits can be increased when firms grow the difference between their revenues and costs, or when they reduce costs. Digital technologies can reduce costs by streamlining internal processes and improving efficiencies (Fitzgerald et al., 2013). These can include adopting cloud services to increase the efficiency of business processes and reduce costs, where these services are maintained outside of the organisation without needing a dedicated IT team (Vial, 2019). Firms can also leverage the internet of things to improve the connectivity of their products, which can provide them with insights to streamline their internal business processes (Dremel et al., 2017; Porter & Heppelmann, 2015). As an example, Audi has introduced connectivity into their vehicles, which allows them get insights from their vehicles' data to improve their maintenance, product and service offerings. These can help reduce costs by improving efficiency, for example the design process lead time of vehicles in the automotive industry can be significantly reduced using simulation software (Hanelt et al., 2015). This can save costs in the design process and give firms a competitive advantage in terms of the cost of producing their vehicles, which increases their profitability. Similarly, digital technologies enable the automation of business processes through technologies like robotic process automation (Gurumurthy et al., 2020; Porter & Heppelmann, 2015; Westerman & Bonnet, 2015). This can add efficiencies to existing processes and reduce labour costs, which can create competitive advantage and improve profitability.

2.3.5 Firm performance in terms of ROI

ROI is an indication of an organisation's ability to generate a higher return per unit capital invested (Ward & Price, 2019), and can be measured by profit divided by capital invested. ROI thus depends on the ability of firms to generate a higher profit, as discussed above, but with the same or less capital invested to create a competitive advantage. This can be achieved through the scalability of digital technologies such as cloud computing or digital platforms (Bhadradwaj et al., 2013; Sebastian et al., 2017; Vial, 2019). This can result in firms leveraging economies of scale without significantly changing their capital invested in digital technologies. An example of a firm that uses digital platforms is First National Bank, which has created a banking app. The company is able to add several features quickly to the app to improve customers' experiences and grow their customer base.

Cloud computing has the benefit of being-service based, where a firm does not need to invest in the IT infrastructure required while still gaining the computing power it needs for its business processes through service- and subscription-based payment structures. These can enable firms to scale up their services with less capital, which increases their competitive advantage through ROI.

In summary, competitive advantage can be measured through firm performance. The adoption of digital technologies can provide firms with competitive advantages across all the sub-constructs of firm performance. The next section discusses the theory base used in this study to understand how the dependent variable in this study, firm performance, relates to the variables EA and DM.

2.4 Theory: Resource based view and dynamic capabilities

As discussed earlier, firm performance is a measure of competitive advantage that organisations can realise through DT. An organisation can create higher value for customers by how it directs its digital resources and capabilities through the DBS (Bhadradwaj et al., 2013). These resources and capabilities are developed as the organisation progresses through the DT (Verhoef et al., 2019). This is co-ordinated and managed by the DT strategy (Hess et al., 2016), which supports the DBS (Bhadradwaj et al., 2013). Within a DT, these resources and capabilities are developed, configured and reconfigured over time as the firm adopts new digital technologies (Chanias et al., 2019). The DT environment within a firm is thus dynamic. Similarly, in the external environment, which is also being impacted by digital technologies, as consumers and industries adopt these technologies, this triggers changes in the environment (Vial, 2019). A company thus needs to constantly sense these market changes, whilst also being cognisant of its internal changes due to its DT. The external market changes are identified and managed through the DBS (Bhadradwaj et al., 2013) in terms of how a organisation competes in the environment (Sebastian et al., 2017). The DT strategy then guides the DT efforts, which effects the changes required in the organisation (Hess et al., 2016; Matt et al., 2015). In order to understand how these resources and capabilities change over time, the resource based view (RBV) (Wernerfelt, 1984; Barney, 1991) and the dynamic capabilities framework (DCF) (Teece & Pisano, 1994) were found to be appropriate theoretical lenses.

The RBV of a firm is a theoretical lens that analyses a firm based on its resources, which was introduced by Penrose (1959) and further described by Wernerfelt (1984). A firm's resources were defined by Barney (1991, p. 101) as "all assets, capabilities, organisational processes, firm attributes, information and knowledge" that are controlled by a firm, which enable strategies to be developed and implemented to improve its effectiveness and efficiency. These resources can be divided into organisational, human and physical resources. Organisational resources include a firm's organisational structure; planning, coordinating and controlling systems; and informal relationships between groups within a firm and between the firm and the environment. Physical resources include technology, plants and equipment, geographic location and raw materials, while human resources include the experience, training, judgement, intelligence, relationships and insights of both workers and individual managers in a firm. Barney (1991) noted that these resources need to be valuable, rare, imperfectly imitable, and non-substitutable (VRIN) in order to achieve sustained competitive advantage. A firm undergoing a DT would develop new digital resources and capabilities as required (Verhoef et al., 2019) by the DBS, which can span across the organisational, physical and human resources. The assumption with Barney's (1991) theory is that the firm's resources remain stable over time, but this is not the case with DT, as the firm is undergoing a continuous resource and capability configuration and reconfiguration because of the changing environment.

Teece and Pisano (1994) identified adapting to changing environments as an important component in achieving competitive advantage, which is why they introduced the dynamic capabilities framework (DCF). The authors used the term "dynamic" to describe the changing nature of the environment, the accelerating pace of innovation, and the future competition and market that is difficult to determine. Thus this dynamic environment applies to DTs. They emphasised "capabilities" as being able to adapt, integrate, and reconfigure internal and external organisational skills, resources and functional competencies to the changing environment through strategic management (Teece & Pisano, 1994). Teece and Pisano (1994, p. 6) described dynamic capabilities as "the subset of the competences/capabilities which allow the firm to create new products and processes, and respond to changing market circumstances". Teece et al. (2016) further described dynamic capabilities as having sensing, seizing and transforming capabilities. Sensing capabilities were described by the authors as identifying, developing, and assessing market opportunities that are identified in relation to customer needs for anticipating unknown future needs. Seizing, meanwhile, was described as being able to mobilise resources to cater for these needs and opportunities, and being able to capture value from them. Finally, transforming was described as the continued renewal of these capabilities over time through implementing processes or systems. Hence considering the changing environment created by DTs and the purpose of competitive advantage, dynamic capabilities may be an important lever for firms undergoing DTs.

In summary, as a firm progresses through a DT, fundamental changes occur which can result in new digital resources and capabilities being created across the organisation. The RBV of the firm can help in understanding how these resources can be VRIN to enable a competitive advantage, as well as how dynamic capabilities in terms of sensing, seizing and transforming are required to respond to the changing environment to support DT in achieving a competitive advantage. The capability that firms may use to respond to environmental changes is called organisational agility, which will be discussed in the next section.

2.5 Organisational agility

2.5.1 Organisational agility as a dynamic capability

Organisational agility (OA) can be defined as the ability of firms to sense competitive market opportunities, and the use of their resources to seize these opportunities (Goldman, Nagel & Preiss, 1995). Teece, Peteraf and Leih (2016) described agility simply as being flexible to change and the valuable capability or competence that firms have to face uncertainty. If firms were able to predict the future, they would reconfigure their resources in order to best compete, but as they cannot, Teece, Peteraf and Leih (2016) argued that firms need to continuously reconfigure and transform themselves ahead of their competitors to achieve a competitive advantage. Felipe, Roldán and Leal-Rodríguez (2016), meanwhile, described organisational agility as the ability to sense environmental changes and respond effectively and efficiently, which is a dynamic capability (Teece, Peteraf & Leih, 2016). Understanding how OA as a dynamic capability can lead to competitive advantage in a DT is thus relevant for this study.

Several authors have used the DC framework to view OA as a dynamic capability because of the continuous need to reconfigure a firm's resources and capabilities in responding to external market changes (Chakravarty et al., 2013; Felipe et al., 2016; Teece, Peteraf & Leih, 2016; Overby, Bharadwaj & Sambamurty, 2006; Sambamurthy, Bharadwaj, & Grover, 2003). A DT that requires a firm's resources and capabilities to be reconfigured over time because of the changing environment, organisational agility can be described as dynamic capability that describes how these resources and capabilities can be combined over time to achieve competitive advantage through sensing and seizing dynamic capabilities.

2.5.2 Organisational agility and digital transformation

The majority of the information systems (IS) literature on organisational agility in the last two decades have focused on the information technology (IT) context, where the role of IT in enabling organisational agility and firm performance were investigated (Sambamurthy, Bharadwaj, & Grover, 2003; Overby, Bharadwaj & Sambamurty, 2006; Sambamurthy, Lim, Lee, Lee, & Lim, 2007; Lu & Ramamurthy, 2011; Chakravarty et al., 2013; Chen et al., 2014; Tallon et al., 2019). This followed the findings of Sambamurthy et al. (2003), who indicated that IT plays a significant role in enabling agility and digital options for firms, while also enabling entrenpreneural actions. These digital options, agility and entrepreneural actions were seen by the authors as possible sources of achieving competitive advantage.

The literature largely demonstrates the significance of IT in enabling agility (Chakravarty et al., 2013; Y. Chen et al., 2014; Lee, Sambamurthy, Lim, & Wei, 2015; Overby et al., 2006; Sambamurthy et al., 2003; 2007; Tallon, Queiroz, Coltman, & Sharma, 2019), but also describes the moderating effect of the external environment's dynamism and hostility between agility and firm performance (Chakravarty et al., 2013; Y. Chen et al., 2014). In DT, the context is different because it focuses on more than just the IT function, i.e. it impacts across the entire organisation through the DT strategy and DBS (Vial, 2019; Chanias, Myers, & Hess, 2019; Matt, Hess, & Benlian, 2015). Furthermore, both Vial (2019) and Warner and Wäger (2019) identified agility as an important lever in both being able to generate new value creation paths, as well as being an ongoing mechanism for dynamic capabilities to renew an organisation's strategy through DTs. Similarly Verhoef et al. (2021) identified agility as a critical component for a successful DT. In addition, Vial (2019) called for further research in order to understand digital transformations using dynamic capabilities. The subconstructs of organisational agility will be discussed in the next section.

2.5.3 Adaptive agility and entrepreneurial agility as a function of organisational agility

Organisational agility in literature is a multi-dimensional construct which is largely described as having both proactive and reactive components (Chakravarty et al., 2013; Felipe et al., 2016; Overby et al., 2006; Sambamurthy et al., 2003; 2007). Chakravarty, Grewal and Sambamurthy (2013) and Sambamurthy, Lim, Lee, Lee and Lim (2007) described these components as entrepreneural agility (EA) and adaptive agility (AA). Similarly Lu and Ramamurthy (2011) described two types of agility which they called market capitalising agility and operational adjustment agility, which demonstrate overlap and similar thinking around the multi-dimensional constructs of agility.

2.5.4 The use of entrepreneurial agility as opposed to adaptive agility as a construct of organizational agility for digital transformations

In the context of DTs, which are prompting organisations to introduce radical fundamental changes to their business strategies, business models, business processes, firm capabilities, products and services, both types of organisational agility are discussed in this context to understand their relevance for DT. The differences in both types of OA lies in how an organisation responds to DT.

EA anticipates changes in the environment and responds by conducting strategic experiments with new business models and approaches, in order to capitalise on first mover advantage through radical changes (Sambamurthy et al., 2007). Within EA, a firm foresees future scenarios, modifies its strategic position, modifies or changes existing strategic assets and resources, and rapidly takes advantage of opportunities. EA captures an organisational entrepreneurial mindset (Sambamurthy et al., 2007), which according to

Lee et al. (2015) and Teece, Peteraf and Leih (2016) is necessary for a firm to remain competitive in dynamic environments, which is the case in DT. EA manifests as a dynamic capability both in the ability to sense trends in the environment, as well as its ability to reconfigure the organisation rapidly to take advantage of opportunities (Teece et al., 2016). This can result in new products, new markets, new business models, acquiring new assets, changing organisational structure and changing strategy to be able to capitalise on market opportunities (Chakravarty et al., 2013; D. Teece et al., 2016) which may arise through the DBS. This aligns with the dynamic capabilities which are required in DT to proactively sense changes and reconfigure digital resources and capabilities to respond to the environment in order to achieve a competitive advantage.

AA is adaptive to environmental changes in order to maintain its competitive position, by keeping industry best practices and to manage threats and emerging business opportunities. It focuses on recovering quickly from disruption without fundamentally changing products or processes (Chakravarty et al., 2013; Sambamurthy et al., 2003). This capability can result in firms institutionalising best practice methods which enable them to preserve competitive advantage and market changes, but it is incremental in its approach rather than radical (Sambamurthy et al., 2007). This leaves firms at risk where the external disruption requires a fundamental change to business models, strategies, products and processes (Teece et al., 2016). When considering the requirements for a DT, AA is thus not suitable.

Further to the above argument, the results of Chakravarty et al.'s (2013) study within the electronic market place which simulated a digital operating environment, that EA played a much stronger role than AA on firm performance in this environment which was dynamic and required fundamental organisational changes. In fact, AA was found to have no significant relationship with firm performance. Similarly, Sambamurthy et al. (2007) demonstrated in separate study that EA was found to be superior to AA in terms of a firm's competitive position for similar reasons. Therefore, in the context of DT which involves fundamental changes to an organisation, EA was used in this study to understand its impact on firm performance in DTs. The following definition of EA was used for this research: EA is a dynamic capability in a DT that enables a firm to proactively sense opportunities and reconfigure its internal resources and capabilities, which can include assets, structure, strategy, and resources, to bring about fundamental changes in the firm to capitalise on those opportunities (Chakravarty et al., 2013; Lu & Ramamurthy, 2011; Sambamurthy et al., 2003).

2.6 Entrepreneurial agility and firm performance

The effect of entrepreneurial agility on firm performance has been established in information systems (IS) literature (Chakravarty et al., 2013; Lu & Ramamurthy, 2011; Sambamurthy et al., 2003; Tallon et al., 2019) as having a positive relationship with firm performance. This is particularly true in changing environments (Liu, Song, & Cai, 2014) as it is able to actively sense changes in the market and respond quickly to them. Sambamurthy et al. (2007) indicated that EA has a positive relationship with a firm's competitive position but no significant relationship with profitability, because EA favours rapid responses to innovative market opportunities rather than focusing on improving internal efficiencies. There may cases where both efficiency and effectiveness can be achieved through digital technologies however, such as the examples of Uber and Airbnb, which are able to scale up and down rapidly with low marginal costs. Nevertheless, the majority of this research focused on the capabilities of IT within an organisation (Chakravarty et al., 2013; Sabherwal & Jeyaraj, 2015; Sambamurthy et al., 2007; Tallon et al., 2019; Tippins & Sohi, 2003).

The adoption of digital technologies in DTs are much broader and more integrated into the firm's business strategy (DBS), i.e. they are not a functional IT strategy supporting the business strategy (Bhadradwaj et al., 2013; Chakravarty et al., 2013; Sambamurthy et al., 2003; Tallon et al., 2019). The role of EA in a DT could therefore have much more profound effects on the organisation with the adoption of digital technologies. This is relevant considering the wider impacts of integrating IT and business strategies (Bhadradwaj et al., 2013) on the organisation. The effect of EA on firm performance within a DT has not been empirically determined, however, with recent literature noting the importance of agility in DTs (Verhoef et al., 2019; Vial, 2019; Warner & Wäger, 2019). A contribution to the body of knowledge would thus be to determine the relationships between EA and firm performance in a DT.

In summary, EA is a dynamic capability of a firm's ability to sense market opportunities, and to seize these opportunities by being able to fundamentally reconfigure the resources and capabilities in the organisation in order to rapidly capitalise on opportunities (Teece, Pisano, & Shuen, 1997; Teece et al., 2016). These digital resources and capabilities created within a DT will be reconfigured through EA to bring about fundamental changes to strategies, assets, positioning, and the business model. The speed, breadth and impact of the changes required in a DT enable EA to be more effective in uncertain changing environments created by DT, which may require fundamental changes to the firm (Teece et al., 2016). The key features of EA are proactive sensing, speed of response, breadth of response, as well as the ability to capitalise and realise the value from opportunities. The benefits of EA will be discussed in the next sections in terms of supporting proactive market strategies for firms, as well as the DBS, to achieve competitive advantage.

2.6.1 Entrepreneurial agility and proactive market strategies

The ability to sense market changes and trends in a proactive way has benefits for the firm, as it creates superior knowledge of the market and customers ahead of competitors which can provide a valuable, rare and hard to imitate resource (Barney, 1991). This can, in turn, lead to competitive advantage and improved firm performance (Cegarra-Navarro, Soto-Acosta, & Wensley, 2016; Chung, Liang, Peng, & Chen, 2010; Liu et al., 2014).

In the case of DT, where the superior knowledge of customers and opportunities can differentiate firms from their competitors, this is an importance source of competitive advantage (Chung et al., 2010). Similarly, having the ability to reconfigure resources to rapidly respond to this superior knowledge and capitalise on opportunities is a source of competitive advantage (Teece & Pisano, 1994). Having superior knowledge ahead of competitors and the ability to rapidly reconfigure resources and strategies can enable firms to have first mover advantages and apply prospector or analyser organisational strategies in a DT because of their suitability for changing environments (Feng & Feng, 2020; Miles, Snow, Meyer, & Coleman Jr., 1978; Zachary, Gianiodis, & Markman, 2015).

Miles et al. (1978) developed a strategic type framework which divides a firm's approaches to strategy into prospectors, defenders, analysers or reactors. Prospectors tend to continuously seek new opportunities in the market rather than just focus on what is existing; analysers try to balance finding new opportunities with managing their firm's existing portfolio; defenders focus on maintaining their position in the market within their existing domain; and reactors have an inconsistent and unstable response to their environment (Lee et al., 2015; Miles et al., 1978). Prospectors and analysers are similar in that both proactively seek market opportunities, with analysers also maintaining and strengthening their existing portfolio. Defenders and reactors do not explore new opportunities and are vulnerable to environmental changes such as digital disruption. In the context of integrating a business and IT strategy, research by Sabherwal and Chan (2001) indicated a positive correlation to firm financial performance for prospectors and analysers, but not for defenders and reactors. Prospectors and analysers, through their proactive search for new opportunities, are able to respond to market changes better by understanding customer trends and changes, and by developing new products or services. This enables firms to capitalise on entering new markets or developing new products ahead of their competitors, which would improve sales and market share through being the first to market (Miles et al., 1978; Sabherwal & Chan, 2001). These strategies can form part of the overall DBS, which can also highlight requirements for the DT strategy to prevent firms from being forced into a defender/reactor strategy due to disruption because they did not develop the required digital resources and capabilities in order to compete in new digital markets (Bughin & van Zeebroeck, 2017).

EA may also impact firm performance in a DT, as described above, by enabling first or second mover advantage, by being able to sense market opportunities ahead of the competition, and by being able to rapidly respond to them. First mover advantage refers to the phenomenon where the first or early firms to enter a new market are more likely to achieve better performance in terms of market share or profitability than later entrants, while second mover advantage occurs when firms learn from the pioneering firm and are better prepared to enter new markets or products (Feng & Feng, 2020; Lieberman & Montgomery, 1988). Early entrants can establish a customer base, earn loyalty, learn from customers and impose buyer switching costs onto competitors who have to invest to gain market share (Feng & Feng, 2020; Lieberman & Montgomery, 1988). In the case where profits improve through first mover advantage, Lieberman and Montgomery (1988) considered this to be due to superior entrepreneurial action from the firm, since in practice entrepreneurial decisions can lead to success or failure and therefore carry an element of risk.

According to a report by HBR Analytic Services (2014), which surveyed 672 firms in business and technology on the adoption of digital technologies and their business performance, firms that are “pioneers” or that use first mover advantage with digital offerings are more likely to lead in revenue growth and market share than the lagging firms. These results also indicated that firms that are more likely to make first mover advantages are also more “digitally transformed”, particularly with regards to their core strategy, business model and changes to products and services offered (HBR Analytic Services, 2014). Similarly, the first mover advantage strategy can exist in the DBS of firms (Sebastian et al., 2017) to enable competitive advantages, which can be enhanced through EA.

2.6.2 Entrepreneurial agility and digital business strategies

Sebastian et al. (2017) indicated that firms with a DBS commonly adopt either a customer engagement strategy or a digitised solutions strategy in order to improve customer satisfaction and firm performance. Customer satisfaction can be measured by perceived quality, perceived value and customer expectations (Mithas et al., 2016; Otto et al., 2020). Similarly, several other authors indicated that the majority of firms are trying to improve customer interactions and satisfaction through the use of digital technologies (Gurumurthy et al., 2020; Kane et al., 2016, 2017; Westerman et al., 2014). The customer engagement strategy focuses on building customer loyalty and trust, as well as enhanced customer experiences, through the improved understanding of customers (Sebastian et al., 2017). The digitised solutions strategy focuses on proactively developing products for customers based on digitising existing products or developing new products for customers based on their needs (Sebastian et al., 2017).

Both of these strategies can be enhanced by EA, firstly through proactive sensing of the market to better understand customer needs and trends. This improves the perceived quality and value of products and services provided to customers by anticipating their needs, which leads to improved customer satisfaction, customer loyalty and trust (Otto et al., 2020; Sebastian et al., 2017). This can improve firm performance in terms of sales and market share (Edeling & Himme, 2018; Otto et al., 2020). A digitised solutions strategy would be enhanced by EA because it enables a rapid response by developing new products and/or services, or possibly even business models. This would improve the speed and effectiveness of translating opportunities into financially viable solutions for customers, which can improve sales, profitability, market share and ROI (Sebastian et al., 2017).

In summary, it is expected that EA would positively enhance the implementation of proactive market strategies like prospector/analyser and first mover advantages, as well as commonly used strategies within the DBS, which can result in improved firm performance through improved customer satisfaction in a DT (sales, market share, profitability and ROI). The capabilities required for these strategies would be identified by the DBS, and executed through the DT strategy. As described earlier, in DT, firms create digital resources and capabilities. The progress firms make in creating these resources and capabilities is described by the DM of the firm. These can impact the competitive advantage of firms and will be discussed in the next section.

2.7 Digital maturity

2.7.1 Digital maturity and digital transformation

Digital maturity as a construct has not been well defined in literature (Berghaus & Back, 2016; Chanias & Hess, 2016; Remane, et al., 2017); most of the explanations come from practice based literature and management consultants through the development of digital maturity models (DMMs) (Anderson & Ellerby, 2018; Carolis, Macchi, Negri, & Terzi, 2017; Fitzgerald, Kruschwitz, Bonnet, & Welch, 2013; Gill & VanBoskirk, 2016; Kane et al., 2017; Valdez-de-Leon, 2016). These digital maturity models largely use expert interviews, literature analysis, or quantitative analysis (Remane, et al., 2017) to develop these models. These DMMs take a normative approach to compare the firm's DT resources and capabilities to a defined measure of best practice. This, of course, does not consider the firm and industry specific challenges that firms may experience, but it is currently used as indication of how a firm's digital transformation is progressing in the absence of a empirically validated model of digital maturity (Chanias & Hess, 2016).

According to Becker, Niehaves, Poeppelbuss and Simons (2010), maturity models are conceptual models that describe anticipated, logical and desired evolution paths to maturity. Maturity can be regarded a measure which evaluates the capabilities of an organisation in regards to a certain discipline (Becker et al., 2010). Remane et al. (2017) described maturity as the degree of completion of a desired transformation which can be applied in the context of an organisation's DT. Chanias and Hess (2016) provided two definitions of digital maturity; the first defines it from a technological perspective, which is the extent to which a firm's tasks and information flows are handled by IT, while the second definition is from a management perspective, which is the status in an organisation's DT, or how much progress the firm has made in digitally transforming. The DT process occurs when an organisation develops digital resources and capabilities guided by the DT strategy. Based on the above, the following definition of DM is proposed in the context of this study: DM is the firm's progress in developing digital resources and capabilities in a DT, as an outcome of the DT strategy.

Some of the shortcomings of the DMM approach include viewing the digital maturity as a linear process; this assumes that all industries follow the same path, from low maturity to high maturity, which is seen as an oversimplification (Remane et al., 2017). Empirical work in IS research in industries such as healthcare, automotive, newspaper, photography and commercial printing, indicate that digtal transformations depend on context and can have their own digital maturity paths, which may be non-linear (Remane, Hanelt, Wiesboeck, & Lutz, 2017). Similarly, research has also indicated internal and external barriers to digital transformation paths in some asset intensive industries like mining and manufacturing, which can hinder digital maturity (Gao, Hakanen, Töytäri, & Rajala, 2019; Vogelsang, Liere-netheler, & Packmohr, 2019). Furthermore, digital transformation and digital maturity have a moving target, because as digital technologies advance, so the requirements for digital maturity and DTs change (Chanias et al., 2019; Remane et al., 2017).

2.7.2 Digital technology, digital culture, digital organisational structure and digital insights as a function of digital maturity

Digital maturity as a construct has not been well defined in literature (Berghaus & Back, 2016; Chanias & Hess, 2016; Remane, et al., 2017), however there are several themes which are consistent in the way digital maturity is measured across DMM (Anderson & Ellerby, 2018; Berghaus & Back, 2016; Carolis et al., 2017; Gill & VanBoskirk, 2016; Valdez-de-Leon, 2016). These include the use of digital technology, digital organisational culture, digital organisational structure and digital insights. Digital technology measures the level of adoption of digital technologies in an organisation, while digital culture refers to the extent to which an organisation's behaviour has been adapted and changed to be supportive of the DBS. Digital organisational structure, meanwhile, refers to the structure of the organisation and how resources are configured to support the DBS. Finally, digital insights refer to the use of customer insights in decision making, as well as feedback of information incorporating lessons learned, for continuous improvement in the DT. These common themes were used to measure digital maturity in this study, as adapted from the DMM provided by Gill and Van Boskirk (2016).

The digital technology measure is a logical inclusion in the measure of digital maturity because the adoption of digital technologies is driving DTs (Chanias & Hess, 2016; Hess et al., 2016; Matt et al., 2015; Vial, 2019). This includes the extent of adoption of various digital technologies within the firm. According to the RBV, digital technologies are considered to be a resource of the firm because they can be considered to be physical assets (Barney, 1991). These digital technologies are not unique to the firm and can be imitated by others, hence it is not the digital technologies alone that impact DT (Kane et al., 2016; Westerman & Davenport, 2018). It is therefore the knowledge of how to use these digital technologies and how well they are adopted within the organisation that create digital capabilities, which are important in that they can create economic value that is difficult to imitate, which provides a competitive advantage. The digital technology construct thus describes the types of digital technologies used, which are resources, the level of adoption into their DBS, and the capabilities a firm develops in order to generate value from these.

Digital culture is also considered to be critically important in the large scale change processes associated with DTs (Anderson & Ellerby, 2018; Chanias et al., 2019; Dremel et al., 2017; Fitzgerald et al., 2013; Kane et al., 2016; Teece et al., 2016; Vial, 2019). Culture in an organisation can generally be defined as a set of unconscious basic assumptions within a group based on its history of solving external and internal problems (Schein, 1992), which is typically difficult to change. In the RBV of the firm, this is considered an organisational resource that can leveraged for competitive advantage. For DT, there is a preferred "digital culture" which fosters collaboration between employees across functions, is innovation focused, is willing to take risks and experiment, is aspirational, and is developed within the DT process (Chanias et al., 2019; Dremel et al., 2017; Kane et al., 2016; Vial, 2019). For this reason, although culture is considered a resource and is generally difficult to change (Schein, 1992; Warner & Wäger, 2019), digital culture can be considered to be a set of strategic capabilities that an organisation needs to develop as part of its DT strategy (Kane & Kiron, 2015), which is configured over time with the long term strategic vision of changing the organisation's culture (Warner & Wäger, 2019). Culture can hinder DT progress or the implementation of changes due to politics, inertia or resistance to change within the organisation, thus the supportive role of leadership is considered important in driving change efforts from the top down (Chanias et al., 2019; Teece et al., 2016; Vial, 2019; Warner & Wäger, 2019). Organisations have appointed change leaders, as well as Chief Digital Officers, to manage the DT process, and in some cases the CEOs themselves take this role (Chanias et al., 2019; Hauari, 2020; Mckinstry, 2019; Singh & Hess, 2017; Vial, 2019). An element of creating a digital culture can also include digital training and the talent development of employees, or some rely on the skills of external contractors. More digitally mature companies invest in equipping and developing these skills and knowledge internally (Kane et al., 2016).

The digital organisational structure measure is an indication of the organisational structural changes required during DTs. Similarly, organisational structure can be considered a capability of the firm which describes how activities, processes and human resources are organised, which can be configured for competitive advantage (Barney, 1991). The digital organisational structure is the set of capabilities the organisation needs to develop in order to be agile enough to operate and respond to changes required within the DT process. These work on experimenting and integrating digital opportunities across various business functions (Chanias et al., 2019; Vial, 2019; Verhoef et al., 2019). An example of this is Audi, which has a dedicated data analytics team that operates outside line management. The team is focused purely on its digital initiatives, which are integrated with other functions to provide products and solutions (Dremel et al., 2017).

Dedicated teams are created to ensure independence from organisational politics and resistance to change to support the long term sustainability of their DT efforts. Having the right digital skills is important for work execution, and the digital organisational structure may also be adapted to include the use of external consultants to help navigate the DT process as they bring valuable expertise and experience (Chanias et al., 2019). Similarly, the role of the Chief Digital Officer (CDO) has been introduced within the C-suite structure to help the CEO manage DTs (Singh & Hess, 2017). Furthermore, a structure which is less hierarchical to facilitate top down and bottom up engagement, as well as the generation of ideas from employees, is preferred (Chanias et al., 2019; Kane et al., 2016, 2017). Some organisations also incorporate the use of dedicated management committees, which adjudicate on and manage the flow of ideas into commercially ready products through innovation processes (Chanias et al., 2019).

Digital insights refer to capturing customer insights and incorporating changes, continuous feedback and learning processes through the DT process, which shapes all the other components, including digital technology, digital culture, digital organisational structure, and developing knowledge management processes (Chanias et al., 2019; Chung et al., 2010; Kane et al., 2016; 2017). Hence digital insights can be defined as being able to capture knowledge both internally and externally in a DT, and continuously learning and acting on this within the organisation (Chanias et al., 2019; Chung et al., 2010; Gill & Van Boskirk, 2016). Knowledge within an organisation, according to the RBV, is considered to be a resource, which can be configured for competitive advantage if is valuable, unique and difficult to imitate (Barney, 1991). Internally, this refers to learning from experimenting on new products or services which feeds back into strategy, processes and products (Chanias et al., 2019; Chung et al., 2010; Kane et al., 2016, 2017). Externally, this includes capturing knowledge about customer needs and interacting with customers, which generates data that can be used to better design products and services (Sebastian et al., 2017). Digital technologies have been able to enhance this ability by enabling the measurement of customer trends and preferences, which have been leveraged by digital firms such as Amazon, Facebook, Netflix, and Google through the use social media platforms, data captured on their platforms, machine learning and big data analytics, all of which can improve firm performance (Vial, 2019; Wamba et al., 2017). This is providing competitive advantages for these firms as they can better understand their own needs as well as those of their customers. As such, their growth has been exponential over the last few years (Verhoef et al., 2019).

2.8 The relationship between digital maturity and firm performance

This application of the digital maturity models in global executive surveys has shown that there is a positive relationship between a firm’s digital maturity and its firm performance in terms of sales, market share, profitability and return on investment. (Fitzgerald et al., 2013; Gurumurthy et al., 2020). An alternative approach by Eremina, Lace and Bistrova (2019) measured the financial performance of a sample of Baltic firms by analysing their financial reports for key words, which was translated into a digital maturity score. This was measured and compared against the reported corporate financial performance over time, which indicated a positive relationship between the firm’s digital maturity scores and financial performance across the dimensions of sales, market share, profit, and ROI. This improved performance was attributed to a higher level of digital resources and capabilities.

The adoption and use of digital technologies such as cloud services increases efficiencies (Dremel et al., 2017; Gurumurthy et al., 2020; Vial, 2019), while improved customer interactions and engagements through the use of digital technologies also results in improved customer experience (Anderson & Ellerby, 2018; Fitzgerald et al., 2013; Kane et al., 2016; 2017). In turn, improved customer experience and engagement increases customer satisfaction and loyalty (Gurumurthy et al., 2020; Kane et al., 2016; Sebastian et al., 2017), which grows overall firm performance. A key observation by Kane et al. (2016) is that DT is not only enhanced by the adoption of digital technologies, but also through broader digital resources and capabilities such as digital culture, digital organisational structure and integrating digital insights.

The link between customer satisfaction and firm performance has further been shown to improve firm performance in terms of sales and market share (Otto et al., 2020), as well as increasing customer lifetime value through customer loyalty (Gurumurthy et al., 2020). In terms of digital technology, Mithas et al. (2016) demonstrated a positive link between IT, customer satisfaction and firm performance. Similarly, more digitally mature firms have stronger digital cultures which are more collaborative, integrated and innovation focused, which enable the creation of new products and services, resulting in improved sales and revenues as well as improved quality (Gurumurthy et al., 2020; Kane et al., 2016, 2017; Sebastian et al., 2017). Furthermore, stronger leadership support from executive leadership were a feature of more digitally mature and successful firms (Chanias et al., 2019; Hauari, 2020; Mckinstry, 2019; Singh & Hess, 2017). The digital organisational structures of more mature firms focus on developing in-house talent and digital skills by investing in their own employees as opposed to external consultants. This improves employee engagement (Gurumurthy et al., 2020) and provides the skills required for developing new innovative products and services. The digital organisational structures have the flexibility to respond to market needs quickly (Teece et al., 2016), support innovation, and integrate with other functions to develop new products and services (Dremel et al., 2017).

In summary, DM correlates with improved firm performance, which has been confirmed in literature (Anderson & Ellerby, 2018; Eremina et al., 2019; B. M. Fitzgerald et al., 2013; Gurumurthy et al., 2020; Kane et al., 2017; Westerman & Mcafee, 2012). The effect of DM on EA and firm performance will be explored in the next section to understand how competitive advantage can be enhanced through DM.

2.9 The effect of digital maturity on entrepreneurial agility and firm performance

As mentioned, through the adoption of digital technologies, a company develops digital resources and capabilities which are described as digital technology, digital culture, digital organisational structure and digital insights. DM is defined as a firm's progress in developing digital resources and capabilities in a DT, as an outcome of the DT strategy. The effects of DM on EA and firm performance have not been studied widely in literature; Chakravarty et al. (2013) showed that IT competencies can have a moderating effect on entrepreneurial agility and firm performance, however no research has measured the moderating effects of DM on EA and firm performance (Vial, 2019). A moderating effect is a measure of whether a moderator variable can increase or decrease the effects between the independent and dependent variables. Researchers have highlighted the relevance of some interactive relationships between aspects of digital organisational structure and culture on enhancing agility in DT, but this has not been tested empirically (Verhoef et al., 2019; Warner & Wäger, 2019). The second contribution of this research to the body of knowledge is thus testing the effects of DM and EA on firm performance.

EA is defined as a dynamic capability in a DT that enables a firm to proactively sense opportunities and reconfigure its internal resources and capabilities, which can include assets, structure, strategy, and resources, to bring about fundamental changes in the firm to capitalise on those opportunities (Chakravarty et al., 2013; Lu & Ramamurthy, 2011; Sambamurthy et al., 2003). These opportunities can be capitalised by superior knowledge of customers and the market, as well as rapidly responding to customer needs. First mover advantages also depend on the firm's resource mix which can either hinder or support the relationship between first mover advantage and firm performance (Zachary et al., 2015).

Applying this framework to a DT, technology advantages could take the form of a learning curve through experience gained from adopting digital technologies, research and development initiatives, which can be in new patents or trade secrets. Physical assets can be the digital technologies themselves, while scarce resources could be digital skills, digital organisational structure, digital culture, knowledge, and capabilities in the form of digital insights, which the firm secures ahead of competitors (Lieberman & Montgomery, 1988; Zachary et al., 2015) to provide economic rents in the future. These are the current economic rents the digital behemoths like Amazon, Google, and Facebook are enjoying. Hence, as a firm increases its DM, its digital resources and capabilities can be expected to be superior, which according to the above argument can be expected to enhance EA. A positive moderating effect of DM on EA and firm performance was thus expected in this study.

Teece (2007) and Warner and Wäger (2019) indicated that legacy-related organisational inertia, where innovation investment decisions are being managed through corporate finance, particularly with investments in products with uncertain outcomes as may be the case in DT, may hinder investments and create resistances to change. This is quite relevant for DT, as transforming organisations are largely traditional, i.e. their traditional methods of determining investment decisions and their fear of cannibalising existing traditional products may hinder them from making bold investments (Bughin & van Zeebroeck, 2017; Warner & Wäger, 2019) in favour of incremental, smaller changes. Warner and Wäger, (2019) identified change resistance, high levels of hierarchy and rigid strategic planning as barriers to dynamic capabilities in DTs. In addition, Gao, Hakanen, Töytäri and Rajala (2019) and Vogelsang, Liere-netheler and Packmohr (2019) indicated that firms in specific asset-intensive industries like mining and manufacturing may have industry specific barriers to investing in digital technologies, due to industry level skills shortages; legacy cultures and legacy technologies; and legislative restrictions such as employment, safety and health laws. These exogenous factors may influence the DT of these firms, thereby impacting the effects of DM on EA and firm performance due to both industry and organisational level factors. These factors are acknowledged but were beyond the scope of this study.

The next section describes the effects of each of the subconstructs – digital technology, digital culture, digital organisational structure and digital insights – on the relationship between EA and firm performance.

2.9.1 The effect of digital technology on entrepreneurial agility and firm performance

Porter and Heppelmann (2015) described how the use of smart connected devices can improve how a firm communicates with its customers and senses, monitors and analyses data. Digital technologies can impact the capabilities of firms to sense and interpret market data by connecting with customers via software like customer relationship management (CRM), social media platforms, big data analytics, machine learning and smart connected devices (Porter & Heppelmann, 2015; Vial, 2019). More digitally mature organisations can be expected to be more advanced with their adoption of digital technologies (HBR Analytic Services, 2014; Kane & Kiron, 2015; Kane et al., 2016; 2017). An example of a digital technology capability that is generating superior insights, both externally in terms of customers and markets as well as internally in terms of a firm's processes, is big data analytics, which is the ability to process high volumes of unstructured (non-numerical) and structured (numerical) data. This is creating value across several different industries (Acharya, Singh, Pereira, & Singh, 2018; Chen & Zhang, 2014; Chen, Preston, & Swink, 2015; Dremel et al., 2017; Rehman, Chang, Batool, & Wah, 2016; Simchi-Levi & Wu, 2018; Vial, 2019; Wamba et al., 2017). Higher digital technology maturity in a firm results in a stronger relationship between EA and firm performance, because it enhances the sensing capabilities of EA. This enables firms to make better decisions than their competitors because of superior knowledge (Chung et al., 2010), which can be expected to enhance firm performance.

Similarly, a higher adoption of digital technologies can provide more advanced digital infrastructures such as digital platforms and cloud computing, which can be used to speedily develop new products and services through rapid prototyping and innovation processes (Chanias et al., 2019; Sebastian et al., 2017) . The use of more advanced digital technologies may be a feature of more digitally mature firms, especially those with a greater understanding of the network effects that these technologies bring with regards to synergies between the technologies themselves (Verhoef et al., 2019). The HBR Analytic Services (2014) report indicated that the level of digital technology adoption may impact whether a firm uses a first mover strategy. The results indicated that firms that are the most likely to use first mover strategies are those that have the highest adoption of digital technologies. These firms benefited the most from their first mover advantages, with increases in their revenues and market share. A positive moderating effect between digital technology on EA and firm performance can therefore be expected.

An additional finding was that the majority of firms that capitalised on their first mover advantage and transformed their business models were largely in the technology industry, and less so in financial services, manufacturing and the public sector. The technology industry was also the most “digitally transformed” in terms of business model changes. In addition, there were trends with the industry types where the majority of technology firms were in the pioneer category, while financial services were followers, and the least likely industry to be pioneers was the public sector (HBR Analytic Services, 2014). This indicates that the industry type and industry digital maturity level may play a role in influencing the EA and firm performance relationship.

2.9.2 The effect of digital insights on entrepreneurial agility and firm performance

Digital insights can offer enhancements to the end user experience; allow for the customisation of product features; and capture trends on usage, reliability, customer preferences and feedback, which provide insights to the firm as well as its partners and customers (Dremel et al., 2017; Porter & Heppelmann, 2015). These insights can present and interpret market opportunities for firms to capitalise on, which can enhance the sensing capability of EA in terms of being able to determine what improvements/changes should be made to products or services, the business model, and the digital organisational structure. These digital insights can be used to provide more efficient and effective products and services, which create a competitive advantage (Anderson & Ellerby, 2018; Gurumurthy et al., 2020; Sebastian et al., 2017). The improved sensing capabilities, feedback of digital insights and learning back into the organisation also adjust a firm’s DT strategy, which can enhance other capabilities such as digital technologies, digital cultural changes, and digital structural changes (Chanias et al., 2019). This ability to accurately sense the environment would thus be enhanced by digital insights, which can be expected to enhance EA which relies on sensing and interpreting the environment. Overall, this would increase the customers’ perception of the quality of the firm by producing products and services aligned to their needs. This, in turn, will improve loyalty, trust and share of customers’ wallet, customer satisfaction and firm performance (Otto et al., 2020). The expectation is thus for digital insights to have positive moderating effects on EA.

2.9.3 The effect of digital culture on entrepreneurial agility and firm performance

Digital culture depends on the levels of collaboration between employees across functions, innovation focus, willingness to take risks and experiment, training and development of talent, and leadership support (Chanias et al., 2019; Dremel et al., 2017; Kane et al., 2016; Vial, 2019). These attributes will enable a digital culture that is suitable for a changing environment like that of a DT (Warner & Wäger, 2019). EA can thus be enhanced by this culture in terms of being able to reconfigure the human resources in the firm to execute the changes required. Trained and competent employees and a collaborative workforce can be expected to execute better (Chanias et al., 2019; Gurumurthy et al., 2020; Kane et al., 2017; Vial, 2019) through innovation processes like rapid prototyping to create new products or services. Recent research (Cai, Huang, Liu, & Wang, 2018) found that the use of social media platforms like Slack has had psychological benefits for teams that support agility by being proactive, adaptable and resilient. Digital culture can therefore enhance the seizing aspect of EA in terms of being able to reconfigure human resources and capabilities, as well as rapidly respond to opportunities. This ability to respond quickly will result in faster responses to opportunities sensed in a DT, which can result in improved customer satisfaction (Chen, Preston, & Swink, 2015; Feng & Feng, 2020).

Similarly, leadership support from the C-suite can help the firm to overcome organisational politics (Vial, 2019; Warner & Wäger, 2019), which is due to the organisation's legacy processes (Chanias, et al., 2019). In order to further support digital transformative changes, organisations may appoint change leaders to manage the DT process. In some cases the CEOs themselves take on this role, particularly to address organisational inertia and to enable sustainable change efforts (Chanias et al., 2019; Hauari, 2020; Mckinstry, 2019; Singh & Hess, 2017; Vial, 2019). The ability to reconfigure resources and capabilities and rapidly respond to changes within the firm can therefore be expected to improve with an augmented digital culture, which can be expected to enhance the seizing component of the EA and firm performance relationship. It is expected that a deeper digital culture will enable more rapid EA responses compared to when digital culture is lower, which will result in a positively moderating effect on EA and firm performance across sales, market share, profit and ROI.

2.9.4 The effect of digital organisational structure on entrepreneurial agility and firm performance

In DTs, the digital organisational structure should enable the organisation to be agile enough to operate and respond to the changes required within the DT process that work on experimenting and integrating digital opportunities across various functions (Chanias et al., 2019; Verhoef et al., 2019; Vial, 2019; Warner & Wäger, 2019). This structure can have dedicated DT teams, less hierarchical structures, C-suite Chief Digital Officers, upskilled and trained internal teams, and/or external consultants (Chanias et al., 2019; Kane et al., 2016; Singh & Hess, 2017; Vial, 2019). This structure enables the team to respond to new opportunities quickly, and can also enhance the reconfiguration of resources within the firm in terms of being able to experiment and develop prototypes, adopt new digital technologies, improve engagement between senior management and employees, and create dedicated innovation management committees to drive ideas from inception into commercial products (Chanias et al., 2019; Dremel et al., 2017). More mature digital organisational structures can thus be expected to enhance EA by improving their responses to opportunities. This, in turn, can enable quicker turnaround on opportunities ahead of the competition and enhance firm performance.

2.10 Conclusion

This literature review explored the multi-level impacts of the phenomenon digital transformation, as well as the reasons for it and its purpose. The rapid development and capabilities of these digital technologies in recent years was discussed, as was the strategic role of IT shifting from supporting the business strategy to integrating with it through what is termed digital business strategy. DT creates digital resources and capabilities within in a firm, the process of which is co-ordinated and managed through a DT strategy.

The literature identified organisational agility as an important aspect for digital transformation, but the majority of the literature on this topic is based on the role of IT as an antecedent of organisational agility and positive relationships with firm performance. This study aimed to extend the knowledge regarding the relationship between the OA and firm performance in the context of digital transformations, using the proactive component of OA, i.e. entrepreneurial agility, using the RBV and DCF theories. The role of EA in supporting proactive firm strategies, such as prospector/analyser and first mover advantages and their associated benefits, were discussed in the context of DT. Similarly, the role of EA in supporting commonly used DBS such as customer engagement and digital solutions strategies, as described by Sebastian et al. (2017), was discussed. It was hypothesised that EA will have a positive relationship with firm performance in DT.

The literature review further discussed the concept of digital maturity models and the construct digital maturity. Digital maturity was defined in this study as a firm's progress in developing digital resources and capabilities in a DT, as an outcome of the DT strategy. Digital maturity was viewed as not having a linear path due to the impact of contextual factors like industry type, which influence how firms progress through a DT. Digital maturity was concluded in the literature review to have a positive relationship with firm performance.

Lastly, the literature review explored the moderating effects between these digital resources and capabilities, which are measured in the organisation through digital maturity, as well as how these interact with entrepreneurial agility and firm performance as the organisation increases its digital maturity. These digital resources and capabilities were described as digital technologies, digital culture, digital organisational culture and digital insights. These were hypothesised to positively enhance the effects of EA and firm performance as digital maturity increases. Other industry specific factors and barriers were identified as possible inhibitors of these effects, which were beyond the scope of this study.

Chapter 3: Research questions and hypotheses

DT is defined as the process of the adoption of digital technologies across an organisation, which fundamentally transforms its business strategy, business processes, firm capabilities, products and services, with the aim of achieving a competitive advantage (Bhadradwaj et al., 2013; Hess, Benlian, Matt, & Wiesböck, 2016; Matt et al., 2015; Vial, 2019). The RBV (Wernerfelt, 1984; Barney, 1991) and the DCF (Teece & Pisano, 1994; Teece et al., 2016) were used in this study as appropriate theoretical lenses to understand the DT phenomenon. The following research questions and hypotheses were identified through the literature review.

Research question 1:

What is the relationship between entrepreneurial agility and firm performance for firms undergoing DT?

Based on the review of literature on organisational agility (Sambamurthy, Bharadwaj, & Grover, 2003; Overby, Bharadwaj & Sambamurty, 2006; Sambamurthy, Lim, Lee, Lee, & Lim, 2007; Lu & Ramamurthy, 2011; Chakravarty et al., 2013; Chen et al., 2014; Tallon et al., 2019) and the defintion of DT, EA as a subconstruct of OA was identified as more applicable for a DT in understanding how improved firm performance could be achieved.

EA is defined as a dynamic capability in a DT that enables a firm to proactively sense opportunities and reconfigure its internal resources, which can include assets, structure, strategy and resources, to bring about fundamental changes in the firm to capitalise on those opportunities (Chakravarty et al., 2013; Lu & Ramamurthy, 2011; Sambamurthy et al., 2003). EA enabled by IT has been shown to improve firm performance through a functional IT strategy (Chakravarty et al., 2013; Sambamurthy et al., 2007), but its effect on firm performance has not yet been measured empirically in a DT under a DBS. The possible benefits of EA were discussed relative to proactive market strategies, such as first mover advantage and prospector/analyser strategies, as well as the commonly used digital business strategies to improve firm performance in DTs (HBR Analytic Services, 2014; Miles et al., 1978; Sebastian et al., 2017; Zachary et al., 2015). A positive relationship between EA and firm performance was hypothesized by the researcher; this study tested the relationship through the following hypotheses:

<u>Hypotheses</u>

$H1_0$: EA has a positive relationship with firm performance

$H1_A$: EA does not have a positive relationship with firm performance

Research question 2:

What is the effect of digital maturity on the relationship between EA and firm performance for firms undergoing DT?

DM can be a defined as a firm's progress in developing digital resources and capabilities in a DT, as an outcome of the DT strategy (Becker et al., 2010; Chanias & Hess, 2016; Remane, et al., 2017). According to the literature (Anderson & Ellerby, 2018; Cai et al., 2018; Chanias et al., 2019; Gurumurthy et al., 2020; HBR Analytic Services, 2014; Kane et al., 2016, 2017; Verhoef et al., 2019; Vial, 2019;). It was also hypothesised by the researcher that increased digital maturity may positively moderate the effect of EA on firm performance in a DT.

<u>Hypotheses:</u>

$H2_0$: Digital maturity has a positive moderating effect on the relationship between EA and firm performance

$H2_A$: Digital maturity does not have a positive moderating effect on the relationship between EA and firm performance

Research question 3:

What is the relationship between DM and firm performance for firms that have commenced with DT initiatives?

The positive relationship between digital maturity and firm performance has been established in the literature (Fitzgerald et al., 2013; Gurumurthy et al., 2020; Eremina, Lace, & Bistrova, 2020; Anderson & Ellerby, 2018; Kane et al., 2016; 2017).

Chapter 4: Research methodology

4.1 Introduction

The purpose of this research was to understand the effect of digital maturity on entrepreneurial agility and firm performance for firms that have commenced with digital transformation initiatives. The research methodology describes the approach and methods the researcher took in order to achieve the research objectives, which were founded on the research philosophy.

The purpose of this section is to describe the research design and philosophy used by the researcher in order to address the research objectives. This includes the choice of methodology and its alignment with the researcher's personal beliefs and assumptions of the world; the unit of analysis in which the phenomena in this study occurs; the population, sample size and sampling methods utilised to obtain the necessary data; the measurement instrument used; the data gathering methods and analysis approach taken; the quality controls; and the limitations of the research methods used.

4.2 Research philosophy

The philosophy used by the researcher in this study was positivism. This philosophy takes a scientific view of social realities and uses data to objectively describe phenomena (Saunders & Lewis, 2018; Wamba et al., 2017). This aligns with the researcher's personal philosophy of the world, which takes a scientific lens to objectively describe cause and effect relationships due to the researcher's engineering background. This is important because it reveals the personal beliefs and assumptions made by the researcher in developing knowledge, and because it shaped the researcher's approach, his methods of conducting the research, and how he interpreted the results. The positivistic philosophy is indicative of the research methods being more quantitative in nature, which resulted in findings that are more objective and generalizable (Delice, 2001). In this way, the philosophy of the research and the personal philosophy of the researcher are aligned in this study. This philosophy also aligns with the approach taken by other authors such as Wamba et al. (2017), Mhlungu, Chen and Alkema (2019) and Chakravarty et al. (2013), who had similar research questions. This researcher aimed to understand the relationships of the constructs – entrepreneurial agility, digital maturity and firm performance – in the phenomenon digital transformation in an objective and quantifiable way in order for the findings to be replicated and generalizable.

4.3 Approach to theory development

In this study, the phenomenon ‘digital transformation’ was investigated, based on the deductive review of literature set out in Chapter 2. Zikmund et al. (2010) defined deductive reasoning as the logical process of developing a conclusion about a specific issue based on something known to be true. A deductive review of literature led to the following research questions based on what is currently known (Agresti & Franklin, 2007) to answer research questions about what is unknown in measurable way. This approach was also used by Wamba et al. (2017) and Chakravarty et al. (2013).

4.4 Research methodology

The research methodology used in this study was quantitative because it asserts and assumes that the constructs within the phenomenon, digital transformation, can be measured objectively with quantifiable data (Wamba et al., 2017). Zikmund, Babin, Carr, and Griffin (2010) defined quantitative research as that which addresses the research objectives by using empirical assessments which involve both numerical measurement and analysis approaches. Similarly, the research questions required that the relationships between the constructs entrepreneurial agility, digital maturity and firm performance be quantified. Quantitative research was thus more suited to this study than qualitative, because it uses numerical data to objectively measure relationships. This research study is also descriptive in that it describes what the relationships are between the constructs, and quantifies these (Zikmund et al., 2010; Sanders & Lewis, 2012).

A mono method was used to conduct the study as a single method had been sufficient to answer similar research questions in previous studies (Wamba et al., 2017; Chakravarty et al., 2013; Cegarra-Navarro, Soto-Acosta, & Wensley, 2016). A structured survey questionnaire was considered best suited to this quantitative research as questionnaires are objective, can be measured (Saunders & Lewis, 2018), and provide generalisable results (Wamba et al., 2017). A structured survey questionnaire was administered online for this study, similar to the approach taken by Wamba et al. (2017) and Mhlungu, Chen and Alkema (2019).

The survey questionnaire was administered online via Google forms, i.e. it was an internet-based questionnaire. The benefits of internet-based questionnaires are that they are generally low cost, data entry is simple, and they provide format flexibility compared to paper questionnaires (Saunders & Lewis, 2018; Granello & Wheaton, 2004). The drawbacks of online questionnaires are difficulty in assessing the sampled population, a lack of access to respondents' details, and low response rates (Wright, 2005). A self-completed questionnaire was used in this study because it is less intrusive and allows for more respondent privacy. It also supported objectivity by eliminating the influence of interviewer bias or variance, which can affect the responses of the interviewees (De Leeuw, 2008). Other researchers in the same field have used self-completed questionnaires (Mhlungu et al., 2019; Wamba et al., 2017). The negative consequences of self-completed questionnaires is that the researcher has no control over the response time to complete the surveys, nor can they clarify any ambiguities or lack of understanding of the questions by the respondents, which could lead to response errors (Zikmund, Babin, Carr, & Griffin, 2010). Low response rates were experienced in this research, which will be discussed later.

The time horizon was cross-sectional, which is defined as a study of a subject at a moment in time (Saunders & Lewis, 2018). This approach, which has been used by other researchers in the field (Chakravarty et al., 2013; Mhlungu et al., 2019; Nwankpa & Roumani, 2016; Wamba et al., 2017), was selected largely because the research questions can be answered with a time horizon, which was necessary due to time constraints. The limitation of a cross-sectional research design is that the findings may change over time, however.

4.5 Population and sampling frame

A population can be defined as the complete set of members of the group under study (Delice, 2001; Saunders & Lewis, 2018). The population for this study included all companies that are undergoing digital transformations, whether they were private or public. This was included as a qualifying question upfront to ensure that the respondents would be able complete the survey questionnaire. The reason for the population is the pervasive nature of digital transformations which impacts almost every industry size, type and region (Matt et al., 2015; Pihir, Tomičić-Pupek, & Furjan, 2018), which makes it impossible to determine the population size in this study. As it was not possible to determine the sampling frame or the total list of companies that are undergoing digital transformation initiatives, a probability-based sampling method had to be ruled out, as selecting a representative sample was not possible because the population could not be identified (Zikmund et al., 2010).

4.6 Unit of analysis

Li, Xiang, Chen, Xie and Li (2017) described the unit of analysis in a study as the level where the research takes place. The unit of analysis in this study was at the level of the organisation, as the digital transformation occurs at that level. What was being measured was how an organisation responds within the DT process. Similarly, both the independent variable and moderator, i.e. the EA and DM respectively, as well as the dependent variable, i.e. firm performance, are measured at an organisational level

4.7 Sampling method and sample size

The sampling method and sample size are important factors in research because they impact the generalisability of the results obtained to the population, as well as the detection of significant differences, relationships and interactions (Bartlett II, Kotrlik, & Higgins, 2001). They are thus important for determining the accuracy of the results obtained, as well as if they can be generalised back to the larger population under study. Purposive sampling is a non-probability sampling technique that relies on the researcher’s judgement to select the sample members based on a set of reasons (Zikmund et al., 2010). This sampling technique was used for this research as it specifically targeted individuals in organisations that had commenced with digital transformation initiatives. On an individual level, it targeted individuals who were familiar with their organisation’s digital strategy who had more than a year of experience in the organisation. These were also used as filters in the survey questionnaire to ensure that the individuals were from the population being studied, and that they had an understanding of, and experience in, their organisation’s digital strategies. The sampling technique also had an element of snowball sampling in that the respondents were allowed to pass the survey questionnaire to others whom they thought it would be relevant to. This was allowed due to the low response rates achieved and the time constraints of the study, which will be discussed later.

The approach for the sampling method was heterogeneous (Saunders & Lewis, 2018) in order to get as wide a variety as possible of respondents across different industries, regions and organisation sizes. The sampling was done by posting on several LinkedIn groups with a diverse audience in the digital transformation field across different regions and geographies, using the GIBS MBA network, which has a diverse population. The researcher also sent direct invitations to over 100 individuals, who according to their LinkedIn profiles had characteristics of the target population. The limitations of the sampling methods in this study are that the generalisability of the results are limited to the characteristics of the sample population, because non-probability sampling methods and snowball sampling can result in individual bias, where an individual may recommend people similar to themselves (Zikmund et al., 2010).

When selecting a sample size, several factors need to be considered such as population size, population variability, research objectives and design, analytical techniques used, and sample size of similar research (Delice, 2001). In this study, the population characteristics were not possible to determine. The research design was quantitative analysis and the statistical methods required to answer the research questions were correlation analysis and moderated regression. The researcher considered the sample sizes of studies in a similar field of research, which was 95 for Mhlungu et al. (2019), while Chakravarty et al. (2013) had samples of 73 and 36 across two sample populations, which were analysed by regression. A sample size of 120 was thus targeted for the study in order to collect more data than were required in the case of incomplete surveys or survey errors, as well as to limit the impact of sample size on the analysis.

A sample size can cause type 1 and type 2 errors in statistical hypothesis testing (Bartlett II et al., 2001), however an increasing sample size typically reduces the likelihood of making both errors (Zikmund et al., 2010). Type 1 errors are made when the null hypothesis is rejected when it is in fact true, while type 2 errors are made when the null hypothesis is not rejected when the alternative hypothesis is true (Zikmund et al., 2010). Typically, the risk of making a type 1 error can be improved by reducing the alpha or significance level in in the statistical test, but a reduction in a type 1 error increases the likelihood of making a type 2 error (Zikmund et al., 2010). According to Chakravarty et al.

(2013), a smaller sample is more likely to cause a type 2 error, thus given their smaller sample sizes, they used the two tailed test of significance to mitigate this effect. A sample size of 75 respondents was achieved in the study, which was below the target of 120 due to low response rates and time constraints. The two tailed significance test for statistical inference was also conducted, as per Chakravarty et al. (2013).

4.8 Measurement instrument

The measurement scale for entrepreneurial agility used in this study was adapted from the work done by Chakravarty et al. (2013), who tested this scale with high convergent validity as a construct using confirmatory factor analysis. The scale for firm performance was adapted from Chakravarty et al. (2013) and Wamba et al. (2017), who used subjective financial measures to describe firm performance, which have been validated as acceptable measures of firm performance linked to the RBV (Newbert, 2008).

The measurement scale for digital maturity used in this study was largely adapted from Gill and Van Boskirk (2016). This has also successfully been used in prior MBA research (Niland, 2018) because of the absence of a developed empirically validated scale in literature (Berghaus & Back, 2016; Chanias & Hess, 2016; Remane, et al., 2017). Whilst the construct validity was not available, the researcher did validate the scale in this study. The entrepreneurial agility construct was defined by measurement scales from Chakravarty et al. (2013), who demonstrated validity using confirmatory factor analysis and revealed the discriminant validity of the constructs. Using composite scale reliabilities, Chakravarty et al. (2013) yielded values of 0.72 for EA and 0.93 for FP, with an AVE (average variance explained) of 0.55 and 0.73 for EA and FP respectively, which were found to be reliable and valid. For firm performance, Wamba et al. (2017) obtained Cronbach's α= 0.93; CR (composite reliability) = 0.95; and AVE = 0.78, which were confirmed to be reliable and valid.

4.9 Data gathering process

The survey questionnaire, which had six sections, was administered online using Google forms, as shown in Appendix A. The first section included two qualifying questions, which were:

1. Has your organisation embarked on a digital transformation activity with the use of digital technologies for its internal business processes or to develop new markets and product offerings?
2. Are you familiar with your organisation's digital strategies?

If the respondents qualified by answering yes to both questions, they went on to section A, but if not, they were taken to the end of the survey. Section A consisted of demographic questions, which included gender, seniority, years of experience in the organisation, organisation size in terms of number of employees, annual revenue of the organisation, and industry type. Sections B to D consisted of questions on firm performance (sales, market share, profit and ROI), entrepreneurial agility, and digital maturity (digital technology, digital culture, digital organisation and digital insights) respectively, which were answered according to a five point Likert scale ranging from strongly disagree to strongly agree. The five point Likert scale was used for the construct questions due its wide use, ease of use and its validity (Preston & Coleman, 2000).

A pilot test was conducted, as this is considered critical for refining survey questions to reduce the risk that a study will be flawed. It also provides guidance that the survey instrument works as intended, and can be used to gain feedback to improve on the larger study (Zikmund et al., 2010). A pilot test of the questionnaire was run over three weeks with a pre-selected set of respondents, who were typical of the sample population being tested from the researcher's business network. A total of 13 respondents participated in the pilot survey. The purpose was to test that the questions were properly understood, were not leading, and would provide the required data (Saunders & Lewis, 2018). A pilot test was also conducted by Wamba et al. (2017) in their research, to ensure that their measures were reliable and valid. The feedback received from this study's pilot test included the following:

1. Three respondents to the pilot test indicated that it would be better to target people who were knowledgeable about digital strategies in their organisations, as those who were unsure might choose neutral for answers that they were not sure of. This was addressed by qualifying question two in the questionnaire.

2. It was recommended that the researcher review some of the questions as some sounded quite similar and the survey was repetitive. This was expected as the scales selected were measuring a single construct. Hence no changes were made.
3. One respondent recommended changing the structure of the survey questions on the survey instrument for those using mobile phones. The researcher considered this, but as it was only the view of one respondent, it was not changed.
4. Some of the vocabulary used in the questionnaire was identified as potentially being unclear, such as the terms “best in class” and “functional silos”. These terms were thus explained for clarity in parentheses in the survey questionnaire.
5. The rest of the survey was considered easy to understand and quick to complete (less than 10 minutes).

The researcher posted the survey on LinkedIn, targeting responses from businesspeople who worked in organisations that had commenced with digital transformation initiatives. The researcher also used selected digital transformation LinkedIn groups to target respondents, and extended the invitation to the GIBS business network. The researcher did not use other social media platforms in order to ensure a high quality of respondents, as platforms such as Facebook and Twitter do not have a strictly business audience. The following timeline for data collection was used:

1) Initial group post on LinkedIn inviting respondents to complete the survey (week 1).
2) Tagging the researcher’s supervisor in the post on LinkedIn to attract a wider network of people (week 2).
3) Inviting the researcher’s GIBS MBA network to complete the survey (week 3).
4) Joining the following groups on LinkedIn and posting on the group (weeks 3 and 4):
    a. Digital Strategy & Transformation (30,915 members);
    b. It’s All About IoT, AI, and Digital Transformation (2,055 members);
    c. Digital Transformation MENA (3,701 members); and
    d. Change Consulting, Digital Transformation, Change Management, Strategy, Social Distancing, Disruption (119,475 members).
5) Sending direct LinkedIn message requests to over 100 respondents, inviting them to complete the survey (weeks 5 and 6)

There was an element of snowball sampling as some participants forwarded the survey to other people in their network. This may have introduced sampling bias, both towards the researcher's network as well as the respondents themselves sharing with people who were similar to them. The sample response rate was very low considering the size of the groups and the networks used. Due to time constraints, the researcher had to end the survey after 8 weeks (including two weeks for the pilot survey) of data collection. The total number of respondents to the survey was 75, of which six did not meet the two qualifying criteria and one had less than one year of experience in the organisation. These respondents were thus removed from the sample population. The data retrieved were also checked for any missing values for all the survey questions. As there were no missing values, a total of 68 usable responses were recorded.

4.10 Analysis approach

Zikmund et al. (2010: 462) described the importance of the first stages of converting "raw data" into "intelligence" by editing, coding and filing the data. Data need to be checked for both respondent and non-respondent errors, which in this study occurred when the researcher transferred the data into an electronic file. Editing is described as checking the consistency, legibility and completeness of the data before coding and transferring to storage. Editing was done to check for any missing values or errors in the raw data, before being transferred to a Microsoft Excel spreadsheet. No errors or missing values were picked up. Coding, which refers to the assignment of numerical scores to previously edited data, was done according to the table shown in Appendix B. This was done to provide meaning to the data for analysis using a computer (Zikmund et al., 2010). Coding for the Likert scales used numerical numbers from 1 (strongly disagree) to 5 (strongly agree).

4.10.1 Detection and removal of outliers

As per the assumptions for linear regression, there must be no outliers in a sample population as these could skew the results obtained from the statistical analysis (Osborne & Overbay, 2004). Similarly, outliers can also have a negative impact on scale reliability in the reported Cronbach's alpha, which can skew higher values (Y. Liu, Wu, & Zumbo, 2010) and create an incorrect measure of scale reliability. Outliers can further impact the results obtained from correlation analysis and normality, which may skew the results obtained and also risk type 1 and type 2 errors in the hypothesis testing (Osborne &

Overbay, 2004). Outliers may be due to response bias, which can compromise the reliability of measurements (Zikmund et al., 2010). Considering that the research objectives in this study were dependent on statistical methods that would be compromised by outliers, their removal was considered critical to generate reliable results.

The methodology followed for detecting outliers included plotting them on Box and Whisker plots on IBM SPSS, which is a common method using statistical software that identifies the variables that are outside of the interquartile range as potential outliers (Pallant, 2001). In order to simplify the process, the item total scores for each scale, except the dependent variables of firm performance (sales, market share, profit, ROI), were computed. This was plotted together with the firm performance items to identifier outliers outside of the interquartile range. **Error! Reference source not found.** and **Error! Reference source not found.** indicate the plots before outlier removal; the points sitting outside the range on the Box and Whisker plots, identified by the circles, were considered outliers. The outliers detected were then checked against the actual data measurements to see if there were any anomalous records for either of the constant values, which could be due to response biases that were not representative of the majority of the data. Examining the recorded data also revealed extremely low scores across several of the items, which were considered to be caused by extremity bias. The process was followed a few more times, and saw a total of eight outliers being removed from the dataset. **Error! Reference source not found.** and **Error! Reference source not found.** show the plots after all the outliers were removed and there are no more circles highlighted outside the Box and Whisker plots.

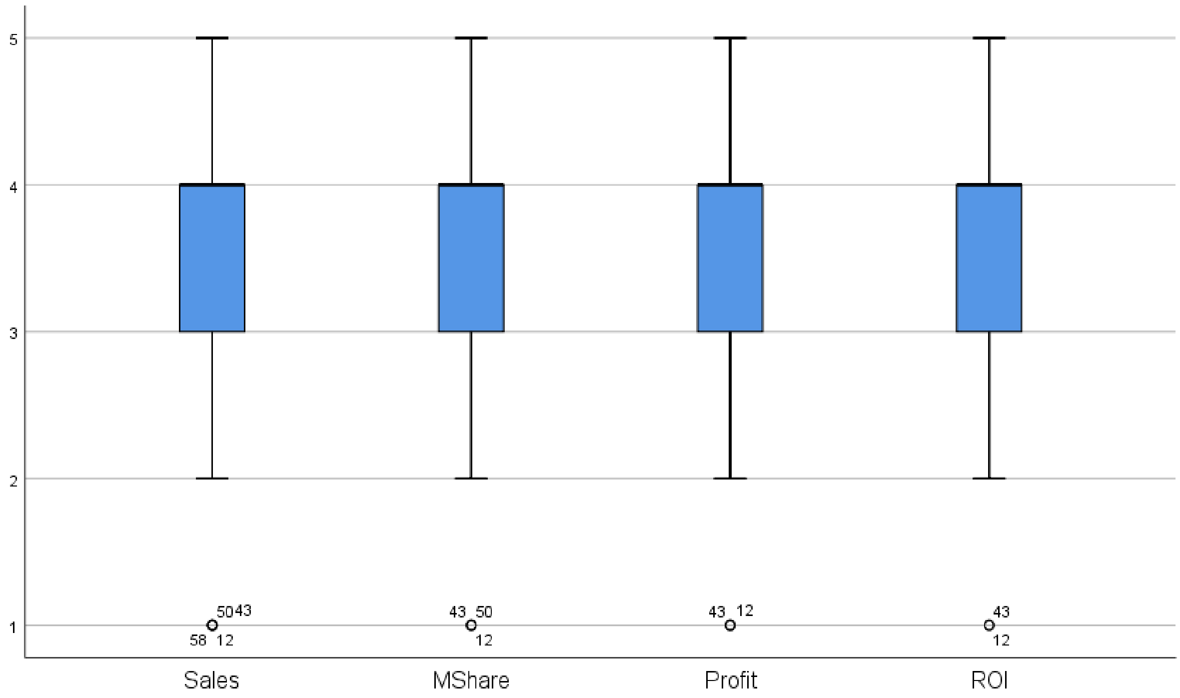

Figure 1: Box and Whisker plot for firm performance construct scores (before outlier removal)

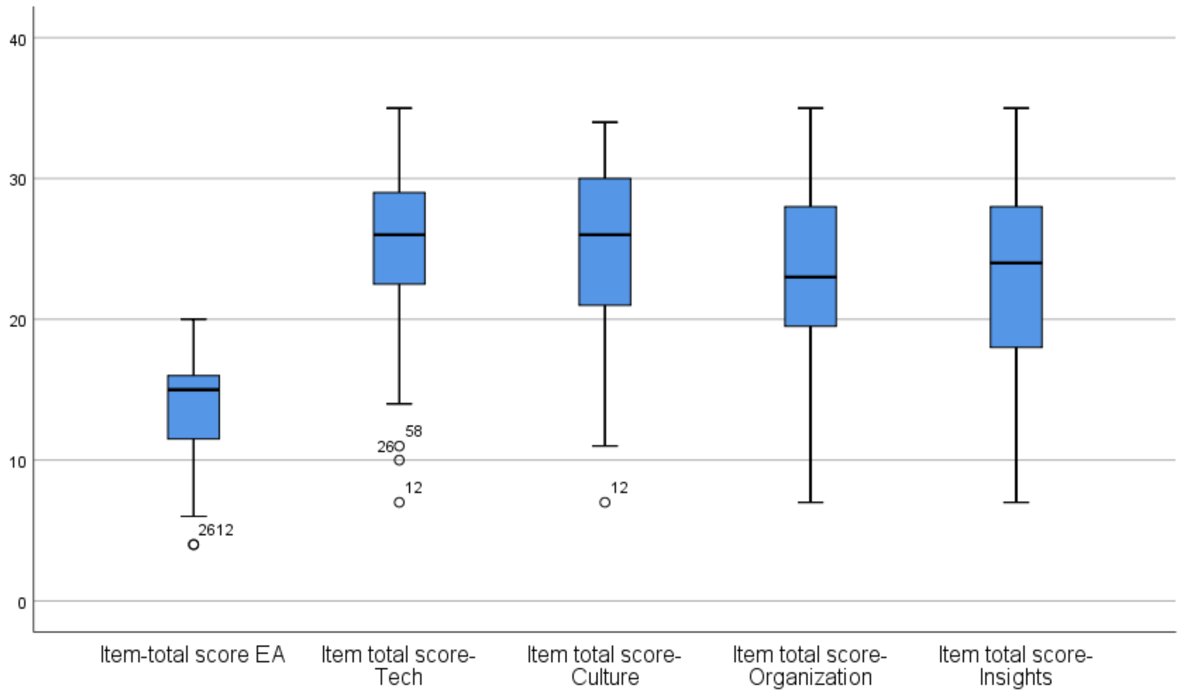

Figure 2: Box and Whisker plot for item total scores for EA and DM constructs (before outlier removal)

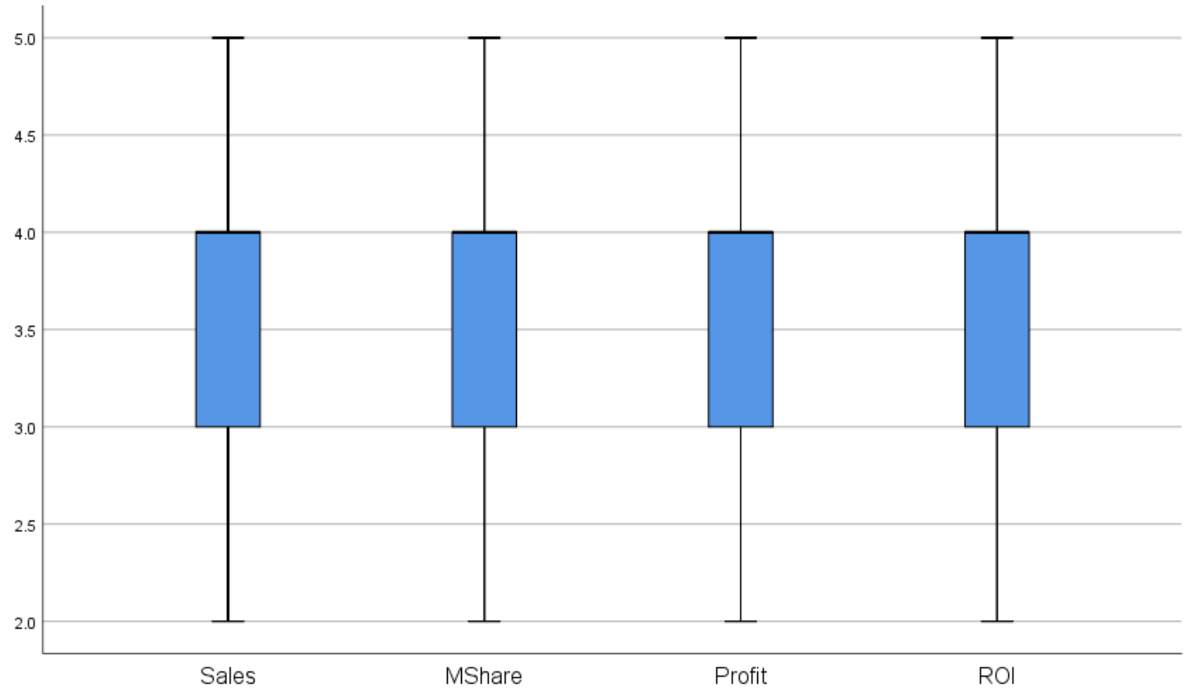

Figure 3: Box and Whisker plot for firm performance construct scores (after outlier removal)

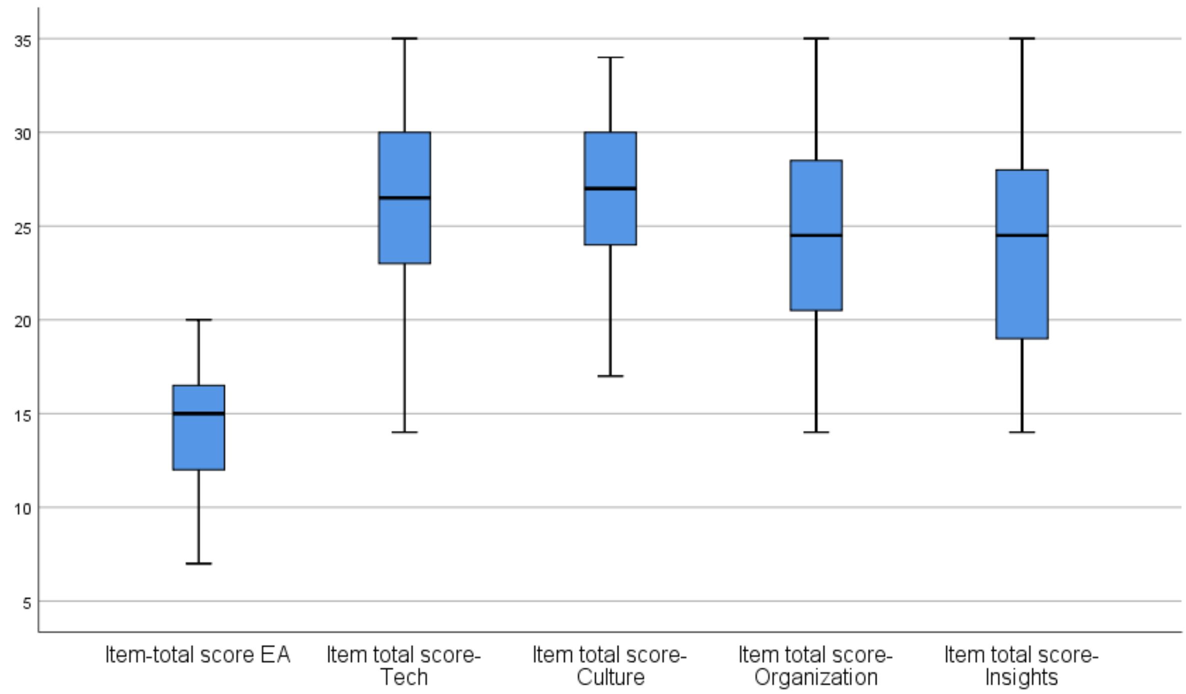

Figure 4: Box and Whisker plot for item total scores for EA and DM constructs (after outlier removal)

The above analysis was cross-checked with the mean and a 5% trimmed mean, which by removing the top and bottom 5% of values is also an indicator of effect of the upper and lower 5% of data on the mean (Pallant, 2001). The mean and 5% trimmed mean were compared after the outliers were removed using IBM SPSS, as cross checked on the Box and Whisker plots shown in **Error! Reference source not found.** below. The means and 5% trimmed means were found to be very similar, indicating minimal impact of any outlying values on the mean as a check on the Box and Whisker plots. A total of eight outliers were removed through this process, leaving a total of 60 usable responses.

Table 1: Table showing the mean and 5% trimmed mean after outlier removal for the scale scores

	Mean	5% trimmed mean
Sales	3.80	3.83
Market share	3.65	3.67
Profit	3.68	3.70
ROI	3.68	3.70
Item total score - EA	14.47	14.54
Item total score - DM technology	26.30	26.43
Item total score - DM culture	26.25	26.33
Item total score - DM organisation	24.32	24.30
Item total score - DM insights	23.98	23.94

4.10.2 Test for normality

The next part of the process involved testing for normality. Normality refers to the central tendency data in distribution and is an assumption for several statistical parametric tests (Ghasemi & Zahediasl, 2012; Pallant, 2001) to ensure the validity of the results obtained. According to the central limit theorem, large enough samples of greater than 30 can be assumed to approximate a normal distribution, but the extent of the deviations from normality should be assessed when using parametric tests (Ghasemi & Zahediasl, 2012; Pallant, 2001). The characteristics of the shape of the distribution can be determined by the kurtosis and skewness parameters from the descriptive statistics, which indicate the peaks and skewness of the distribution. For normal distributions these values are close to

0 (Pallant, 2001). The first approach was to plot the histograms; the box and whisker plots from the earlier outlier detection was also useful in identifying the spread and central tendency of the data, as well as to what extent the data deviated from normality. The Shapiro Wilk test was used to test for normality, which influenced the statistical tests used for further analysis in the study. The Shapiro-Wilk test indicates non-normal data if the sig value is below 0.05. It can be seen in **Error! Reference source not found.** below that only two out of the nine scales used (digital technology and digital organisational structure) showed normally distributed data. Non-parametric statistical tests were thus used when required.

The researcher did closely examine the histograms, as well as skewness and kurtosis values, which indicated slight deviations from normality. For the regression analysis, the researcher thus decided to continue noting that one of the key assumptions for regression analysis later on in the study was the normality of the residuals and not the strict normality of all the variables (Pallant, 2001).

Table 2: Shapiro Wilk test for normality for the scales

Tests of Normality			
	Shapiro-Wilk		
	Statistic	df	Sig.
Sales	0,837	60	0,000
Market share	0,862	60	0,000
Profit	0,846	60	0,000
ROI	0,866	60	0,000
Item total score - EA	0,963	60	0,066
Item total score - Digital technology	0,974	60	0,228
Item total score - Digital culture	0,945	60	0,009
Item total score - Digital organisational structure	0,974	60	0,219
Item total score - Digital insights	0,958	60	0,038
*. This is a lower bound of the true significance.			
a. Lilliefors Significance Correction			

4.10.3 Reliability and validity

Validity measures the accuracy of a measure and the extent to which a score truthfully measures a concept (Zikmund et al., 2010). Construct validity in this study was important to ensure that the scales adopted from the literature accurately measured the constructs which were hypothesised in order to answer the research questions. Validity was tested using bi-variate correlation of the item total score per question, as well as the score for each question, to ensure that all the questions were measuring the same construct. Validity was tested for each construct and the respective sets of questions.

The reliability of the scales used in this study is an indication of a measure's internal consistency, which is important to ensure homogeneity of measurements (Zikmund et al., 2010). This homogeneity is the ability of the questions in a scale to consistently measure the same thing (Wamba et al., 2017; Mhlungu, Chen & Alkema, 2019). In order to measure the reliability of the scales used, Zikmund et al. (2010) indicated that Cronbach's alpha is the most commonly used method to test multiple-item scale reliability. Cronbach's alpha was used to test the reliability of the measurement scales in this study which was also used byWamba et al. (2017), Mhlungu, Chen and Alkema (2019), and Chakravarty, Grewal and Sambamurthy (2013). This ensures that the measurement scale is, in fact, reliably measuring the construct of interest and is internally consistent (Wamba et al., 2017; Mhlungu, Chen & Alkema, 2019). This means that the set of questions per measurement scale are measuring the same variable.

4.10.4 Descriptive statistics

Once a clean data set was obtained, descriptive statistics of the sample population characteristics were plotted in Microsoft Excel to check for the spread of data and sample skewness. The central tendency of the data was examined by using descriptive statistics such as the mean, standard deviation and shapes and characteristics of the histograms, such as skewness and kurtosis. Skewness indicates whether the data are skewed to the left or right, while kurtosis refers to the peaks of the histogram; for normally distributed data these values should be close to 0. Normality is an important consideration for deciding whether parametric or non-parametric statistical tests will be applied (Pallant, 2001). These statistical tests are important to test the hypotheses and answer the research questions with confidence.

4.10.5 Factor analysis

As per Zikmund et al. (2010), factor analysis is a statistical technique that is used to identify a reduced number of factors from a large number of measured variables, where the reduced number of factors describe the majority of the variance. This is thus a statistical data reduction technique which ensures the rule of parsimony, i.e. fewer rather than more variables explain a behaviour (Zikmund et al., 2010). There are two types of factor analysis – exploratory factor analysis (EFA) and confirmatory factor analysis (CFA) (Yong & Pearce, 2013). CFA is used when hypothesising the relationships between variables and testing them, whilst EFA attempts to uncover patterns in the data (Pallant, 2001; Yong & Pearce, 2013). EFA was used in this study because there were no hypothesised relationships between the variables within the constructs, and the objective was to determine the minimum number of factors that describe the majority of the variance for each of the constructs. EFA provides two important pieces of information from a set of variables, i.e. the number of factors that exist among a set of variables, and which variables are related to which factors (Zikmund et al., 2010).

Principal component analysis (PCA), which is a type of EFA, was used to determine the minimum number of factors per scale. Prior to factor analysis, to check suitability the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy and Bartlett's test of sphericity had to be done to confirm that factor analysis was appropriate. The results are shown in Table 3 below. A KMO value should be above 0.5 (Kaiser, 1974; Pallant, 2001; Yong & Pearce, 2013); in this study they were all above 0.7, ranging from middling to meritorious (Kaiser, 1974). The Bartlett's test of sphericity sig. value was <0.05 (Yong & Pearce, 2013), which indicated that there were patterns amongst the variables. Together with the KMO result, this implied that factor analysis could be applied.

Table 3: KMO and Bartlett's test of sphericity for factor analysis

Scale	**Kaiser-Meyer-Olkin Measure of Sampling Adequacy.**	**Meaning**	**Bartlett's Test of Sphericity (Sig.)**
Entrepreneurial Agility	0,707	Middling	0,000

DM: Technology	0,733	Middling	0,000
DM: Culture	0,772	Middling	0,000
DM: Organisation	0,835	Meritorious	0,000
DM: Insights	0,848	Meritorious	0,000

4.10.6 Correlation analysis

In order to test hypothesis $H1_0$ on the relationship between EA and FP (sales, market share, profit, ROI), a test for correlation was performed. Correlation analysis is used to test the strength and direction of a linear relationship between variables (Pallant, 2001). The two correlation tests that were considered for this study were Pearson's product moment correlation and Spearman's ranked correlation (Pallant, 2001). Pearson's has the requirement that the data need to be normally distributed, however since the majority of the data were not normally distributed, Spearman's ranked correlation was used for the analysis. It is important to note that the significance of the correlation analysis between EA and FP was a pre-requisite to test the second hypothesis in this study.

4.10.7 Moderated linear regression

In order to test the second hypothesis, which concerned the moderating effect of digital maturity (digital technology, digital culture, digital organisation structure, digital insights) on the relationship between EA and FP (sales, market share, profit, ROI), a moderated linear regression analysis was performed. There are several statistical assumptions for a moderated regression which are described below (Laerd Statistics, 2020):

Assumption 1: The dependent variable should be measured on a continuous scale, i.e. it is either an interval or ratio data.
Assumption 2: There is at least one continuous independent variable and one moderator variable.
Assumption 3: There is independence of observations.
Assumption 4: Linear relationships exist between the dependent and independent variables.

Assumption 5: The data must show homoscedasticity, which is where for all combinations of independent and moderator variables, the error variances are the same.
Assumption 6: The data must not show multi-collinearity, which occurs when two or more independent variables are highly correlated with each other.
Assumption 7: No significant outliers, high leverage points or highly influential points should be included in the data.
Assumption 8: The residuals must be normally distributed.

It is important to highlight that moderated linear regression does not explicitly require the variables to be normally distributed, but does require that the residuals are approximately normally distributed (Pallant, 2001). This was considered important for validating the assumptions in the moderated linear regression tests, which would indicate the level of confidence in the result obtained, to help prevent type 1 or type 2 errors.

4.11 Quality controls

The researcher was cognisant of potential errors and biases during the data collection, which included subject biases and errors that may have impacted the reliability of the study. These included subject error, subject bias, observer error and observer bias. Subject error, which considers the impact of a survey that is administered at different times, was mitigated by conducting the survey over a continuous fixed period of eight weeks. This was considered adequate for the subject under study. Subject bias occurs when respondents may give unreliable information because they think telling the truth may show them in a negative light. This was mitigated by administering the survey anonymously and only reporting the aggregate data. Observer error occurs when the researcher asks a question in different ways or in a way that may be misinterpreted. The pilot survey was done to ensure the questions would be easily understood and any ambiguity or misunderstanding of the questions was addressed. Observer bias is due to the way different researchers may interpret the same data (Saunders & Lewis, 2018), however this was not the case in this study as quantitative research aims to measure responses in an objective way.

Additional biases which were considered in the data analysis were non response errors and response biases. Non response error is caused by respondents not completing the survey, thus the survey was administered for eight weeks and to an extensive sample population to increase the number of respondents. Response biases are caused by deliberate falsification, i.e. by misinterpreting the answers or knowingly responding falsely, and unconscious misinterpretation, which could be due to the format of questions, the content of questions and the possible ambiguity of questions (Zikmund et al., 2010). In order to mitigate response bias, a pilot survey was tested to ensure that the questions were not leading or ambiguous, and could be easily understood. The findings from the pilot survey were incorporated into the full study. In order to manage deliberate falsifications, the analysis included the detection of outliers in the data.

In order to test the validity of the constructs in this study, bivariate correlation was used between the item total scores of the scales. In order to ensure the internal reliability of the data and constructs, Cronbach's alpha was used to test the reliability of the measurement scale, as per Wamba et al. (2017) and Mhlungu et al. (2019). This was necessary to ensure that the measurement scale was, in fact, reliably measuring the construct of interest and was internally consistent (Wamba et al., 2017; Mhlungu, Chen & Alkema, 2019).

4.12 Limitations

Since a non-probability sampling method was used, the findings cannot be generalised to the entire population, i.e. the findings are based on individual responses and thus carry individual bias. The survey approach, i.e. using social media and elements of snowball sampling, may also have contributed to individual bias. The survey required individuals to answer on behalf of their organisations, which may have influenced their responses depending on their experience of the organisation. This issue was filtered out by removing individuals with less than a year of experience in the organisation. Finally, the experience of the researcher plays a role in performing quantitative research and non-probability sampling, therefore the researcher may not have had adequate experience in this field.

Chapter 5: Results

5.1 Introduction

This chapter discusses the results obtained in this study. The purpose of this section is to provide a description of the sample population, which is relevant for the generalisability of the results based on non-probability sampling. The scales results are then presented in terms of reliability and validity. Factor analysis through principal component analysis, and statistical inferential statistics were performed in order to test the hypotheses, which was necessary to answer the research questions.

The study had two hypotheses, the first of which was aimed at testing the relationship between entrepreneurial agility and the constructs of firm performance (sales, market share, profit and ROI). The second was aimed at testing the moderating effect of the latent constructs of digital maturity (digital technology, digital culture, digital organisational structure and digital insights) on the constructs of firm performance as described above.

5.2 Details of the sample collected

5.2.1 Total data sample

The total data sample was comprised of 75 respondents, of which only 60 useful surveys were analysed. Six of the respondents did not qualify based on their inability to positively respond to the two qualifying questions asked upfront. One respondent did not meet the qualifying criteria in terms of years of experience in the organisation, and eight were removed as outliers.

Table 4: Summary of survey respondents and data filtering

Total responses	75
Non qualifying questions	6
Remove respondents < 1	1

year of experience in firm	
Outlier removal	8
Useful data	60

The survey response rate was very difficult to quantify given the use of the social media platform, LinkedIn. This was due to the network effect and snowball sampling, which made it difficult to quantify how many people were reached as people may have shared the survey link numerous times. However, based on the number of members in the LinkedIn groups and all the other channels explored, it can be considered that the response rate in this study was very low. There could be several reasons for this, which the researcher did not analyse, including survey fatigue, a lack of time to respond due to other commitments, a lack of incentives, or the respondents may have found the topic too complex or abstract (Fan & Yan, 2010).

5.3 Demographics of the sample

5.3.1 Gender

The total sample consisted of predominantly male respondents (73.5%). One quarter (25%) were female, with 1.5% preferring not to respond (see Table 5).

Table 5: Gender characteristics of population

	Number	Percentage (%)
Male	46	76,67
Female	13	21,67
Prefer not to say	1	1,67
Total	60	100,00

5.3.2 Seniority in organisation

At 93%, middle, senior and executive managers made up the majority of the sample; just 7% were in junior management (see Table 6). This was favourable as the more senior managers would have a better understanding and visibility of their organisation's digital strategy and firm performance.

Table 6: Seniority of respondents within the sample

	Number	Percentage (%)
Junior manager	5	8,33
Middle manager	17	28,33
Senior manager	22	36,67
Executive manager	16	26,67
Total	60	100,00

5.3.3 Years of experience in organisation

The respondents' years of experience in their organisation were more evenly spread, as seen in Table 7 below. The highest weighting was in the 10 to 15 years category, while the lowest was in the > 15 years category.

Table 7: Years of experience in the organisation within the sample

	Number	Percentage (%)
1 to 5 years	17	28,33
5 to 10 years	13	21,67
10 to 15 years	21	35,00
>15 years	9	15,00
	60	100,00

5.3.4 Organisation size

The organisation size in terms of number of employees saw 53% of the sample being >5,000 employees, while the remainder were relatively evenly spread across the other size categories (see Table 8).

Table 8: Organisation size in terms of number of employees within the sample

Organisation size (no of employees)	Number	Percentage (%)
0-99	10	16,67
100-499	9	15,00
500-999	4	6,67
1,000-4,999	5	8,33
5,000 or more	32	53,33
	60	100,00

5.3.5 Annual revenues

The annual revenues of the organisations in the sample were largely > R1,000m at 66%, with R100-999.9m being 19% and R10-99.99m being 12%. The least common were in the <R0.99m and R1m-R9.9m categories, i.e. the sample was skewed towards high annual revenue organisations.

Table 9: Annual revenues of organisations within the sample

Annual revenues in organisations	Number	Percentage (%)
<R0.99m	1	1,67
R1m - R9.9m	1	1,67
R10m - R99.99m	5	8,33
R100m - R999.99m	13	21,67
>R1,000m	40	66,67
Total	60	100,00

5.3.6 Industry type

Several industries were covered within the sample, as shown in Appendix B. The majority of organisations were in mining at 35.3%, while financial services were at 13.2%, manufacturing was at 6.7%, and the automotive industry was at 5%. The rest of the organisations were spread across a wide variety of different industries. The spread of the data were aligned to the researcher's heterogeneous approach, which was taken in order to measure the effects of the phenomenon being studied.

5.4 Validity of the constructs used in the study

Validity measures the accuracy of a measure and the extent to which a score truthfully measures a concept (Zikmund et al., 2010). Construct validity in this study was important to ensure that the scales accurately measured the constructs which were hypothesised in order to answer the research questions. Validity was tested using bi-variate correlation of the item total score per question and the score for each question to ensure all the questions were measuring the same construct. Since all the data were not normally distributed, a Spearman's rank correlation was run for all of the scales (see Appendix C). There were four questions for FP, four questions for EA, seven questions for DM Technology, seven questions for DM Culture, seven questions for DM Organisation, and seven questions for DM Insights.

Table 10: Bi-variate correlation using Spearman's rank for scale validity for firm performance

	N	Spearman's rho coefficient (against item total score)	Sig. (2-tailed)
Firm Performance			
Q1. Sales	60	.762**	0,000
Q2. Market Share	60	.850**	0,000
Q3. Profit	60	.796**	0,000
Q4. ROI	60	.875**	0,000

Table 10 shows significant positive correlations for all questions on firm performance, which implies that the scale was a valid measure of firm performance.

Table 11: Bi-variate correlation using Spearman's rank for scale validity for EA

	N	Spearman's rho coefficient (against item total score)	Sig. (2-tailed)
Entrepreneurial Agility			
Q5. EA-Scenarios	60	.622**	0,000
Q6. EA-Opportunities	60	.725**	0,000
Q7. EA-Strategic assets	60	.826**	0,000
Q8. EA-Positioning	60	.879**	0,000

Table 11 shows significant positive correlations for all questions on EA, which implies that the scale was a valid measure of EA.

Table 12: Bi-variate correlation using Spearman's rank for scale validity for digital technology

	N	Spearman's rho coefficient (against item total score)	Sig. (2-tailed)
DM: Digital Technology			
Q9. Technology-Fluid budget	60	.495**	0,000
Q10. Technology-Road map	60	.699**	0,000
Q11. Technology-Approach	60	.770**	0,000
Q12. Technology-Modern architecture	60	.628**	0,000
Q13. Technology-Measurement	60	.745**	0,000
Q14. Technology-Customer experience assets	60	.641**	0,000
Q15. Technology-Digital tools	60	.740**	0,000

Table 12 shows significant positive correlations for all questions on digital technology, which implies that the scale was a valid measure of digital technology.

Table 13: Bi-variate correlation using Spearman's rank for scale validity for digital culture

	N	Spearman's rho coefficient (against item total score)	Sig. (2-tailed)
DM: Digital Culture			
Culture-Competitive strategy	60	.577**	0,000
Culture-Board support	60	.648**	0,000
Culture-Right leaders	60	.650**	0,000
Culture-Education and training investment	60	.792**	0,000
Culture-Communicate digital vision	60	.740**	0,000
Culture-Measured risks	60	.604**	0,000
Culture-Customer experience	60	.670**	0,000

Table 13 shows significant positive correlations for all questions regarding digital culture, which implies that the scale is a valid measure.

Table 14: Bi-variate correlation using Spearman's rank for scale validity for digital organisational structure

	N	Spearman's rho coefficient (against item total score)	Sig. (2-tailed)
DM: Digital organisational structure			
Organisation-Customer journeys	60	.672**	0,000
Organisation-Resources	60	.844**	0,000
Organisation-Best in class staff	60	.824**	0,000
Organisation-Digital skills	60	.778**	0,000
Organisation-Collaboration	60	.704**	0,000
Organisation-Processes	60	.770**	0,000
Organisation-Vendor partners	60	.670**	0,000

Table 14 shows significant positive correlations for all questions of digital organisational structure, and hence implies that the scale is a valid measure.

	N	Spearman's rho coefficient (against item total score)	Sig. (2-tailed)

DM: Digital Insights			
Insights-Quantifiable goals	60	.754**	0,000
Insights-Employee understanding of contribution	60	.804**	0,000
Insights-Customer centred measures	60	.744**	0,000
Insights-Multiple channels	60	.881**	0,000
Insights-Digital strategy	60	.843**	0,000
Insights-Digital tools	60	.802**	0,000
Insights-Lessons learned	60	.826**	0,000

5.5 Reliability of the constructs used in the study

The reliability of the scales used in this study is an indication of a measure's internal consistency. Internal consistency of the measurement scales is important to ensure the homogeneity of measurements (Zikmund et al., 2010), which is the ability of the questions in a scale to consistently measure the same thing (Wamba et al., 2017; Mhlungu, Chen & Alkema, 2019). A Cronbach's alpha of above 0.7 was obtained for all constructs, which was considered a good indication of reliability (Wamba et al., 2017; Mhlungu, Chen & Alkema, 2019, Zikmund et al., 2010, Gliem & Gliem, 2003).

Table 15: Test for reliability of scales

Scale	Number of questions	Cronbach's Alpha	Decision
Firm performance	4	0,852	Acceptable
Entrepreneurial agility	4	0,787	Acceptable
DM: Digital technology	7	0,816	Acceptable
DM: Digital culture	7	0,799	Acceptable
DM: Digital organisational structure	7	0,879	Acceptable
DM: Digital Insights	7	0,908	Acceptable

5.6 Exploratory factor analysis

As discussed in Chapter 4, exploratory factor analysis was conducted to reduce the number of factors in the measurement scales to ensure the rule of parsimony. The KMO and Bartlett's test for sphericity indicated that factor analysis was appropriate, while a principal component analysis was conducted to reduce the number of variables into a smaller set of factors that described the majority of the variance. The first step in the analysis was plotting the correlation matrix between the variables for each scale, which is shown in Table 32 to Table 36 in Appendix D. The correlation matrices for all the scales indicated that the majority of coefficients were greater than 0.3, which was indicative that there were linear relationships.

For the entrepreneurial agility scale, the PCA analysis resulted in just a single factor, as shown in the component matrix in Table 38 in Appendix D.1. The total variance explained was 61.14% and the factor was termed entrepreneurial agility (EA), as shown in Table 39 in Appendix D.1.

For the digital technology scale, the PCA analysis resulted in two factors being identified, as shown in the rotated component matrix in Table 40 in Appendix D.2. These two factors were defined as digital technology strategy (DTS) and digital technology embeddedness (DTE), which explained 48.07% and 15.53% respectively, as shown in Table 41 in Appendix D.2.

For the digital culture scale, the PCA analysis resulted in two factors being identified, as shown in the rotated component matrix in Table 42 in Appendix D.3. These two factors were defined as digital culture embeddedness (DCE) and leadership support (LS), which explained 48.07% and 15.53% respectively, as shown in Table 43 in Appendix D.3.

For the digital organisational structure scale, the PCA analysis resulted in just a single factor, as shown in the component matrix in Table 44 in Appendix D.4. The total variance explained was 58.15%, and the factor was termed digital organisational structure (DOS), as shown in Table 45 in Appendix D.4.

For the digital maturity insights scale, the PCA analysis resulted in just a single factor, as shown in the component matrix in Table 46 in Appendix D.5. The total variance explained was 65.27% and the factor was termed digital insights, as shown in Table 47 in Appendix D.5.

These results led to the creation of the following conceptual model for testing the correlation and regression analyses, in order to test the hypotheses and answer the research questions as shown in Figure 5 below.

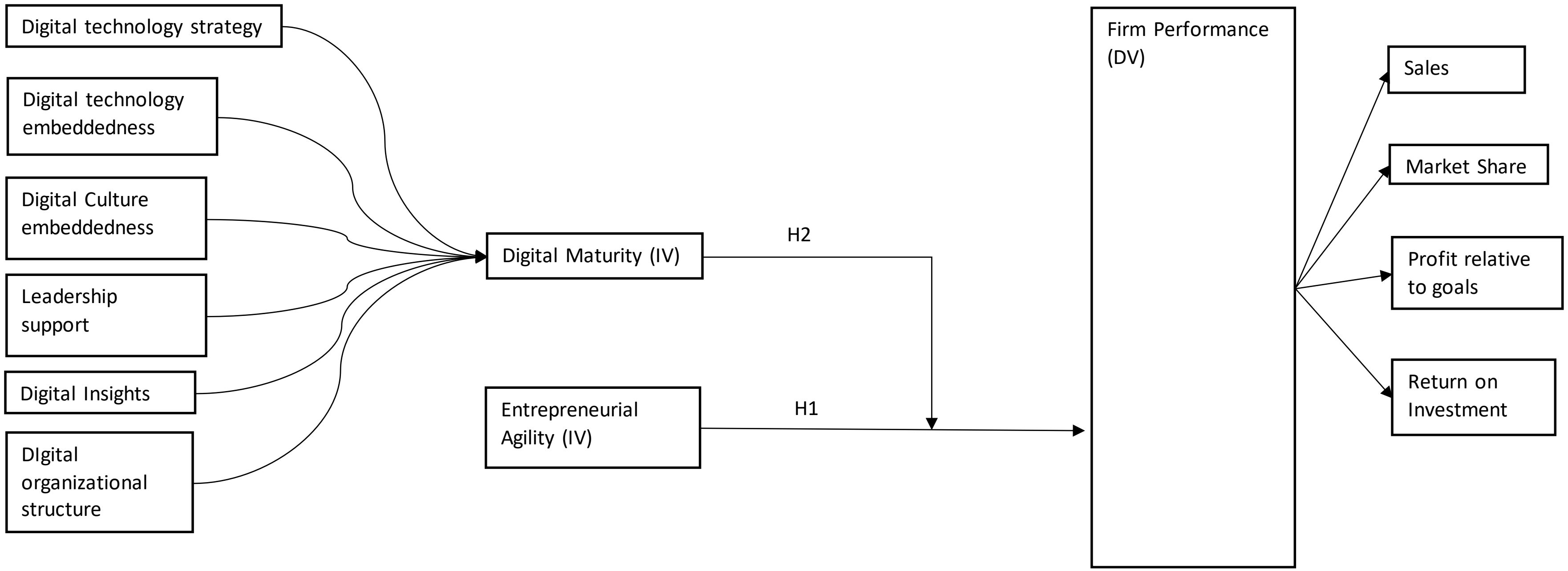

Figure 5: Conceptual model to be tested with correlation and moderated regression analysis

5.7 Descriptive statistics

Table 16: Descriptive statistics of constructs used in correlation and moderated regression analysis

Descriptive statistics												
		Sales	Market Share	Profit	ROI	EA	DTE	DTS	DCE	LS	DOS	DI
Mean		3,80	3,65	3,68	3,72	3,62	3,68	3,82	3,68	3,85	3,47	3,43
95% Confidence Interval for Mean	Lower Bound	3,61	3,44	3,49	3,50	3,40	3,46	3,63	3,46	3,65	3,27	3,20
	Upper Bound	3,99	3,86	3,88	3,93	3,83	3,90	4,00	3,89	4,05	3,68	3,65
5% Trimmed Mean		3,83	3,67	3,70	3,74	3,63	3,72	3,84	3,69	3,89	3,47	3,42
Median		4,00	4,00	4,00	4,00	3,75	3,67	3,88	3,75	4,00	3,50	3,50
Variance		0,57	0,64	0,56	0,68	0,68	0,74	0,51	0,68	0,57	0,61	0,77
Std. Deviation		0,75	0,80	0,75	0,83	0,82	0,86	0,72	0,82	0,76	0,78	0,88
Minimum		2,0	2,0	2,0	2,0	1,75	1,33	2,0	2,0	1,7	2,00	2,00
Maximum		5,0	5,0	5,0	5,0	5,00	5,00	5,0	5,0	5,0	5,00	5,00
Range		3,0	3,0	3,0	3,0	3,25	3,67	3,0	3,0	3,3	3,00	3,00
Interquartile Range		1,0	1,0	1,0	1,0	1,19	1,00	0,8	1,0	1,0	1,21	1,29
Skewness		-0,38	-0,10	-0,16	-0,17	-0,28	-0,61	-0,62	-0,36	-0,74	0,04	0,05
Kurtosis		0,10	-0,38	-0,17	-0,45	-0,61	0,19	0,38	-0,59	0,28	-0,59	-1,02

Table 16 shows the descriptive statistics for the dependent variables (sales, market share, profit, ROI), the independent variable EA, and the moderator variables, DTE, DTS, DCE, LS, DOS and DI, which are sub-constructs of digital maturity. The general means for all the variables were between 3.43 and 3.85. For sales, market share, profit and ROI, the respondents felt on average that their performance in these financial measures were better than their competitors over the last three years, leaning closer to agree on the Likert scale. For the remaining variables, the respondents on average were also closer to agree for the majority of the questions. This shows a general skew of the data to the right, which is also indicated by the negative skewness for the majority of the variables. The standard deviations across all the data were fairly similar, ranging from 0.72 to 0.88 across all the variables, indicating that the spread of data for all the variables were fairly similar. The mean and 5% trimmed mean are close to each other for all variables, indicating the minimal impact of the outlying variables on the mean.

5.8 Recheck for normality after factor analysis

Table 17: Test for normality for all variables prior to correlation and regression analysis

Tests of Normality						
	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Sales	0,305	60	0,000	0,837	60	0,000
MShare	0,253	60	0,000	0,862	60	0,000
Profit	0,281	60	0,000	0,846	60	0,000
ROI	0,251	60	0,000	0,866	60	0,000
EA	0,163	60	0,000	0,963	60	**0,066**
DTE	0,145	60	0,003	0,951	60	0,017
DTS	0,196	60	0,000	0,934	60	0,003
DCE	0,149	60	0,002	0,947	60	0,011
LS	0,162	60	0,000	0,938	60	0,005
DOS	0,100	60	.200*	0,974	60	**0,219**
DI	0,107	60	0,082	0,958	60	0,038
*. This is a lower bound of the true significance.						
a. Lilliefors Significance Correction						

All the variables were tested for normality using the Shapiro-Wilk test; only two variables with $p<0.05$ showed normal data, which were EA and DOS. A non-parametric test, i.e. the Spearman's rank, was thus used for correlation analysis to answer research question 1. For regression analysis, the decision was made to continue since the assumptions for regression required the residuals to be normally distributed, and not necessarily that the data should be normally distributed.

5.9 Correlation analysis

5.9.1 Research Question 1

What is the relationship between entrepreneurial agility and firm performance for firms undergoing DT?

H1: Entrepreneurial agility has a significant positive relationship with firm performance (sales, market share, profit and ROI)

In order to answer this research question, a Spearman's rank correlation analysis was run between the construct entrepreneurial agility and the sub-constructs of firm performance, being sales, market share, profit and ROI. The analysis of results was at a confidence level of 95% ($p<0.05$).The correlation table is shown in Table 18 below.

Table 18: Research question 1: Correlation analysis between entrepreneurial agility and firm performance (sales, market share, profit, ROI) relative to competitors

Correlations			
			EA
Spearman's rho	Sales	Correlation Coefficient	.502**
		Sig. (2-tailed)	0
		N	60
	Market Share	Correlation Coefficient	.370**
		Sig. (2-tailed)	0,004
		N	60
	Profit	Correlation Coefficient	.331**
		Sig. (2-tailed)	0,01
		N	60
	ROI	Correlation Coefficient	.403**

		Sig. (2-tailed)	0,001
		N	60
**. Correlation is significant at the 0.01 level (2-tailed).			

There was a strong positive correlation, i.e. r = 0.502, p (two tailed) <0.05, between sales and entrepreneurial agility, as shown in Table 18.

There was a moderate positive correlation, i.e. r = 0.370, p (two tailed) <0.05, between market share and entrepreneurial agility, as shown in Table 18.

There was a moderate positive correlation, i.e. r = 0.331, p (two tailed) <0.05, between profit and entrepreneurial agility, as shown in Table 18.

There was a moderate positive correlation, i.e. r = 0.403, p (two tailed) <0.05, between profit and entrepreneurial agility, as shown in Table 18.

5.10 Moderated regression analysis

5.10.1 Research Question 2

What is the effect of digital maturity on the relationship between entrepreneurial agility and firm performance for firms undergoing digital transformations?

$H2_0$: Digital maturity has a positive moderating effect between entrepreneurial agility and firm performance (sales, market share, profit, ROI)

In order to answer this research question, a moderated regression analysis was run with all the sub-constructs of digital maturity. Moderated regression, as discussed in Chapter 4, was run using the process macro for moderated regression by Hayes (2020). The assumptions for the regression analysis were also tested using IBM SPSS to confirm the validity of the regression models. A total of 24 moderated regressions were run.

Assumption 1: The dependent variable should be measured on a continuous scale, i.e. it is either an interval or ratio data

Yes, measurements are on a continuous scale.

Assumption 2: There is at least one continuous independent variable and one moderator variable

Yes, the continuous variable is EA, and each of the digital maturity constructs (DTE, DTS, DCE, LS, DOS, DI) form the moderator variables.

Assumption 3: There is independence of observations

Yes, there were no relationships between the samples taken.

Assumption 4: There are linear relationships between the dependent and independent variables

Figure 6 below shows the linear relationships between the dependent and independent variables through a scatter plot and trend lines. It can be seen that a straight lines can be plotted against the dependant and independent variables which shows the relationships generally follow a straight line.

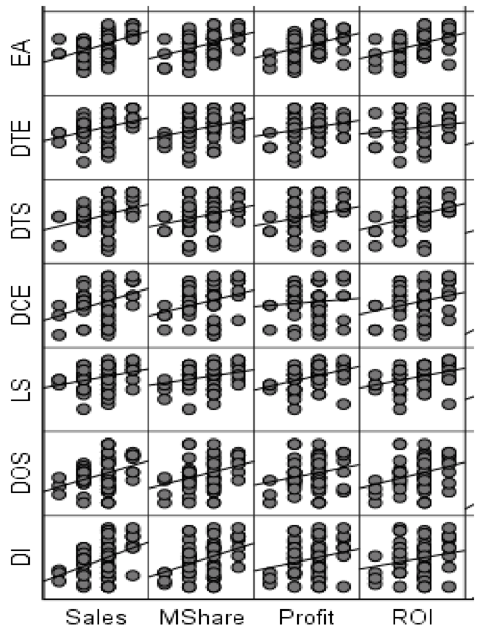

Figure 6: Matrix scatter plot showing the linear relationships between the dependent and independent variables

Assumption 5: The data must show homoscedasticity, which is when for all combinations of independent and moderator variables, the error variances are the same

All the data were mean centred in the regression analysis to minimise the impact of multi-collinearity, which did not impact the analysis of moderator variable (Pallant, 2001). This was first inspected on the scatter plots of residuals against predicted values. From the scatter plot, there was no clear shape that indicated heteroscedastic data, hence the Breusch pagan test for homoscedastic data was used. The tests wer done by running a regression analysis between the square of the unstandardized residuals and the independent variables in each of the regression analyses; a sig value of >0.05 indicated that the null hypothesis cannot be rejected and the data are homoscedastic. For all the regression analyses run, the data was homoscedastic, as per Table 48 in Appendix E.1.

Assumption 6: The data must not show multi-collinearity, which occurs when two or more independent variables are highly correlated with each other

All regressions collinearity statistics had low tolerances and VIF (variance inflation factor) values within acceptable range, where tolerances are >0.1 and VIF<10 (Hair, 1995)

Assumption 7: Data must not contain any significant outliers or high influence points

All outliers were removed from the dataset, as discussed in Chapter 4.

Assumption 8: All the residuals (errors) are approximately normally distributed

Tests for normality were conducted for the residuals from each regression (see Table 49 in Appendix E.1), with most of the residual data being normally distributed. The exceptions were two moderator variables, i.e. Sales – EA and DCE, and Sales – EA and DOS. Due to all the other assumptions being met for the remaining 22 regressions, the researcher decided to continue with the analysis with consideration of the impacts on type 1 and type 2 errors for these two regressions.

5.10.1.1 Moderated regression results for DV, sales

Table 19 below provides a summary of the moderated regression results for the dependent variable sales. For the detailed regression tables, please refer to Appendix E.2. The results indicate three significant moderating effects, which are for digital technological embeddedness ($p < 0.05$; $\beta = 0.28$), leadership support ($p < 0.05$; $\beta = 0.24$), and digital insights ($p < 0.05$; $\beta = 0.32$). The regression models explained 29%, 23% and 29% of the variance respectively for the above moderating effects.

Table 19: Summary of moderating effects of digital maturity for EA and Sales

				Moderation Coefficient		**Regression Model**	
DV	**IV**	**MV**	**Moderation effect (Y/N)**	**P value**	**Coefficient**	**Adjusted R^2**	**P value**
Sales	**EA**	**DTE**	**Y**	**0,01**	**0,28**	**0,29**	**0,00**
Sales	EA	DTS	N	0,34	0,11	0,22	0,00
Sales	EA	DCE	N	0,08	0,21	0,23	0,00
Sales	**EA**	**LS**	**Y**	**0,05**	**0,24**	**0,23**	**0,00**
Sales	EA	DOS	N	0,18	0,16	0,21	0,00
Sales	**EA**	**DI**	**Y**	**0,01**	**0,32**	**0,29**	**0,00**

These moderating effects are shown graphically below:

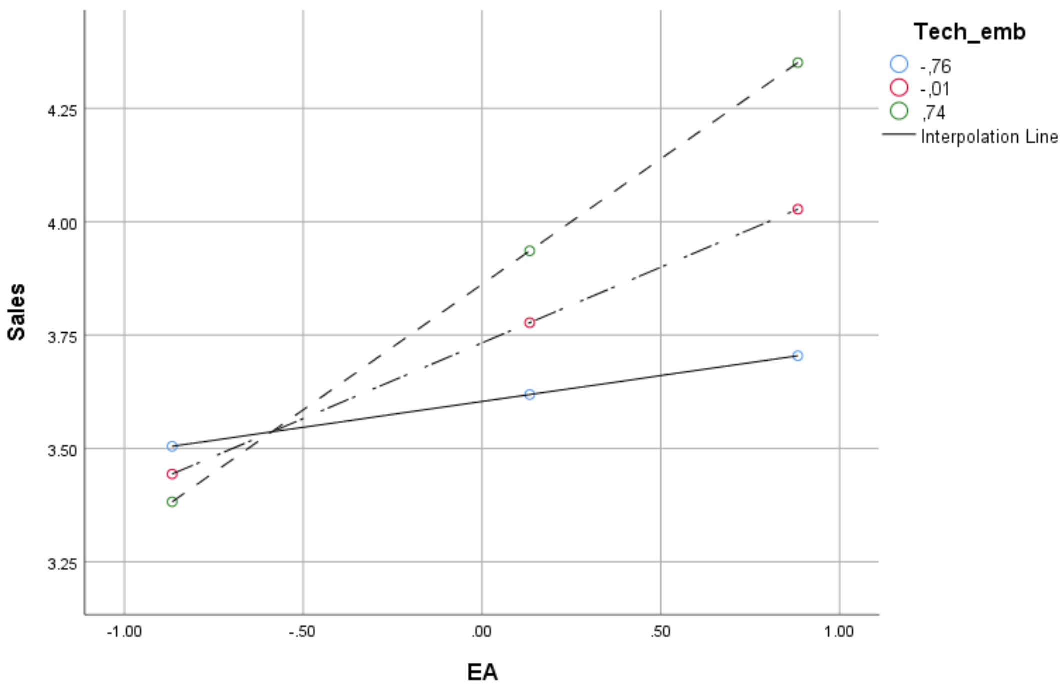

Figure 7: Moderating effect of DTE on the relationship between EA and Sales

Figure 7 shows the moderating effect of DTE on EA and Sales. An increase in DTE increases the slope of the Sales vs. the EA relationship. This implies that an increased DTE positively improves the effect of EA on Sales.

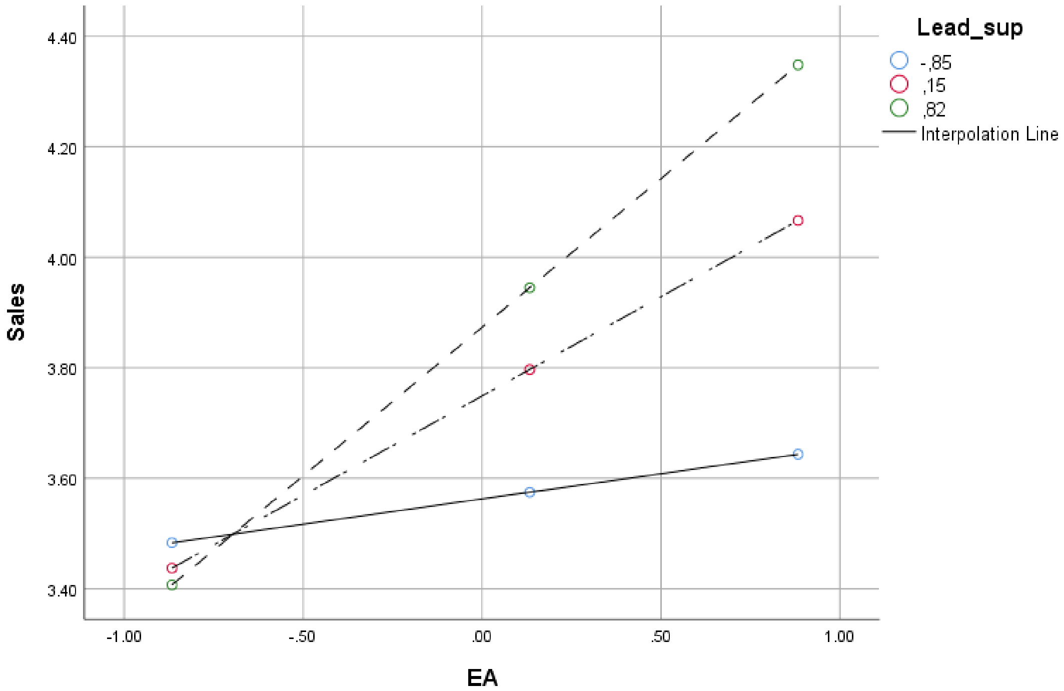

Figure 8: Moderating effect of LS on the relationship between EA and Sales

Figure 8 shows the moderating effect of LS on EA and Sales. An increase in LS increases the slope of the Sales vs. EA relationship, which implies that an increase in LS positively improves the effect of EA on Sales.

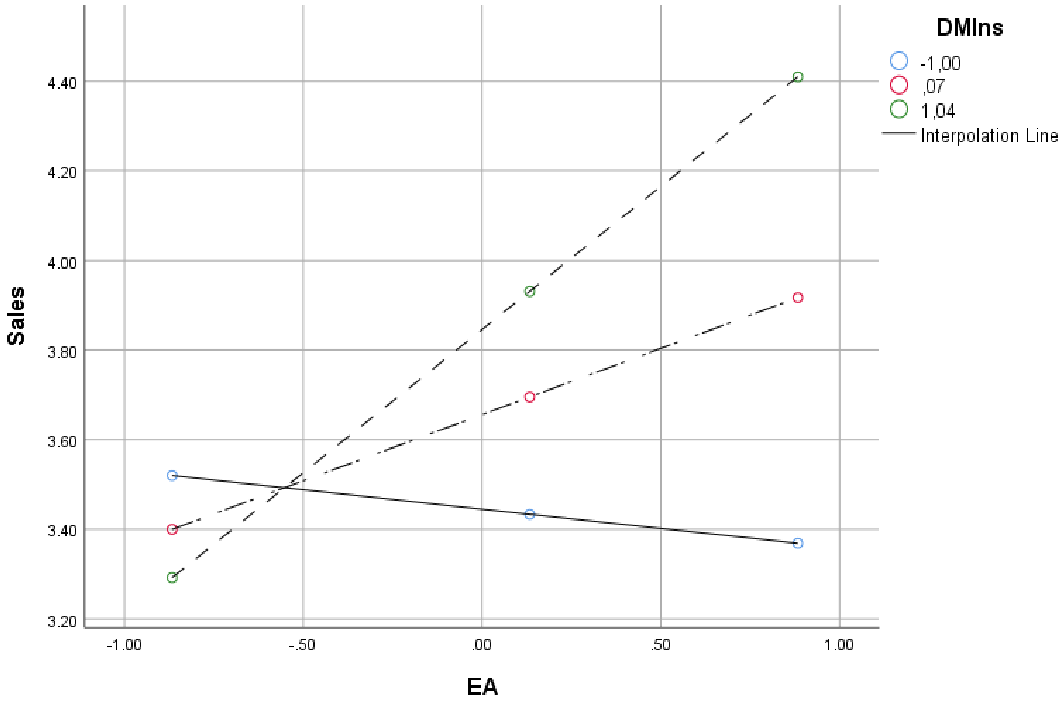

Figure 9: Moderating effect of DI on the relationship between EA and sales

Figure 9 shows the moderating effect of DI on EA and Sales. At low levels of DI, the relationship between Sales and EA is negatively sloped. As DI increases, the relationship becomes positive and increases the slope of the Sales vs. the EA relationship. This implies that an increase in DI positively improves the effect of EA on Sales, whereas without DI or with low levels of DI, the relationship between EA and Sales is negative.

5.10.1.2 Moderated regression results for DV, market share

Table 20 provides a summary of the moderated regression results for the dependent variable, market share. For the detailed regression tables, please refer to Appendix E.3. All the regression models were significant ($p<0.05$); the results indicate just one significant positive moderating effect, which was for digital culture embeddedness ($p <0.05$; $\beta = 0.24$). The regression model explains 20% of the variance between DCE, EA and Market share, which is considered low.

Table 20: Summary of the moderating effects of digital maturity on EA and Market Share

				Moderation Coefficient		Regression Model	
DV	IV	MV	Moderation effect (Y/N)	P value	Coefficient	Adjusted R^2	P value
Market Share	EA	DTE	N	0,55	0,07	0,17	0,00
Market Share	EA	DTS	N	0,86	-0,02	0,16	0,01
Market Share	**EA**	**DCE**	**Y**	**0,04**	**0,24**	**0,20**	**0,00**
Market Share	EA	LS	N	0,40	0,11	0,14	0,01
Market Share	EA	DS	N	0,39	0,10	0,15	0,01
Market Share	EA	DI	N	0,10	0,20	0,19	0,00

The moderating effect of digital culture embeddedness on EA and market share is shown graphically below:

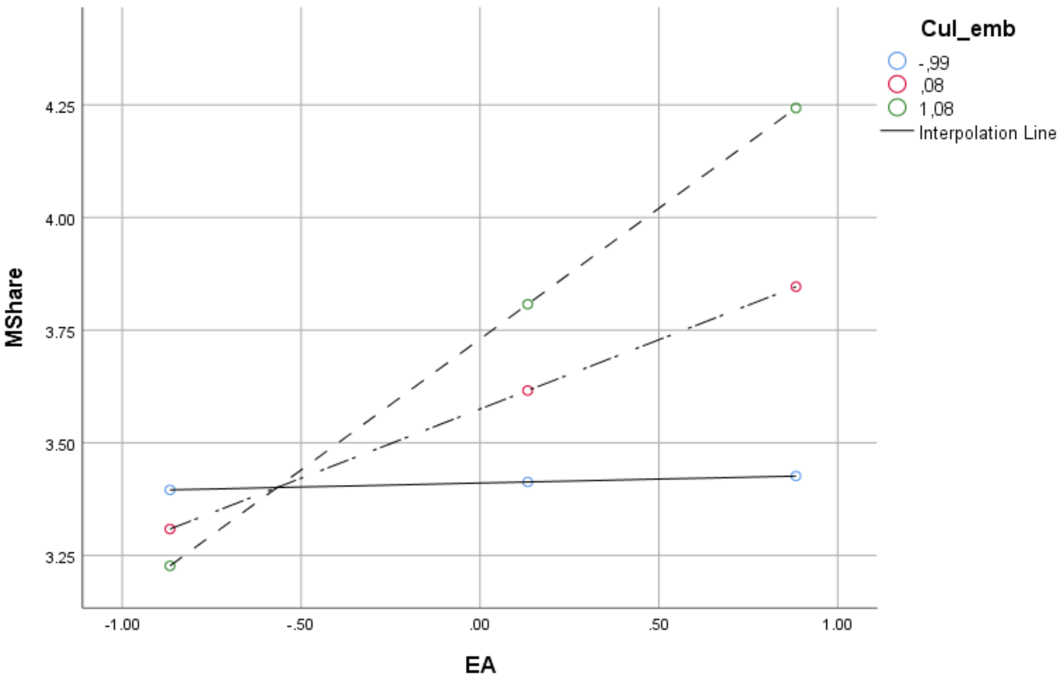

Figure 10: Moderating effect of DCE on the relationship between EA and Market share

Figure 10 shows the moderating effect of DCE on EA and Market share. At low levels of DCE, the relationship between Market share and EA is almost flat, with a very small positive slope. As DCE increases, the relationship becomes positive and increases the slope of the Market share vs. the EA relationship. This implies that an increase in DCE positively improves the effect of EA on Market share.

5.10.1.3 Moderated regression results for DV, profit

Table 21 below indicates a summary of the moderated regression results for the dependent variable, Profit. For the detailed regression tables, please refer to Appendix E.4. All the regression models were significant ($p<0.05$); the results indicate no significant moderating effects, with no coefficients being statistically significant ($p>0.05$).

Table 21: Moderated regression results for the DV, profit

				Moderation Coefficient		Regression Model	
DV	**IV**	**MV**	**Moderation effect (Y/N)**	**P value**	**Coefficient**	**Adjusted R^2**	**P value**
Profit	EA	DTE	N	0,93	0,01	0,10	0,03
Profit	EA	DTS	N	0,90	0,02	0,10	0,03
Profit	EA	DCE	N	0,47	0,09	0,10	0,03
Profit	EA	LS	N	0,15	0,18	0,17	0,00
Profit	EA	DOS	N	0,77	0,04	0,08	0,05
Profit	EA	DI	N	0,42	0,10	0,09	0,04

5.10.1.4 Moderated regression results for DV, ROI

Table 21 below indicates a summary of the moderated regression results for the dependent variable, ROI. For the detailed regression tables, please refer to Appendix E.5. All the regression models were significant ($p<0.05$); the results indicate no significant moderating effects with no coefficients being statistically significant ($p>0.05$).

Table 22: Moderated regression results for the DV, ROI

				Moderation Coefficient		Regression Model	
DV	**IV**	**MV**	**Moderation effect (Y/N)**	**P value**	**Coefficient**	**Adjusted R2**	**P value**
ROI	EA	DTE	N	0,76	0,04	0,13	0,01
ROI	EA	DTS	N	0,88	0,02	0,19	0,00
ROI	EA	DCE	N	0,08	0,22	0,18	0,00
ROI	EA	LS	N	0,06	0,24	0,21	0,00
ROI	EA	DOS	N	0,15	0,17	0,17	0,00
ROI	EA	DI	N	0,10	0,20	0,17	0,00

Chapter 6: Discussion of results

6.1 Introduction

The purpose of the research was to understand the relationship between DM and EA on firm performance for firms undergoing DTs, and as well as the effect of DM on the EA and firm performance relationship. This chapter discusses the results obtained in the study relative to the research questions and hypotheses developed in Chapter 3 which was guided by the literature review in Chapter 2. The results are discussed in the context of the theoretical lens which is the resourced based view of the firm and dynamic capabilities. Comparisons with extant literature will be made to describe the relationships between constructs and to draw insights from the study.

6.2 Research question 1: What is the relationship between entrepreneurial agility and firm performance?

The purpose of this research question was to understand whether EA as a dynamic capability in a firm can improve firm performance within digital transformations. The results indicate that across all constructs of firm performance which are sales, market share, profit and ROI, that there were significant positive correlations. This is as expected in the study which is agreement with prior literature showed positive relationships between EA and overall firm performance (Chakravarty et al., 2013) and positive relationships between EA and a firm's competitive position (Sambamurthy et al., 2007), however these results extends the findings to digital transformations. This supports the framework by Vial (2019) where EA was described as a mechanism for new value creation paths in a digital transformation and Verhoef et al. (2019) that indicates agility as an important capability for firms undergoing digital transformations. This finding also agrees and is supported by theory through the DCF (Teece & Pisano, 1994; Teece et al., 2016). The ability of EA to improve firm performance may be described by its ability to enhance first mover and prospector/analyser strategies (Miles et al., 1978; Zachary et al., 2015) which has been observed to improve firm performance (Fitzgerald et al., 2013; HBR Analytic Services, 2014). This corroborates with the findings in this study. Similarly EA may through proactive sensing of the market, rapidly produce products better suited to customer needs in changing environments, hence this may improve customer satisfaction through the customer engagement and digitized solutions strategies that are typical of common DBS's

(Sebastian et al., 2017). These DBS strategies have been found to improve firm performance which corroborates with the findings in the study. The next sections discuss the results in terms of sales, market share, profit and ROI.

6.2.1 Entrepreneurial agility and sales

The positive correlation between EA and increase in sales relative to competitors ($r = 0.502$, $p < 0.05$) is supported by the DCF (Teece & Pisano, 1994; Teece et al., 2016) where EA as a dynamic capability may enhance competitive advantage of firms. Similarly the work done by Sambamurthy et al. (2007) also indicated the postive relationship between entrepreneurial agility and competitive position of firms particularly in changing environments which supports the DT context of this study.

EA may enhance sales in a DT both in being able to proactively sense the market and also being able to rapidly respond to customer needs. The ability to sense market changes and trends in proactive way has benefits for the firm in creating superior knowledge of the market and customers ahead of competitors which may provide a valuable, rare and hard to imitate resource (Barney, 1991) that leads to competitive advantage and improved firm performance (Cegarra-Navarro, Soto-Acosta, & Wensley, 2016; Chung, Liang, Peng, & Chen, 2010; Liu et al., 2014) which is supported in this study. This may enable firms to create products that are aligned to customer needs and as a result improve customer satisfaction through improved perception of value and quality (Mithas et al., 2016). Some of the benefits of improving customer satisfaction in digital transformations have been discussed by several authors (Fitzgerald et al., 2013; Gurumurthy et al., 2020; HBR Analytic Services, 2014; Westerman & Mcafee, 2012). Similarly, sales may increase when rapid responses to opportunities may result in more frequent innovative digital products or services being produced, which may improve customer satisfaction and firm performance (Mithas et al., 2016; Otto et al., 2020; Sambamurthy et al., 2007) through the customer engagement and digitized solutions strategies of the DBS (Sebastian et al., 2017).

These proactive sensing capabilities and rapid responses may enable proactive strategies like first mover/prospector strategies which enable first/second mover advantages. The reasons are that early entrants may establish customer base, loyalty, learning from customers and also impose buyer switching costs from competitors who have to invest to gain market share (Feng & Feng, 2020; Lieberman & Montgomery, 1988).

6.2.2 Entrepreneurial agility and market share

Similarly increased market share relative to competitors is considered a measure of improved competitive advantage (Edeling & Himme, 2018). The positive correlation between EA and market share ($r = 0.502$, $p < 0.05$) is supported by the DCF (Teece & Pisano, 1994; Teece et al., 2016) where EA as a dynamic capability can enhance competitive advantage of firms. According to Edeling & Himme (2018), market share in an organisation is the share of the total market either monetary or volume. Similarly to sales, if an organisation is generating more market share relative to its competitors, it is an indication of customer preference to their products and services over their competitors (Edeling & Himme, 2018) which is driven by improved customer satisfaction (Otto et al., 2020). Similarly as firm's progress through a DT, being able to sense customer needs in terms of digital products or services that may add value to them, firms may introduce new product offerings which may differentiate themselves from their competitors. These may increase their perceived levels of innovation and value which can increase customer's perception of value which links to improved customer satisfaction, loyalty and trust (Otto et al., 2020). This in turn may improve metrics customer lifetime value, word of mouth marketing and increasing the share of the customer's wallet which improves market share (Otto et al., 2020). This is provided their offerings are unique and not easily imitated. For example, the use of digital assistants and remote experts in the retail industry who can communicate with customers in real time about products through video conferencing to enhance the overall customer experience. These are differentiated benefits that may draw customers to a firm's product, if their perceived value from that product exceeds others.

6.2.3 Entrepreneurial agility and Profit

The increase in profit relative to competitors is a measure of competitive advantage of firms (Newbert, 2008). The results also show that profitability had a positive correlation with EA profit ($r = 0.331$, $p < 0.05$) which was expected based on the DCF (Teece & Pisano, 1994; Teece et al., 2016) where EA as a dynamic capability may enhance competitive advantage of firms in DT. EA however had the weakest correlation with profit compared to other measures. This may be expected as an outcome of proactive and prospective strategies (Miles, Snow, Meyer, & Coleman Jr., 1978) where more frequent responses to changes is favoured over driving efficiencies. This supports the findings in the study.

Hence firms may proactively release several products to customers to favour sales and market share ahead of profitability (Edeling & Himme, 2018). This may be the case for firms trying to enter a new market or developing new markets identified through the DBS (Bhadradwaj et al., 2013). However, the benefits EA provides in terms of enabling prospector/analyser strategies may allow firms to benefit from first and second mover advantages which may result in them enjoying economic rents of high profitability until new market entrants compete (Feng & Feng, 2020), this can improve firm profitability and competitive advantage.

6.2.4 Entrepreneurial agility and ROI

An increase in a firm's ROI relative competitors is considered a competitive advantage because the firm is able to generate a higher return on their investment. The results indicate a positive relationship between EA and ROI ($r = 0.403$, $p < 0.05$) which was expected based on the DCF (Teece & Pisano, 1994; Teece et al., 2016) where EA as a dynamic capability can enhance competitive advantage of firms in DT. ROI was expected to be strongly correlated through improved decision making through the sensing capabilities of EA support by creating superior knowledge for the firm (Chung et al., 2010) which enables the right investments and the ability to rapidly respond and capitalise on these opportunities particularly in a DT (Fitzgerald et al., 2013; Sebastian et al., 2017; Westerman & Mcafee, 2012).

6.3 Research question 2: What is the effect of digital maturity on the relationship between EA and firm performance for firms in DT?

The purpose of this research question was to understand what effects digital maturity has on the relationship between EA and firm performance. In a DT, a firm is developing digital resources and capabilities as required by the DBS. As the level of DM increases it is expected that these digital resources and capabilities will improve in firms as they execute and adapt their DT strategies as required by the DBS (Chanias et al., 2019).
Factor analysis was done in Chapter 5 on the sub-constructs of DM which reduced the constructs digital technology into two constructs digital technology embeddedness (DTE),

and digital technology strategy (DTS). Digital culture was reduced into digital culture embeddedness (DCE) and leadership support (LS). Digital organisational structure (DOS) and digital insights (DI) were reduced to one construct respectively. The results are discussed below in order of the dependant variables in the study.

6.3.1 Effect of digital maturity on EA and sales

The results indicate that there are three significant moderating effects (at 95% confidence) which are DTE ($\beta = 0.28$, $p<0.05$), LS ($\beta = 0.24$, $p < 0.05$) and DI ($\beta = 0.32$, $p<0.05$). DI appears to have the strongest moderating effect, followed by DTE and LS.

6.3.1.1 The moderating effect of digital technological embeddedness on the relationship between EA and sales.

The results indicate that digital technological embeddedness in firms has a positive moderating effect ($\beta = 0.28$, $p<0.05$) on the relationship between EA and sales. This relationship is explained by ***Figure 7***, and implies firms with higher DTE would have a stronger relationship between EA and Sales. The results indicate that firms with higher levels of adoption of digital technologies can expect higher competitive advantages reflected in sales for the same levels of EA. This finding aligns with the expectations of the study which describes that higher digital technology embeddedness in the firm will enable more advanced digital resources and capabilities due to more advanced digital technologies. The implications are that DTE can enhance the firm’s capability to proactively be able to pick up trends in the market, this can relate to customer trends, industry trends or global trends (Chanias et al., 2019; Teece, Pisano, & Shuen, 1997; Teece et al., 2016). For example, the big data analytics capabilities can improve the ability of firms to better sense market opportunities, understand customer needs and correctly respond to them (Wamba et al., 2017). Similarly the use of social media platforms and interacting with customers through digital technologies like CRM tools or apps can enhance customer satisfaction which supports the customer engagement strategy of the DBS (Sebastian et al., 2017). The improvement of customer satisfaction will lead to improved sales (Anderson & Ellerby, 2018; Gurumurthy et al., 2020; Kane et al., 2017; Westerman & Mcafee, 2012).

Higher adoption of digital technologies can provide more advanced digital infrastructures and capabilities which can be used to rapidly develop new products and services through rapid prototyping and innovation processes (Chanias et al., 2019; Sebastian et al., 2017). For example through using digital platforms and cloud computing, can support rapid prototyping and scaling up of products. This can support the digitized solutions strategies of the DBS (Sebastian et al., 2017) to supply more innovative digital products, services or features required by the market.

6.3.1.2 The moderating effect of digital insights (DI) on the relationship between EA and sales

The results indicate that digital insights has a positive moderating effect ($\beta = 0.32$, $p<0.05$) on the relationship between EA and Sales. This moderating effect is the highest when compared to digital technology and leadership support, which may be attributed to to enhancing the sensing capabilities of EA by providing superior knowledge and a competitive advantage (Barney, 1991). This is due to the importance of firm's having the right insights to make correct decisions. This superior knowledge may enable proactive strategies prospector/analyser strategies especially with changing environments which corroborates with improving sales and firm performance (Miles et al., 1978; Zachary et al., 2015).

The moderating effect was shown in ***Figure 8***. It can be seen at low levels of DI, the relationship between EA and Sales is negatively sloped, where increasing EA may result in lower sales relative to competitors. This is an interesting finding and could describe the importance of digital insights in enhancing the sensing capability of EA, as described above. It can be rationalized in the following way, if a firm has low levels of digital insights, it may result in the incorrect interpretation of opportunities. This may result in the organisation responding to incorrect information and therefore not be able to capitalise on the opportunities explored and lose sales with customers because their needs were not well understood. This corroborates with Westerman & Davenport (2018) which indicated indicate some of the reasons for failed DT initiatives included lack of management understanding of the opportunity.

With higher digital insights the slope of the EA and firm performance becomes positive and continues to increase in slope with increasing digital insights. Similarly, this is an indication that digital insights enhances the effect on EA, and considering digital insights provides superior knowledge, this enhances the sensing component of EA. At higher levels of digital insights, a firm may benefit from having superior knowledge compared to competitors which provides a VRIN resource to firms in a DT. This may provide superior knowledge about customers. This may result in rapidly pursuing opportunities more closely aligned to the required customer needs and therefore increase the ability of firms to capitalise on their opportunities. Examples of these applications include the use of smart connected devices by manufacturers which through the use of the internet can capture valuable insights about their product usage, customer behaviour and further improvements which can be made to their products (Porter & Heppelmann, 2015). These new digital insights from the data may feedback into the firm to improve product life and adapt their products to customer needs which may improve customer satisfaction. . Other sources of revenue could result from the data generated, for example smart connected devices in cars can provide traffic related information from the vehicles can attract atypical customers like government who may benefit from this information in their infrastructure planning (Hanelt et al., 2015).

6.3.1.3 The moderating effect of leadership support (LS) on the relationship between EA and sales

The results obtained indicate the positive moderating effect of LS ($\beta = 0.24$, $p<0.05$) on the relationship between EA and Sales. At low levels of LS, the slope of the relationship between EA and Sales, is positive but low, as LS increases the slope gets increasingly steeper indicating that LS increases the strength of the relationship between EA and sales. This may be explained by the role of management in enhancing EA as a dynamic capability which describes the ability of firms to take the opportunities discovered in the sensing step, and being able to co-ordinate and re-organize themselves to take advantage of them (Teece et al., 2016). Within a DT, internal resources such as culture, digital organisational structure, human resources, technology, knowledge processes are being configured and changed by the organisation's leadership and management teams to capitalise on the market opportunities offered by digital technologies (Vial, 2019, Teece et al., 2016). However, this change may conflict with the organisation's existing processes, systems and culture which can cause organisational inertia or resistance to change (Vial, 2019; Chanias et al., 2019) which requires senior leadership support to overcome.

Having the support from senior leadership has also been found to be critical to drive the DT process and the implementation thereof (Kane et al., 2016, 2017; Nickisch, 2019) and indicative of more digitally mature firms, which corroborates with the results. For example, leadership support would help drive the development of new digital products and services especially with an existing pipeline of traditional products and services still in operation, managers within the firm may prioritise traditional offerings over the digital offerings due to a legacy culture which requires leadership support to drive (Chanias et al., 2019). The improved leadership support, particularly if it's made public that the firm is digitally transforming, may attract other industry players to want to partner with the firm for digital projects (Chanias et al., 2019). This may present opportunities that EA can leverage to increase sales.

6.3.1.4 Effect of digital technology strategy, digital culture embeddedness and digital organisational structure on the relationship between EA and sales

The results indicate that there is no moderating effects between DTS, DCE and DOS on the relationship between EA and Sales. This indicates that the relationship between EA and Sales in unaffected by these constructs. This is contrary to the expectation of the literature review (Anderson & Ellerby, 2018; Fitzgerald et al., 2013; Kane et al., 2016, 2017) which anticipated that developing these digital resources and capabilities would enhance the sensing and/or seizing capability of EA which translates into better sales. Considering the industry types in the sample, which were largely mining, financial services, automotive and manufacturing; majority of firms in these industries may have not fundamentally transformed their business models yet (Hanelt et al., 2015; Sebastian et al., 2017; WEF, 2017) which may be due to industry specific inertias or barriers (Gao et al., 2019; Vogelsang et al., 2019) and organisational inertias which may be inhibiting their effects on EA (Warner & Wäger, 2019). This is described by Remane et al. (2017) which emphasizes that perhaps the hype of digital maturity created by practice based literature may be an oversimplification and overstating of their value in the more complex organisational transformative changes. These results may corroborate with some of the concerns raised by Remane et al. (2017) and perhaps the need for more construct definition and clarity in the use of digital maturity as a gauge for general firm progress in a DT and its impact on enabling fundamental transformative changes required to enhance EA.

6.3.2 Effect of digital maturity on entrepreneurial agility and market share

6.3.2.1 The moderating effect of digital culture embeddedness (DCE) on the relationship between EA and market share

The results indicate a positive moderating effect ($p < 0.05$; $\beta = 0.24$) between DCE and the relationship between EA and market share. Figure 10 shows the moderating effect of DCE on EA and Market share. At low levels of DCE, the relationship between Market Share and EA is almost flat with a very small positive slope. As DCE increases, the relationship becomes positive and increases the slope of the Market share vs. EA relationship. This implies with low digital culture embedded, the firm is less likely to see a benefit from EA on market share. As the DCE increases the relationship between EA and market share becomes stronger.

DCE is enhanced by having the right leaders on a day to day basis, investing in digital training and education, collaborative teams and having measured risks for innovation. Similarly this encompasses an innovation focus, engaged and collaborative work environments, and a willingness to experiment with new ideas which have been reported to improve DT and firm performance which corroborates with the findings in literature (Chanias et al., 2019; Dremel et al., 2017; Kane et al., 2016; Vial, 2019). These attributes of DCE is suitable for changing environments like that of a DT and can be expected to support quick responses required by the firm (Vial, 2019). Hence EA may be enhanced by DCE in being able to more easily configure the human resources in the firm to rapidly execute the opportunities identified. The availability of digital skills from employees, and a collaborative workforce may be expected to execute better when the environment changes (Chanias et al., 2019; Gurumurthy et al., 2020; Kane et al., 2017; Vial, 2019) and through innovation processes like rapid prototyping to create new products or services (Sebastian et al., 2017) which may be an outcome of EA. Providing more innovative offerings to customers has been strategies firms have used to gain additional market share (Otto et al., 2020) through improved customer satisfaction (Chen, Preston, & Swink, 2015; Feng & Feng, 2020). This corroborates with the findings in this analysis.

6.3.2.2 Effect of DTE, DTS, LS, DOS and DI on the relationship between EA and market share

The remainder of the digital maturity constructs which are digital technology embeddedness, digital technology strategy, leadership support, digital organisational structure and digital insights were found to have no moderating effects between EA and market share. This is contrary to the expectations in this study which were that these capabilities would enhance of EA in capturing more market share (Gurumurthy et al., 2020; Fitzgerald et al., 2013, Westerman & Mcafee, 2012, HBR Analytics, 2014). A closer examination of the sample demographics showed the firms in the study were from traditional industries that were asset intensive and people intensive like mining, financial services, manufacturing and automotive. Possible reasons for why these digital capabilities did not enhance EA and market share relationships, as well as considering that there were no moderating effects on Profit and ROI across all the DM constructs will be discussed below.

6.3.3 Effect of digital maturity on EA and profit and ROI

There were no moderating effects between all the constructs of digital maturity which are digital technology embeddedness, digital technology strategy, digital culture embeddedness, leadership support, digital organisational structure and digital insights on the relationship between EA and Profit as well as ROI. This does not agree with literature (Chanias et al., 2019; B. M. Fitzgerald et al., 2013; Kane et al., 2016, 2017; Vial, 2019; Westerman & Mcafee, 2012) and reasons for this may include the industry types in the sample. The predominant industries in the sample were mining, financial services, automotive and manufacturing. These industries are still considered to be in the early stages transforming their business models and themselves from their core products (Kane, Palmer, Phillips, Kiron, et al., 2015; Sebastian et al., 2017; WEF, 2017) and are still largely selling traditional products in their markets. The possible reasons for these findings are discussed below:

The report by Kane, Palmer, Phillips, Kiron, & Buckley (2015) on the digital maturity scores of industries placed IT and technology firms at the top of digital maturity. A separate report by HBR analytic services reported that the majority of firms that capitalised on first mover advantages and that transformed their business models were those in the technology industry, and less so in the financial services, manufacturing and the public sector. The technology industry was also the most “digitally transformed” in terms of their business model changes. In addition, there were trends with the industry types where majority of technology firms were in the pioneer category, financial services were followers, and the least likely industry to be pioneers were the public sector (HBR Analytic Services; 2014). Hence indicating that the industry type and industry digital maturity level may play a role in influencing the EA and firm performance relationship, and whether the DM measure is a realistic comparison of digital maturity for traditional firms.

The recent paper by Gao, Hakanen, Töytäri, & Rajala (2019) provides insights on digital transformation in physical asset intensive industries specifically mining and metals industries. The results showed that digital transformation is inhibited by four aspects lack of capabilities to change, goal ambiguity, technological constraints, and external constraints such as legislation. These were specific to the nature of the environment for example, access to basic IT services like Wifi underground, change management across the organisation, legacy technology systems, and legislative restrictions (Gao, Hakanen, Töytäri, & Rajala, 2019). Hence these barriers could be responsible inhibiting these digital resources and capabilities from being developed, and also limiting their use across the entire organisation. Similar findings were found by Vogelsang, Liere-netheler, & Packmohr (2019) for manufacturing industries where in addition to the above, lack of industry related skills was identified as an inhibitor. Hence this was indicative that possibly with industry specific challenges with digital transformations in their specific industries, digital maturity may be more unique to firms rather than a general measure of progress on digital transformations that firms should aspire towards. Furthermore, this indicates that current views on digital maturity may place unrealistic expectations on certain industries because of the industry specific organisational inertia both internally to the firm and externally which may inhibit the overly stated value of digital maturity in these firms (Remane, Andre, et al., 2017). This aligns with the assertion Remane et al. (2017) that the digital maturity path may be different for different industries.

This also aligns with the work done on dynamic capabilities in digital transformations by Warner & Wäger (2019) which indicated that internal organisational factors like rigid strategic planning, high levels of hierarchy, and change resistances may be barriers to dynamic capabilities in the DT process. This may be more pronounced for traditional industries due to the legacy of entrenched cultures and behaviours that may require time through a process of continued strategic renewal (Warner & Wäger, 2019). As Warner & Wäger (2019) indicates before more significant changes to deeply entrenched beliefs like culture and traditional business models can take time. Remane et al. (2017) describe factors like management perception and cognitive path dependencies of management that need to be overcome, where DM as a measure of DT progress in a firm may overlook and oversimplify.

Similarly Teece (2007) indicates that these biases may influence the way organisations make decisions traditionally on investing on new innovations, because these are traditionally managed through project finance and corporate finance methods which are rule based and subject to assumptions of project cash flows and understanding of the value cases in their business. In DT, particularly with traditional firms that are physical asset intensive, the value cases for physical products may be easier to model than the value cases for intangible assets like digital insights or sensing. Teece (2007) indicates in these cases management judgement and decision making skills take precedence. This aligns with Remane et al. (2017)'s argument around the management perception and cognitive path dependencies that may need to shift, and well as the internal barriers (Warner & Wäger, 2019) that may inhibit dynamic capabilities and the renewal of more fundamental changes required for traditional firms. Hence in their context, DM may not have consideration of all the complexities involved in transforming their organisation towards achieving the benefits that are described in digital transformations. This may be why majority of firms embark of DT initiatives and few have seen the expected benefits of it (Sutcliff et al., 2019; Westerman & Davenport, 2018).

Hence an important consideration is the benefits that are stated for digital maturity models because they take a "blanket approach" across several industries (Remane et al., 2017). Several reports show significant benefits of digital transformation but these link to firms changing their business models as an outcome (HBR Analytic Services, 2014; Kane, Palmer, Phillips, Kiron, et al., 2015) which may be required to manage disruptive change and achieve the stated benefits (Bughin & van Zeebroeck, 2017; Matzler et al., 2018). Hence the benefits of digital maturity could be skewed towards much more fundamental changes such as business model changes which are challenging for traditional firms. DM does not consider the industry specific barriers and obstacles particularly for traditional industries that are still physically asset intensive (Hanelt et al., 2015). This may oversimplify the use of a “global” digital maturity metric as a realistic metric for digital transformation of traditional firms.

Hanelt et al. (2015) describes the digital transformation path relevant to physical asset intensive industries for their business model change, which business model creation, extension, revision and termination. The latter two processes require changing existing processes and which are more challenging because of the uncertainty, ambiguity, path dependencies, cognitive shifts, and resistance for firms (Cavalcante, Kesting, & Ulhøi, 2011). These can be both firm (Warner & Wäger, 2019) and industry specific (Gao et al., 2019; Vogelsang et al., 2019) challenges. For example, replacing the parts of the workforce with automation may encounter internal resistance and inertia or industry specific regulatory restrictions, which may be not much of a barrier for other less asset intensive industry types e.g. technology firms. Hence business model changes of these traditional firms are not commonly seen in digital transformations (HBR Analytic Services, 2014; Fitzgerald, 2013). These challenges may not be considered in the metric for digital maturity, and as such simplifies its definition of true progress made in digital transformation particularly with regards to changes in the business models of physical asset intensive industries. Hence Warner & Wäger (2019) propose that digital transformation may be a process of continuous renewal of the firms business model. Therefore supporting Remane et al. (2017) in that digital maturity paths may not be a “one size fits all”.

6.4 Entrepreneurial agility and digital maturity in traditional organisations

The results obtained in the study indicate that entrepreneurial agility correlated positively with firm performance across the various dimensions of sales, market share, profit and ROI. This is indicative that proactively sensing, reconfiguring of resources and rapidly responding to opportunities for these traditional firms can create competitive advantages and improved firm performance particularly in digital transformations. This research extends the application of entrepreneurial agility to the context of digital transformation to help understand this complex phenomenon and how firms can achieve competitive advantages. The research however does not deal with the antecedents of entrepreneurial agility in digital transformations in this study. This may form part of future research to understand how firms can develop this capability in order to leverage it for competitive advantage in a DT context.

Traditional firms also have industry specific and firm specific organisational challenges and inertias that may inhibit entrepreneurial agility as a dynamic capability which may compete with the digital capabilities that are being built as a firm undergoes digital transformation (Gao, Hakanen, Töytäri, & Rajala, 2019; Vogelsang, Liere-netheler, & Packmohr, 2019; Warner & Wäger, 2019). Hence the use of "global" digital maturity as a measure of the progress of the firm's digital transformation may be misleading and present unrealistic expectations of firm performance (Remane et al., 2017). Whilst there were some moderating effects of the capabilities created through digital maturity on sales and market share, majority of these capabilities did not have moderating effects. The implications of this for firms, is that there may be oversimplification of the expectations of the digital maturity path that firm's take. Hence a one size fits all measure of digital maturity may not be indicative of the firm specific and industry specific realities of progress made in a firms digital transformation. This is relevant for traditional organisations that have challenges with legacy cultures, systems and industry challenges that inhibit the fundamental changes to their business models. The best performing firms in terms which are being compared are firms in the technology industries which may have different organisational challenges and industry barriers which enables them to be more entrepreneurially agile to change their business models fundamentally. However these challenges are not the same for traditional firms and should not be used as the same yardstick. Hence further research should explore the construct definition of digital maturity to understand the scope of its use as a measure of firms to gauge their progress in digital transformations.

Chapter 7: Conclusions

7.1 Introduction

The purpose of this chapter is integrate the findings and literature into a cohesive set of conclusions in order to effectively answer the research questions. This chapter synthesises those conclusions into the contributions of this study to theory as well as the business implications of the study, as discussed in the research objectives in Chapter 1. The limitations of this study are also discussed, as are recommendations for future research.

This study aimed at answering the overall research question, which was: "What is the effect of digital maturity and entrepreneurial agility on the performance of traditional firms undergoing DT initiatives?"

7.1 Contributions to theory

7.1.1 Effect of EA on firm performance

The results in this study indicated that EA is positively correlated with firm performance across all the constructs of sales, market share, profit and ROI. This indicates that EA is an important source of competitive advantage for firms undergoing a digital transformation.

The effect of entrepreneurial agility on firm performance and competitive advantage was established in the information systems (IS) literature (Chakravarty et al., 2013; Lu & Ramamurthy, 2011; Sambamurthy et al., 2003; 2007; Tallon et al., 2019). However, the capabilities created in a DT are much broader and more integrated into the firm's business strategy (DBS), as opposed to a functional IT strategy that supports the business strategy (Bhadradwaj et al., 2013; Chakravarty et al., 2013; Sambamurthy et al., 2003; Tallon et al., 2019). To the researcher's knowledge, this effect of EA on firm performance within a DT has not been empirically determined, with recent literature noting the importance of entrepreneurial agility in DTs (Verhoef et al., 2019; Vial, 2019). A contribution to the body of knowledge by this research is the extension of the existing theory of entrepreneurial agility and firm performance to the digital transformation context.

7.1.2 Effect of DM on the relationship between EA and firm performance

The study showed that there were some positive moderating effects between the variables digital technology embeddedness, digital insights and leadership support on the EA and sales relationship. Similarly, there was a positive moderating effect between digital culture embeddedness and the relationship between EA and market share. These may be due to the customer engagement strategies that are commonly executed through the DBS, which may provide these competitive advantages through improved customer satisfaction. However, the study showed that the majority of the DM variables did not have moderating effects on firm performance through sales (DTS, DOS, DCE) and market share (DTE, DTS, LS, DOS, DI). None of the DM variables (DTE, DTS, DCE, LS, DOS, DI) moderated the relationships between EA and profit, or EA and ROI. This may be due to the organisational barriers (Warner & Wäger, 2019) and industry related barriers (Gao et al., 2019; Vogelsang et al., 2019) associated with traditional firms.

The effects of DM on EA and firm performance have not been studied widely in the literature, although Chakravarty et al. (2013) showed that IT competencies can have a moderating effect between entrepreneurial agility and firm performance. This was not in a DT, however, and there has not been any literature measuring the moderating effects of the broader capabilities associated with DM on EA and firm performance (Vial, 2019). Researchers have highlighted the relevance of some of the interactive relationships between aspects of digital organisational structure and culture on enhancing agility in DT, but this has not been tested empirically (Verhoef et al., 2019; Warner & Wäger, 2019). Hence this provides an empirical assessment of the moderating effects based on the current definitions of DM in literature.

These findings also support those of Remane et al. (2017), who studied the complexity and scope of use for the digital maturity construct in traditional industries, which may currently be an oversimplification of the complexities involved in DT. As a result, some of the stated benefits of DM may be unrealistic expectations for traditional firms, because technology firms may be used as a benchmark for DM and may not share the same organizational and industry barriers to fundamentally changing their business models.

7.2 Implications for managers

7.2.1 Potential benefits of EA for managers

Considering the positive relationships between EA and firm performance, firms undergoing DT should thus consider developing EA as a dynamic capability to allow the changes occurring within the DT process to be leveraged via the DBS to create new opportunities. Teece et al. (2016) indicated that there are two requirements for effective dynamic capabilities, i.e. a management team that is entrepreneurially minded and a platform that is flexible and can easily be reconfigured by the management team. EA would therefore need to be driven from the top down from senior leadership, but also supported from the bottom up where the resources and structure of the firm allow for a rapid response to opportunities identified in the changing environment. Therefore, within a DT, EA should be leveraged as well as targeted as part of the organisational capabilities and strategies that are desired by leaders through the DBS. EA will enhance the ability of firms to adopt more proactive market strategies in a DT, such as the first mover and prospector/analyser strategies, which can be included in the firm's DBS.

These strategic changes in an organisation would need to consider the risk appetite of the organisation because rapid responses to market changes will also bring risks of uncertain market responses. Leaders with a low risk appetite or low risk tolerance may not be willing to experiment or take risks in completely unchartered territories where typical entrepreneurs at times find themselves. At the organisational level, therefore, EA will require a change in strategic mind-set, risk tolerance and a longer term view, which may be an iterative process of development rather than a linear one.

For firms that are in defender/reactor strategies currently and trying to develop digital capabilities and resources in their DT strategy, EA may be a strategic organizational dynamic capability that is required to enable improved firm performance in digital transformations (Miles et al., 1978). Considering the disruptive effects of digital technologies and the changes in the environment, this would be a consideration for firms that are looking to remain competitive in the longer term.

7.2.2 Potential issues with using only digital maturity to measure levels of digital transformation for managers in traditional organisations

The use of digital maturity as a measure of digital transformation, as well as its correlation with firm performance, has been widely published in practice based literature and by management consultants (Anderson & Ellerby, 2018; Gurumurthy et al., 2020; Kane et al., 2015; 2017; 2016). While there are benefits of DM, as were seen through some of the moderating effects of EA on market share and sales in this study, these can occur through improved customer engagement and interaction strategies in the DBS. These may not provide the full suite of expected benefits that come from transforming an organisation's business model (Bughin & van Zeebroeck, 2017; Fitzgerald et al., 2013; HBR Analytic Services, 2014; Teece, 2018; Westerman & Davenport, 2018).

Other factors that might impact the use of digital resources and capabilities developed in a DT may be at the organisational and industry levels, particularly for traditional firms (Gao et al., 2019; Vogelsang et al., 2019; Warner & Wäger, 2019). The majority of the benefits in DM have been reported using technology companies as benchmarks of high DM (HBR Analytic Services, 2014; Kane et al., 2015), which may be able to more easily transform their business models because they do not have the same barriers to changing their business models as traditional firms. Similarly, a linear path to digital maturity is assumed (Remane, et al., 2017), but this seems unlikely for traditional firms which may need a continuous state of renewal of its digital transformation over time as it aims to change its legacy business models and cultures (Warner & Wäger, 2019).

Managers may also need to change their cognitive processes in terms of how they view their organisation and the long term strategic plans needed to overcome any barriers. Traditional firms that are developing these digital capabilities but are not able to fundamentally change their business models because of these barriers may not realise their expected returns. It may well be that the existing organisation may take too long before it is able to proactively and rapidly take advantage of the digital capabilities it develops, due to these barriers. Other strategic decisions to capitalise on EA may be more beneficial in the short term to compete in the digital environment. Some traditional organisations are starting to develop completely new business units separate from the parent firm, e.g. BMW-Daimler is creating a new business unit for mobility services, Goldman Sach's Marcus and Wells Fargo's greenhouse (Gurumurthy et al., 2020). These are two fully digital banking offerings for their customers that operate as a separate entity to their parent firm. Marcus by Goldman Sachs was launched in 2016, and has seen significant growth by providing a low cost digital banking solution for customers, they had grown (2016-2019) from 0.2 to 5 million customers, increased their revenue from $2m to $860m; they are now partnering with the likes of Apple and Google to scale up their offerings and gain even more efficiencies to reduce costs and increase competitive advantage (Marcus, 2020). This may be a more viable option for traditional companies looking to benefit from being able to rapidly respond to a changing market driven by digital technologies, which the large technology companies (Amazon, Google, Facebook etc.) are enjoying economic rents from. These strategic options need to be considered in the DBS to enable the business model to provide value to, and capture value from, customers. Ultimately, the firm has to be able to create more value for customers as well as themselves (Teece, 2018) if it is to achieve a competitive advantage over others in digitally changing world.

7.2.3 Proposed strategic framework for the digital transformation of traditional organizations

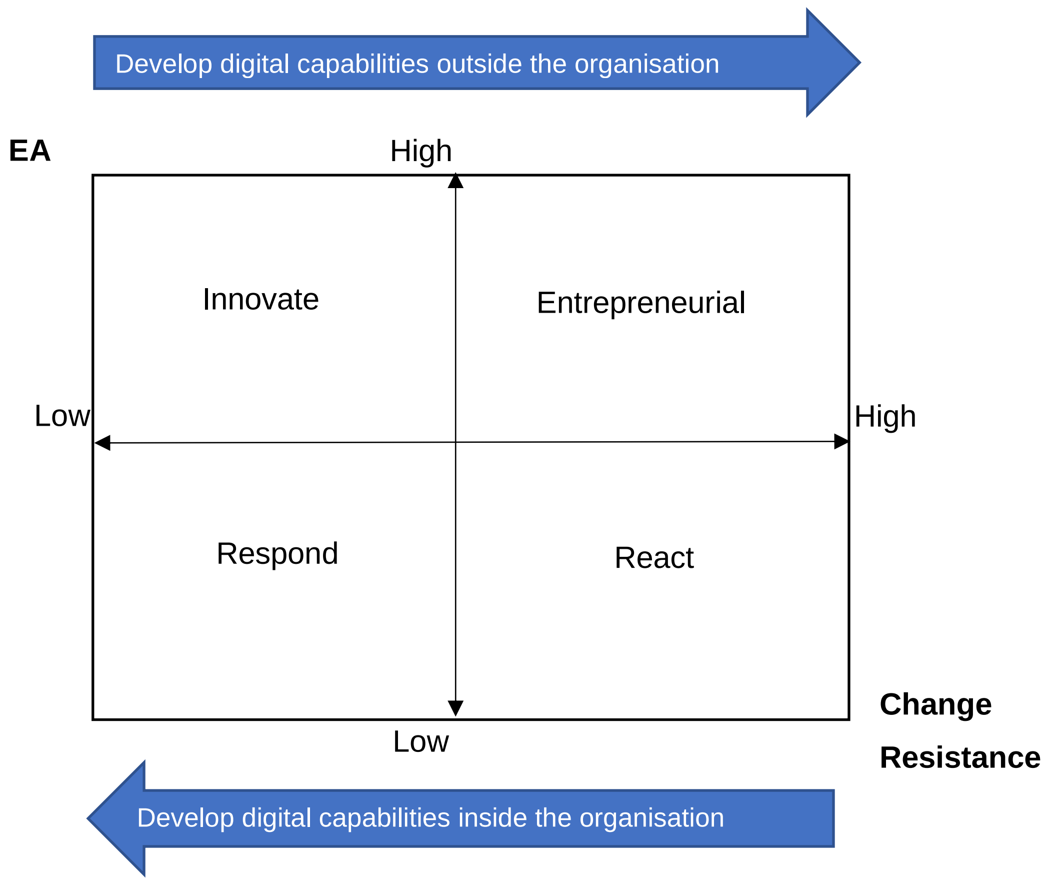

Figure 11: Proposed strategic framework for traditional organizations to consider in digital transformations

The above framework is proposed for traditional industries for strategic planning of their DBS. The purpose is to extend this study's conclusions into a practical application for managers of traditional firms so that they are able to leverage entrepreneurial agility and understand the change barriers to their business models, which can be used to develop strategic responses for competitive advantage in digital transformations.

There are four stages to the framework, each of which is characterised by the state of the firm in terms of the levels of change resistance, as well as the level of entrepreneurial agility. Change resistance includes all the organisational- and industry-related barriers. The firms with high change resistance and low EA may find themselves in a reactive strategy. This means that they are threatened by digital disruption because they are "reactors" in terms of sensing market changes, and are also unable to fundamentally change their organisation or business model. These firms thus need to understand how they can overcome these barriers to enable the change, or if they cannot overcome the resistance and have high entrepreneurial agility, they need to explore developing digital capabilities outside the organisation as "entrepreneurs". This may involve developing these digital capabilities needed for the DBS in an environment that is not constrained by these change resistances, e.g. by developing a start-up, creating a new division, purchasing, or outsourcing to a firm that has the required capabilities. This will give these firms the ability to rapidly capitalise on market opportunities without being constrained by the parent company. This may also involve developing strategic partnerships with firms that have the digital capabilities they require.

If firms are able to overcome their change resistance or reduce it, they may build digital capabilities internally. These may enable them to be "responders" to market changes or defend their market share or competitive advantage, because they are able to change their organisation as required by the DBS. Lastly, if firms are able to overcome their change resistance and build high levels of entrepreneurial agility, they may focus on innovating and fundamentally changing their business models as "innovators" in order to better compete in the changing environment. These four options in the framework may assist traditional firms to develop their strategic options when defining their digital business strategy.

7.3 The limitations of the research

The limitations of this research include the non-probability sampling method used, which limits the findings to the characteristics of the sample in this study. The sample size was also a limitation in that only 60 responses were included in the data analysis. This influenced the likelihood of the researcher making a type 1 or type 2 error in the hypothesis testing, because of the increased variance associated with smaller samples.

Further, the findings are based on individual responses and thus carry individual bias. The survey also required individuals to answer on behalf of their organisations, which may have influenced their responses depending on their experience in the organisation. This limitation was filtered out by removing individuals with less than a year of experience in the organisation. The survey approach, which used social media streams such as LinkedIn, included elements of snowball sampling as the interviewees passed on the survey to people who may have had similar views, which may have also contributed to individual bias.

The researcher's use of only subjective financial measures to measure firm performance was a limitation. Other views on firm performance such as the "shared value approach" proposed by Porter and Kramer (2011), which considers social and environmental performance measures, may have yielded different research outcomes. These measures may have included constructs such as corporate social responsibility and environmental and sustainability metrics in the measure of firm performance. These have been reported as outcomes that other firms are using digital technologies to address (Gurumurthy et al., 2020). Similarly, this study was based on a fixed number of constructs, i.e. there may be other constructs that can influence the dependent variable.

The researcher's experience in performing quantitative research and non-probability sampling can be a limitation, i.e. the researcher may not have had adequate experience in this field. Finally, the research did not consider the antecedents of EA in a DT to explain the enablers of EA for traditional firms in this context.

7.4 Future research

Future research can focus on further understanding the antecedents of entrepreneurial agility in a digital transformation context, to better understand what the enablers of entrepreneurial agility are for traditional firms in digital transformations. The relationships between the digital maturity constructs themselves were not explored in this study, however there may be interdependencies between the constructs and how they may combine to influence digital maturity, EA and firm performance. Further research could provide more clarity on the scope and use of the construct digital maturity, particularly in terms of its relevance for traditional firms.

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Appendix A: Questionnaire

Table 23: Survey questionnaire

Survey Questionnaire							
Qualifying Questions							
1. Has your organisation embarked on a digital transformation activity with the use of digital technologies for its internal business processes or to develop new markets and product offerings?							
Yes	No						
If Yes, go to section A							
If no, go to end							
2. Are you familiar with your organisations digital strategies?							
Yes	No						
If Yes, go to section A							
If no, go to end							
Section A- Demographic and control variables (Tick the relevant box)							
3. What is your gender?							

Male							
Female							
Prefer not to say							
4. What is your seniority in the organisation?							
Junior manager							
Middle manager							
Senior manager							
Executive manager							
5. How many years of experience do you have in your organisation?							
<1 year							
1-5 years							
5-10 years							
10-15 years							
>15 years							
6. How large is your organisation in terms of number of employees?							
0-99							
100-499							
500-999							
1000-4999							
5000 or more							

7. How large is the estimated annual revenue in your organisation?							
R0-0.99m							
R1,0-R9.99m							
R10-99.99m							
R100-1000m							
>R1000m							
8. What industry is your firm operating in?		Tick the relevant box					
Advertising, Marketing and sales							
Agriculture and food production							
Airlines and support services							
Automotive							
Business support and services (consulting, advisory services)							
Construction and building							
Education							
Entertainment & Hospitality							
Financial Services (insurance, banking, finance)							
Food & Beverages							

Government and public sector						
Healthcare & Pharmaceuticals						
Manufacturing						
Mining						
Non for profit						
Retail						
Real Estate						
Telecommunications and internet service providers						
Transportation & Logistics						
Utilities and energy						
I am currently unemployed						
Section B- Firm Performance		**Score**				
Answer: On a 5 point Likert scale from S**trongly Disagree, Disagree, Neutral, Agree, Strongly Agree**						
Use of agility and digital transformation in the organisation over the last three years have improved the following relative to competitors: (Please answer on a 5 point likert scale from Strongly Disagree, Disagree, Neutral, Agree, Strongly Agree):						
9. Sales or Revenue relative to competitors		Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree

10. Market share relative to competitors	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
11. Profits relative to competitors	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
12. Return on investment (ROI) relative to competitors	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
Section C- Entrepreneurial Agility					
Answer: On a 5 point Likert scale from **strongly disagree, Disagree, Neutral, Agree, Strongly Agree**					
13. We believe that our strategy places emphasis on building capabilities to anticipate and predict a wide range of possible scenarios.	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
14. Our organisation believes in quickly and rapidly taking advantage of opportunities.	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
15. We can convert our strategic assets into alternate forms easily.	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
16. Our positioning strategy can be easily modified	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
Section D- Digital Maturity					
Answer: On a 5 point Likert scale from strongly disagree, Disagree, Neutral, Agree, Strongly Agree					
Technology					
Answer the following statements about Technology on a 5 point Likert scale from Strongly Disagree, Disagree, Neutral, Agree, Strongly Agree					

17. Our organisation has a budget for technology that is fluid to allow for shifting priorities	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
18. Our digital technology road map is created by both marketing and technology resources working together	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
19. Our approach to technology development is flexible, collaborative and iterative	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
20. Our organisation leverages modern data architectures like the cloud or application programming interfaces (APIs) for increased speed and flexibility	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
21. Technology teams are measured by business outcomes and not just by the digital system reliability	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
22. Our organisation uses customer experience assets like personas and journey maps to drive our technology design	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
23. Our organisation makes use of digital tools to promote innovation, collaboration, and mobility of our employees.	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
Culture					
Answer the following statements about Culture on a 5 point Likert scale from Strongly Disagree, Disagree, Neutral, Agree, Strongly Agree					
24. Our organisation's competitive strategy depends on digital	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
25. Our digital strategy is backed by our board and C-level executives	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree

26. We believe the organisation has the right leaders to execute our digital strategy on a day to day basis	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
27. Our organisation invests in digital training and education at all levels	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
28. Our organisations digital vision is communicated both internally and externally	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
29. Our organisation takes measured risks to drive innovation	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
30. Overall customer experience is prioritised holistically over a single distribution channel	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
Organisation					
Answer the following statements about Organisation on a 5 point Likert scale from Strongly Disagree, Disagree, Neutral, Agree, Strongly Agree					
31. In our organisation, customer journeys are prioritised over functional silos	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
32. Our organisation dedicates appropriate resources to digital strategy, execution and governance	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
33. We have the best in class staff supporting the critical digital functions	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
34. Our organisation has digital skills embedded throughout.	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
35. Collaboration across functions is encouraged by our organisations model	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
36. Our processes for digital programs are well defined and are repeatable.	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree

37. We have vendor partners that deliver value to enhance our digital competencies.	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
Insights					
Answer the following statements about Insights on a 5 point Likert scale from Strongly Disagree, Disagree, Neutral, Agree, Strongly Agree					
38. Our digital strategy has clear and quantifiable goals for measuring success	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
39. Every employee has an understanding of their performance contribution to the corporate goals of the digital strategy	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
40. Our organisation makes use of customer-centered measures such as Net Promoter Score or customer lifetime value to measure success.	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
41. Our organisation measures how multiple channels work together towards a desired outcome	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
42. We actively use customer insights to steer our digital strategy	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
43. We use our customer insights to develop and design our digital tools	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
44. Our strategy is updated with lessons learned feedback from digital programs	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
END					

Appendix B: Coding catalogue

Table 24: Coding catalogue

Coding	
Gender	
Male	0
Female	1
Prefer not to say	2
Seniority	
Junior manager	0
Middle manager	1
Senior manager	2
Executive manager	3
Years of experience in organisation	
< 1 year	0
1 to 5 years	1
5 to 10 years	2
10 to 15 years	3
>15 years	4
Organziation size (number of employees)	
0-99	0
100-499	1
500-999	2
1000-4999	3
5000 or more	4
Annual Revenue	
<R0.99m	0
R1m - R9.9m	1
R10m - R99.99m	2

R100m - R999.99m	3
>R1000m	4
Industry Type	
Advertising, Marketing and sales	1
Agriculture and food production	2
Airlines and support services	3
Automotive	4
Business support and services (consulting, advisory services)	5
Construction and building	6
Education	7
Entertainment & Hospitality	8
Financial Services (insurance, banking, finance)	9
Food & Beverages	10
Government and public sector	11
Healthcare & Pharmaceuticals	12
Manufacturing	13
Mining	14
Non for profit	15
Retail	16
Real Estate	17
Telecommunications and internet service providers	18
Transportation & Logistics	19
Utilities and energy	20
I am currently unemployed	0
Likert Scale	
Strongly Disagree	1
Disagree	2
Neutral	3
Agree	4
Strongly Agree	5

Table 25: Detailed industry type

Industry type	**Number**	**Percentage**
Advertising, Marketing and sales	1	1,7
Advertising, Marketing and sales, Business support and services (consulting, advisory services), Financial Services (insurance, banking, finance), Healthcare & Pharmaceuticals, Mining, Retail, Telecommunications and internet service providers, Transportation & Logistics, Utilities and energy	1	1,7
Advertising, Marketing and sales, Business support and services (consulting, advisory services), Manufacturing, Mining	1	1,7
Advertising, Marketing and sales, Manufacturing	1	1,7
Automotive	**3**	**5,0**
Automotive, Construction and building, Not for Profit, Transportation & Logistics, Utilities and energy	1	1,7
Business support and services (consulting, advisory services)	1	1,7
Education	2	3,3
Education, Not for Profit	1	1,7
Financial Services (insurance, banking, finance)	**9**	**15,0**
Government and public sector	2	3,3
Government and public sector, Utilities and energy	1	1,7
Healthcare & Pharmaceuticals	2	3,3
Manufacturing	**4**	**6,7**
Manufacturing, Mining	1	1,7
Manufacturing, Retail, Transportation & Logistics, Utilities and energy	1	1,7
Mining	**23**	**38,3**
Telecommunications and internet service providers	3	5,0
Utilities and energy	2	3,3
Total	60	100

Appendix C: Validity test (Bi-variate correlation)

Table 26: Spearmans rank Bi-variate correlation for Firm Performance scale validity

Correlations			
			Item-total score FP
Spearman's rho	Sales	Correlation Coefficient	.762**
		Sig. (2-tailed)	0,000
		N	60
	MShare	Correlation Coefficient	.850**
		Sig. (2-tailed)	0,000
		N	60
	Profit	Correlation Coefficient	.796**
		Sig. (2-tailed)	0,000
		N	60
	ROI	Correlation Coefficient	.875**
		Sig. (2-tailed)	0,000
		N	60
	Item-total score FP	Correlation Coefficient	1,000
		Sig. (2-tailed)	
		N	60
**. Correlation is significant at the 0.01 level (2-tailed).			

Table 27: Spearmans rank Bi-variate correlation for validy tests of the entrepreneurial agility scale.

Correlations			
			Item-total score EA
Spearman's rho	EA-Scenarios	Correlation Coefficient	.622**
		Sig. (2-tailed)	0,000

		N	60
	EA-Opportunities	Correlation Coefficient	.725**
		Sig. (2-tailed)	0,000
		N	60
	EA-Strategic assets	Correlation Coefficient	.826**
		Sig. (2-tailed)	0,000
		N	60
	EA-Positioning	Correlation Coefficient	.879**
		Sig. (2-tailed)	0,000
		N	60
	Item-total score EA	Correlation Coefficient	1,000
		Sig. (2-tailed)	
		N	60
**. Correlation is significant at the 0.01 level (2-tailed).			

Table 28: Spearman rank bi-variate correlation to test validity of the digital technology scale under digital maturity

Correlation			
			Item total score-Tech
Spearman's rho	Digital technology-Fluid budget	Correlation Coefficient	.495**
		Sig. (2-tailed)	0,000
		N	60
	Digital technology-road map	Correlation Coefficient	.699**
		Sig. (2-tailed)	0,000
		N	60

	Digital technology- Approach	Correlation Coefficient	.770**
		Sig. (2-tailed)	0,000
		N	60
	Digital technology-Modern architecture	Correlation Coefficient	.628**
		Sig. (2-tailed)	0,000
		N	60
	Technology-measurement	Correlation Coefficient	.745**
		Sig. (2-tailed)	0,000
		N	60
	Digital technology-customer experience assets	Correlation Coefficient	.641**
		Sig. (2-tailed)	0,000
		N	60
	Digital technology-digital tools	Correlation Coefficient	.740**
		Sig. (2-tailed)	0,000
		N	60
	Item total score-Tech	Correlation Coefficient	1,000
		Sig. (2-tailed)	
		N	60

Table 29: Spearman rank bi-variate correlation to test validity of the digital culture scale under digital maturity

Correlations			
			Item total score-Digital culture

Spearman's rho	Digital culture-competitive strategy	Correlation Coefficient	.577**
		Sig. (2-tailed)	0,000
		N	60
	Digital culture-board support	Correlation Coefficient	.648**
		Sig. (2-tailed)	0,000
		N	60
	Digital culture-right leaders	Correlation Coefficient	.650**
		Sig. (2-tailed)	0,000
		N	60
	Digital culture-education and training investment	Correlation Coefficient	.792**
		Sig. (2-tailed)	0,000
		N	60
	Digital culture-communicate digital vision	Correlation Coefficient	.740**
		Sig. (2-tailed)	0,000
		N	60
	Digital culture- measured risks	Correlation Coefficient	.604**
		Sig. (2-tailed)	0,000
		N	60
	Digital culture-customer experience	Correlation Coefficient	.670**
		Sig. (2-tailed)	0,000
		N	60
	Item total score-Digital culture	Correlation Coefficient	1,000
		Sig. (2-tailed)	
		N	60

**. Correlation is significant at the 0.01 level (2-tailed).
*. Correlation is significant at the 0.05 level (2-tailed).

Table 30: Spearman rank bi-variate correlation to test validity of the digital organisational structure scale under digital maturity

Correlations			
			Item total score-Organisation
Spearman's rho	Organisation- customer journeys	Correlation Coefficient	.672**
		Sig. (2-tailed)	0,000
		N	60
	Organisation-resources	Correlation Coefficient	.844**
		Sig. (2-tailed)	0,000
		N	60
	Organisation- best in class staff	Correlation Coefficient	.824**
		Sig. (2-tailed)	0,000
		N	60
	Organisation- digital skills	Correlation Coefficient	.778**
		Sig. (2-tailed)	0,000
		N	60
	Organisation-collaboration	Correlation Coefficient	.704**
		Sig. (2-tailed)	0,000
		N	60

	Organisation- processes	Correlation Coefficient	.770**
		Sig. (2-tailed)	0,000
		N	60
	Organisation-vendor partners	Correlation Coefficient	.670**
		Sig. (2-tailed)	0,000
		N	60
	Item total score-Organisation	Correlation Coefficient	1,000
		Sig. (2-tailed)	
		N	60
**. Correlation is significant at the 0.01 level (2-tailed).			
*. Correlation is significant at the 0.05 level (2-tailed).			

Table 31: Spearman rank bi-variate correlation to test validity of the digital insights scale under digital maturity

Correlations			
			Item total score-Insights
Spearman's rho	Insights- quantifiable goals	Correlation Coefficient	.754**
		Sig. (2-tailed)	0,000
		N	60
	Insights- employee understanding of contribution	Correlation Coefficient	.804**
		Sig. (2-tailed)	0,000
		N	60

	Insights- customer centered measures	Correlation Coefficient	.744**
		Sig. (2-tailed)	0,000
		N	60
	Insights- multiple channels	Correlation Coefficient	.881**
		Sig. (2-tailed)	0,000
		N	60
	Insights-digital strategy	Correlation Coefficient	.843**
		Sig. (2-tailed)	0,000
		N	60
	Insights-digital tools	Correlation Coefficient	.802**
		Sig. (2-tailed)	0,000
		N	60
	Insights-lessons learned	Correlation Coefficient	.826**
		Sig. (2-tailed)	0,000
		N	60
	Item total score- Insights	Correlation Coefficient	1,000
		Sig. (2-tailed)	
		N	60
**. Correlation is significant at the 0.01 level (2-tailed).			

Appendix D: Factor analysis

Table 32: Correlation matrix for Entrepreneurial agility scale

Correlation Matrix					
		EA-Scenarios	EA-Opportunities	EA-Strategic assets	EA-Positioning
Correlation	EA-Scenarios	1,000	0,454	0,313	0,420
	EA-Opportunities	0,454	1,000	0,427	0,527
	EA-Strategic assets	0,313	0,427	1,000	0,718
	EA-Positioning	0,420	0,527	0,718	1,000

Table 33: Correlation matrix for Digital Maturity- Digital technology scale

Correlation Matrix								
		Digital technology-Fluid budget	Digital technology-road map	Digital technology-Approach	Digital technology-Modern architecture	Digital technology-measurement	Digital technology-customer experience assets	Digital technology-digital tools
Correlation	Digital technology-Fluid budget	1,000	0,382	0,413	0,207	0,465	0,122	0,311
	Digital technolo	0,382	1,000	0,385	0,159	0,368	0,452	0,397

	gy-road map							
	Digital technology-Approach	0,413	0,385	1,000	0,616	0,519	0,352	0,338
	Digital technology-Modern architecture	0,207	0,159	0,616	1,000	0,457	0,197	0,341
	Digital technology-measurement	0,465	0,368	0,519	0,457	1,000	0,421	0,622
	Digital technology-customer experience assets	0,122	0,452	0,352	0,197	0,421	1,000	0,611
	Digital technology-digital tools	0,311	0,397	0,338	0,341	0,622	0,611	1,000

Table 34: Correlation matrix for Digital Maturity- Digital culture scale

Correlation Matrix								
		Digital culture-competitive strategy	Digital culture-board support	Digital culture-right leaders	Digital culture-education and training investment	Digital culture-communicate digital vision	Digital culture-measured risks	Digital culture-customer experience
Correlation	Digital culture-competitive strategy	1,000	0,411	0,133	0,398	0,320	0,002	0,266
	Digital culture-board support	0,411	1,000	0,476	0,439	0,375	0,259	0,476
	Digital culture-right leaders	0,133	0,476	1,000	0,531	0,297	0,428	0,344
	Digital culture-education and training investment	0,398	0,439	0,531	1,000	0,595	0,436	0,448
	Digital culture-communicate	0,320	0,375	0,297	0,595	1,000	0,441	0,369

	digital vision							
	Digital culture-measured risks	0,002	0,259	0,428	0,436	0,441	1,000	0,293
	Digital culture-customer experience	0,266	0,476	0,344	0,448	0,369	0,293	1,000

Table 35: Correlation matrix for Digital Maturity-Digital organisational structure scale

Correlation Matrix								
		Organisation-customer journeys	Organisation-resources	Organisation-best in class staff	Organisation-digital skills	Organisation-collaboration	Organisation-processes	Organisation-vendor partners
Correlation	Organisation-customer journeys	1,000	0,637	0,530	0,417	0,384	0,458	0,291
	Organisation-resources	0,637	1,000	0,674	0,501	0,393	0,580	0,545
	Organisation-	0,530	0,674	1,000	0,613	0,577	0,522	0,477

	best in class staff							
	Organisation-digital skills	0,417	0,501	0,613	1,000	0,582	0,558	0,513
	Organisation-collaboration	0,384	0,393	0,577	0,582	1,000	0,616	0,381
	Organisation-processes	0,458	0,580	0,522	0,558	0,616	1,000	0,428
	Organisation-vendor partners	0,291	0,545	0,477	0,513	0,381	0,428	1,000

Table 36: Correlation matrix for Digital Maturity- Digital insights scale

Correlation Matrix								
		Insights-quantifiable goals	Insights-employee understanding of contribution	Insights-customer centered measures	Insights-multiple channels	Insights-digital strategy	Insights-digital tools	Insights-lessons learned

Correlation	Insights-quantifiable goals	1,000	0,509	0,466	0,647	0,538	0,458	0,650
	Insights-employee understanding of contribution	0,509	1,000	0,566	0,687	0,557	0,557	0,670
	Insights-customer centered measures	0,466	0,566	1,000	0,669	0,491	0,441	0,469
	Insights-multiple channels	0,647	0,687	0,669	1,000	0,646	0,539	0,675
	Insights-digital strategy	0,538	0,557	0,491	0,646	1,000	0,863	0,672
	Insights-digital tools	0,458	0,557	0,441	0,539	0,863	1,000	0,662
	Insights-lessons learned	0,650	0,670	0,469	0,675	0,672	0,662	1,000

Table 37: KMO and Bartlett's test for sphericity results on construct scales

KMO and Bartlett's Test	**Entrepreneurial Agility**	**DM Digital technology**	**DM Digital culture**	**DM Organisation**	**DM Insights**
Kaiser-Meyer-Olkin Measure	0,707	0,733	0,772	0,835	0,848

of Sampling Adequacy.						
Bartlett's Test of Sphericity	Approx. Chi-Square	76,464	146,886	123,253	193,770	277,474
	df	6	21	21	21	21
	Sig.	0,000	0,000	0,000	0,000	0,000

Appendix D.1: Factor analysis results: Entrepreneurial agility

Table 38: Component matrix for entrepreneurial agility

Component Matrix[a]	
	Component
	1
EA-Scenarios	0,669
EA-Opportunities	0,766
EA-Strategic assets	0,805
EA-Positioning	0,873
Extraction Method: Principal Component Analysis.	
a. 1 components extracted.	

Only one component was identified for entrepreneurial agility.

Table 39: Total variance explained for entrepreneurial agility

Total Variance Explained				
Component	Initial Eigenvalues	Extraction Sums of		

				Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2,45	61,14	61,14	2,45	61,14	61,14
2	0,77	19,20	80,34			
3	0,52	12,99	93,33			
4	0,27	6,67	100,000			

The total variance explained for factor 1 is 61.14%.

Appendix D.2: Factor analysis results: Digital technology

Table 40: Rotated component matrix for Digital Maturity- Digital technology

Rotated Component Matrix[a]					
	Component				
	1	2		Questions/variables	Factors
Digital technology- customer experience assets	0,856	0,073		Our organisation uses customer experience assets like personas and journey maps to drive our technology design	
Digital technology- digital tools	0,780	0,299		Our organisation makes use of digital tools to promote innovation, collaboration, and mobility of our employees.	
Digital technology-road map	0,692	0,211		Our digital technology road map is created by both marketing and technology resources working together	Digital Technology strategy

Digital technology-measurement	0,529	0,623		Technology teams are measured by business outcomes and not just by the system reliability	
Digital technology-Fluid budget	0,264	0,560		Our organisation has a budget for technology that is fluid to allow for shifting priorities	
Digital technology-Approach	0,240	0,823		Our approach to technology development is flexible, collaborative and iterative	
Digital technology-Modern architecture	0,027	0,840		Our organisation leverages modern data architectures like the cloud or application programming interfaces (APIs) for increased speed and flexibility	Digital Technology embeddedness
Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization.					
a. Rotation converged in 3 iterations.					

There were two factors identified for Digital Maturity- Digital technology which were termed Digital technology strategy and Digital technology embeddedness. These factor scores were calculated by taking the average of the item scores for the set of questions per factor.

Table 41: Total variance explained for Digital Maturity- Digital technology

Total Variance Explained							
Component	Initial Eigenvalues	Extraction Sums			Rotation Sums		

				of Squared Loadings			of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	3,36	48,07	48,07		3,36	48,07	48,07	2,23	31,83
2	1,09	15,53	63,59		1,09	15,53	63,59	2,22	31,76
3	0,90	12,91	76,50						
4	0,67	9,51	86,02						
5	0,40	5,69	91,70						
6	0,34	4,80	96,51						
7	0,24	3,49	100,00						
Extraction Method: Principal Component Analysis									

The total variance explained for factors 1 is 48.066% and factor 2 is 15.527% with a total variance explained of 63.593%.

Appendix D.3: Factor analysis results: Digital Culture

Table 42: Rotated component matrix for Digital Maturity- Digital culture

Rotated Component Matrix[a]				
	Component			
	1	2	Questions/variables	Factors
Digital culture- measured risks	0,856	-0,075	Our organisation takes measured risks to drive innovation	Digital culture embeddedness

Digital culture-right leaders	0,721	0,214	We believe the organisation has the right leaders to execute our digital strategy on a day to day basis	
Digital culture-education and training investment	0,639	0,525	Our organisation invests in digital training and education at all levels	
Digital culture-communicate digital vision	0,574	0,443	Our organisations digital vision is communicated both internally and externally	
Digital culture-customer experience	0,444	0,517	Overall customer experience is prioritised holistically over a single distribution channel	
Digital culture-board support	0,383	0,666	Our digital strategy is backed by our board and C-level executives	
Digital culture-competitive strategy	-0,104	0,885	Our organisation's competitive strategy depends on digital	Leadership support
Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization.				
a. Rotation converged in 3 iterations.				

There were two factors identified which were defined as Digital culture embeddedness and Leadership support. These factor scores were calculated by taking the average of the item scores for the set of questions per factor.

Table 43: Total variance explained for Digital Maturity: Digital Culture

Total Variance Explained									
Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	3,27	46,67	46,67	3,27	46,67	46,67	2,34	33,49	33,49
2	1,10	15,65	62,32	1,10	15,65	62,32	2,02	28,84	62,32
3	0,79	11,26	73,58						
4	0,64	9,19	82,77						
5	0,48	6,88	89,65						
6	0,44	6,22	95,87						
7	0,29	4,13	100,00						
Extraction Method: Principal Component Analysis.									

The total variance explained for factors 1 is 46.67% and factor 2 is 15.65% with a total variance explained of 62,32%.

Appendix D.4: Factor analysis results: Digital organisational structure

Table 44: Component matrix for Digital maturity- Digital organisational structure

Component Matrix[a]	
	Component
	1

Organisation- customer journeys	0,693
Organisation-resources	0,817
Organisation- best in class staff	0,832
Organisation- digital skills	0,788
Organisation- collaboration	0,737
Organisation- processes	0,784
Organisation-vendor partners	0,672
Extraction Method: Principal Component Analysis.	
a. 1 components extracted.	

There was only one factor identified, an average of all the item scores were taken to calculate the single factor and this factor was defined as organisational structure.

Table 45: Total variance explained for Digital maturity-Digital Organisational structure.

Total Variance Explained						
Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	4,07	58,15	58,15	4,07	58,15	58,15
2	0,80	11,37	69,52			
3	0,71	10,07	79,59			
4	0,48	6,84	86,43			
5	0,38	5,49	91,93			
6	0,36	5,13	97,06			
7	0,21	2,94	100,00			
Extraction Method: Principal Component Analysis.						

The single factor explained 58.15% of the total variance.

Appendix D.5: Factor analysis results: Digital Insights

Table 46: Component matrix for Digital maturity-Digital insights

Component Matrix[a]	
	Component
	1
Insights- quantifiable goals	0,752
Insights- employee understanding of contribution	0,805
Insights- customer centered measures	0,716
Insights- multiple channels	0,862
Insights-digital strategy	0,849
Insights-digital tools	0,805
Insights-lessons learned	0,854
Extraction Method: Principal Component Analysis.	
a. 1 components extracted.	

There was only one factor identified, an average of all the item scores were taken to calculate the single factor and this factor was defined as Digital insights.

Table 47: Total variance explained for Digital maturity- Digital insights.

Total Variance Explained				
Component	Initial Eigenvalues	Extraction Sums of Squared Loadings		

	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	4,57	65,27	65,27	4,57	65,27	65,27
2	0,78	11,10	76,37			
3	0,58	8,27	84,64			
4	0,45	6,44	91,08			
5	0,26	3,73	94,80			
6	0,25	3,54	98,34			
7	0,12	1,66	100,00			
Extraction Method: Principal Component Analysis.						

The single factor explained 65.27% of the total variance.

Appendix E: Moderated regression

Appendix E.1: Moderated regression assumptions

Assumption 5: The data must show homoscedasticity, which is when for all combinations of independent and moderator variables, the error variances are the same.

Table 48: Summary of tests for homoscedasticity

Dependent Variable	**Moderator variable**	**Independent variable**	**Sig.**
Sales	DTE	EA	0,259
	DTS	EA	0,644
	DCE	EA	0,467
	LS	EA	0,385
	DOS	EA	0,42
	DI	EA	0,066
Market Share	DTE	EA	0,425
	DTS	EA	0,92
	DCE	EA	0,146
	LS	EA	0,332
	DOS	EA	0,749
	DI	EA	0,361
Profit	DTE	EA	0,173

	DTS	EA	0,224
	DCE	EA	0,376
	LS	EA	0,039
	DOS	EA	0,233
	DI	EA	0,304
ROI	DTE	EA	0,662
	DTS	EA	0,498
	DCE	EA	0,336
	LS	EA	0,142
	DOS	EA	0,271
	DI	EA	0,671

Table 48 shows that the p values were greater >0.05 for all regression tests using the Breusch pagan test, which tests for homoscedasticity. The null hypothesis in this test is that the data is homoscedastic hence, all the regressions had homoscedastic data.

Assumption 8: All the residuals (errors) are approximately normally distributed.

Table 49: Test for normality of residuals

Tests of Normality									
Residual ID	DV	IV	MV	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
				Statistic	df	Sig.	Statistic	df	Sig.
RE_TE_SA	Sales	EA	DTE	0,097	60	.200*	0,955	60	0,027
RE_TE_MS	Market Share	EA	DTE	0,092	60	.200*	0,980	60	0,447
RE_TE_PR	Profit	EA	DTE	0,092	60	.200*	0,984	60	0,639
RE_TE_RO	ROI	EA	DTE	0,087	60	.200*	0,987	60	0,772
RE_TS_SA	Sales	EA	DTS	0,101	60	.200*	0,956	60	0,030
RE_TS_MS	Market Share	EA	DTS	0,083	60	.200*	0,979	60	0,371
RE_TS_PR	Profit	EA	DTS	0,077	60	.200*	0,987	60	0,783
RE_TS_RO	ROI	EA	DTS	0,089	60	.200*	0,982	60	0,539
RE_DCE_S	Sales	EA	**DCE**	**0,116**	**60**	**0,043**	**0,957**	**60**	**0,034**
RE_DCE_M	Market Share	EA	DCE	0,105	60	0,099	0,975	60	0,250
RE_DCE_P	Profit	EA	DCE	0,081	60	.200*	0,984	60	0,622
RE_DCE_R	ROI	EA	DCE	0,096	60	.200*	0,983	60	0,576
RE_LS_SA	Sales	EA	LS	0,083	60	.200*	0,962	60	0,062
RE_LS_MS	Market Share	EA	LS	0,088	60	.200*	0,982	60	0,498
RE_LS_PR	Profit	EA	LS	0,056	60	.200*	0,985	60	0,679
RE_LS_RO	ROI	EA	LS	0,088	60	.200*	0,986	60	0,708
RE_DOS_S	Sales	EA	**DOS**	**0,118**	**60**	**0,038**	**0,959**	**60**	**0,040**

RE_DOS_M	Market Share	EA	DOS	0,103	60	0,180	0,975	60	0,266
RE_DOS_P	Profit	EA	DOS	0,097	60	.200*	0,982	60	0,535
RE_DOS_R	ROI	EA	DOS	0,100	60	.200*	0,982	60	0,539
RE_DI_SA	Sales	EA	DI	0,111	60	0,063	0,963	60	0,067
RE_DI_MS	Market Share	EA	DI	0,098	60	.200*	0,972	60	0,193
RE_DI_PR	Profit	EA	DI	0,089	60	.200*	0,982	60	0,539
RE_DI_RO	ROI	EA	DI	0,080	60	.200*	0,992	60	0,967
*. This is a lower bound of the true significance.									
a. Lilliefors Significance Correction									

Both the Shapiro Wilk test and Kolmogorov-Smirnov tests were used to test the normality of the residuals, all the tests except for the regression analysis of Sales, EA and DOS; as well as Sales, EA and DCE were found to have non normal residuals.

Appendix E.2: Moderated regression DV, Sales.

E.2.1 DTE, EA and Sales

Table 50: Model summary for moderated regression for DTE-EA-Sales.

Model Summary[b]									
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.568[a]	0,322	0,286	0,638	0,322	8,869	3	56	0,000
a. Predictors: (Constant), TE_EA_C, TE_Cen, EA_cen									
b. Dependent Variable: Sales									

Table 51: Coefficients of moderated regression for DTE-EA-Sales.

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.			Collinearity Statistics	
		B	Std. Error	Beta			Partial	Part	Tolerance	VIF
1	(Constant)	3,73	0,09		43,32	0,00				
	EA_cen	0,34	0,11	0,37	3,16	0,00	0,39	0,35	0,89	1,12
	TE_Cen	0,17	0,10	0,20	1,70	0,09	0,22	0,19	0,90	1,11
	TE_EA_C	0,29	0,11	0,28	2,56	0,01	0,32	0,28	0,99	1,01
a. Dependent Variable: Sales										

E.2.2 DTS, EA and Sales

Table 52: Model summary for moderated regression for DTS-EA-Sales

Model Summary[b]									
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.507[a]	0,257	0,217	0,668	0,257	6,453	3	56	0,001
a. Predictors: (Constant), TS_EA_C, EA_cen, TS_Cen									
b. Dependent Variable: Sales									

Table 53: Model co-efficients and significance for DTS-EA-Sales

Coefficients[a]										
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.			Collinearity Statistics	
		B	Std. Error	Beta			Partial	Part	Tolerance	VIF
1	(Constant)	3,77	0,09		41,53	0,00				
	EA_cen	0,35	0,11	0,39	3,20	0,00	0,39	0,37	0,91	1,10
	TS_Cen	0,20	0,13	0,19	1,53	0,13	0,20	0,18	0,89	1,13

	TS_EA_C	0,16	0,16	0,11	0,96	0,34	0,13	0,11	0,97	1,04
a. Dependent Variable: Sales										

E.2.3 Moderated regression between Leadership Support, Entrepreneurial agility and the dependent variable Sales.

Table 54: Model summary for moderated regression for LS-EA-Sales.

Model Summary[b]									
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.519[a]	0,27	0,23	0,66	0,27	6,89	3,00	56,00	0,00
a. Predictors: (Constant), LS_EA_C, EA_cen, LS_Cen									
b. Dependent Variable: Sales									

Table 55: Model co-efficients and significance for LS-EA-Sales

Coefficients[a]										
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.			Collinearity Statistics	
		B	Std. Error	Beta			Partial	Part	Tolerance	VIF
1	(Constant)	3,72	0,09		39,62	0,00				
	EA_cen	0,32	0,12	0,35	2,61	0,01	0,33	0,30	0,74	1,36
	LS_Cen	0,19	0,14	0,19	1,37	0,18	0,18	0,16	0,71	1,42
	LS_EA_C	0,27	0,13	0,24	2,03	0,05	0,26	0,23	0,92	1,09
a. Dependent Variable: Sales										

E.2.4 Moderated regression between digital culture embeddedness, entrepreneurial agility and the dependent variable Sales.

Table 56: Model summary for moderated regression for DCE-EA-Sales

Model Summary[b]									
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.520[a]	0,271	0,232	0,661	0,271	6,932	3	56	0,000
a. Predictors: (Constant), CE_EA_C, CulE_Cen, EA_cen									
b. Dependent Variable: Sales									

Table 57: Model co-efficients and significance for DCE-EA-Sales

Coefficients[a]										
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.			Collinearity Statistics	
		B	Std. Error	Beta			Partial	Part	Tolerance	VIF
1	(Constant)	3,73	0,09		39,77	0,00				
	EA_cen	0,30	0,12	0,33	2,49	0,02	0,32	0,28	0,75	1,34
	CulE_Cen	0,18	0,12	0,19	1,49	0,14	0,19	0,17	0,77	1,30
	CE_EA_C	0,22	0,12	0,21	1,77	0,08	0,23	0,20	0,97	1,03
a. Dependent Variable: Sales										

E.2.5 Moderated regression between digital organisational structure, entrepreneurial agility and the dependent variable Sales.

Table 58: Model summary for moderated regression for DOS-EA-Sales

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.496[a]	0,247	0,206	0,672	0,247	6,107	3	56	0,001
a. Predictors: (Constant), DOS_EA_cen, DOS_cen, EA_cen									
b. Dependent Variable: Sales									

Table 59: Model co-efficients and significance for DOS-EA-Sales

Coefficients[a]										
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.			Collinearity Statistics	
		B	Std. Error	Beta			Partial	Part	Tolerance	VIF
1	(Constant)	3,73	0,10		36,73	0,00				
	EA_cen	0,33	0,13	0,36	2,57	0,01	0,32	0,30	0,69	1,44
	DOS_cen	0,15	0,13	0,15	1,08	0,28	0,14	0,13	0,70	1,43
	DOS_EA_cen	0,21	0,15	0,16	1,36	0,18	0,18	0,16	0,99	1,01
a. Dependent Variable: Sales										

E.2.5 Moderated regression between digital insights, entrepreneurial agility and the dependent variable Sales.

Table 60: Model summary for moderated regression for DI-EA-Sales

Model Summary[b]									
Model	R	R Square	Adjusted R Square	Std. Error of the	Change Statistics				

				Estimate					
					R Square Change	F Change	df1	df2	Sig. F Change
1	.575[a]	0,330	0,295	0,634	0,330	9,210	3	56	0,000
a. Predictors: (Constant), DI_EA_cen, DI_cen, EA_cen									
b. Dependent Variable: Sales									

Table 61: Model co-efficients and significance for DI-EA-Sales

Coefficients[a]										
		Unstandardized Coefficients		Standardized Coefficients	t	Sig.			Collinearity Statistics	
Model		B	Std. Error	Beta			Partial	Part	Tolerance	VIF
1	(Constant)	3,64	0,10		36,97	0,00				
	EA_cen	0,27	0,13	0,29	2,09	0,04	0,27	0,23	0,60	1,66
	DI_cen	0,20	0,12	0,23	1,63	0,11	0,21	0,18	0,61	1,65
	DI_EA_cen	0,36	0,12	0,32	2,89	0,01	0,36	0,32	0,99	1,01
a. Dependent Variable: Sales										

Appendix E.3: Moderated regression DV, Market share

E.3.1: Moderated regression between DTE, EA and the dependent variable Market Share.

Table 62: Model summary for moderated regression for DTE-EA-Market Share

Model Summary[b]									
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				

					R Square Change	F Change	df1	df2	Sig. F Change
1	.458[a]	0,210	0,167	0,729	0,210	4,957	3	56	0,004
a. Predictors: (Constant), TE_EA_C, TE_Cen, EA_cen									
b. Dependent Variable: MShare									

Table 63: Model co-efficients and significance for DTE-EA-Market Share

Coefficients[a]										
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.			Collinearity Statistics	
		B	Std. Error	Beta			Partial	Part	Tolerance	VIF
1	(Constant)	3,63	0,01		36,87	0,000				
	EA_cen	0,33	0,12	0,34	2,72	0,01	0,34	0,32	0,89	1,12
	TE_Cen	0,18	0,12	0,20	1,58	0,12	0,21	0,19	0,90	1,11
	TE_EA_C	0,08	0,13	0,07	0,61	0,55	0,08	0,07	0,99	1,01
a. Dependent Variable: MShare										

E.3.2: Moderated regression between DTS, EA and the dependent variable Market Share

Table 64: Model summary for moderated regression for DTS-EA-Market Share

Model Summary[b]									
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change

1	.446[a]	0,199	0,156	0,734	0,199	4,625	3	56	0,006
a. Predictors: (Constant), TS_EA_C, EA_cen, TS_Cen									
b. Dependent Variable: MShare									

Table 65: Model co-efficients and significance for DTS-EA-Market Share

Coefficients[a]										
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.			Collinearity Statistics	
		B	Std. Error	Beta			Partial	Part	Tolerance	VIF
1	(Constant)	3,66	0,10		36,60	0,00				
	EA_cen	0,35	0,12	0,36	2,86	0,01	0,36	0,34	0,91	1,10
	TS_Cen	0,20	0,14	0,18	1,43	0,16	0,19	0,17	0,89	1,13
	TS_EA_C	-0,03	0,18	-0,02	-0,18	0,86	-0,02	-0,02	0,97	1,04
a. Dependent Variable: MShare										

E.3.3: Moderated regression between Leadership support, entrepreneurial agility and the dependent variable Market Share

Table 66: Model summary for moderated regression for LS-EA-Market Share

Model Summary[b]									
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.431[a]	0,186	0,142	0,740	0,186	4,262	3	56	0,009
a. Predictors: (Constant), LS_EA_C, EA_cen, LS_Cen									

b. Dependent Variable: MShare

Table 67: Model co-efficients and significance for LS-EA-Market Share

Coefficients[a]										
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.			Collinearity Statistics	
		B	Std. Error	Beta			Partial	Part	Tolerance	VIF
1	(Constant)	3,61	0,10		34,43	0,00				
	EA_cen	0,33	0,14	0,34	2,45	0,02	0,31	0,30	0,74	1,36
	LS_Cen	0,13	0,15	0,12	0,86	0,39	0,11	0,10	0,71	1,42
	LS_EA_C	0,13	0,15	0,11	0,85	0,40	0,11	0,10	0,92	1,09
a. Dependent Variable: MShare										

E.3.4: Moderated regression between Digital culture embeddedness, entrepreneurial agility and the dependent variable Market Share

Table 68: Model summary for moderated regression for DCE-EA-Market Share

Model Summary[b]									
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df 1	df 2	Sig. F Change
1	.491[a]	0,241	0,201	0,714	0,241	5,937	3	56	0,001
a. Predictors: (Constant), CE_EA_C, CulE_Cen, EA_cen									
b. Dependent Variable: MShare									

Table 69: Model co-efficients and significance for DCE-EA-Market Share

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.			Collinearity Statistics	
		B	Std. Error	Beta			Partial	Part	Tolerance	VIF
1	(Constant)	3,56	0,10		35,17	0,00				
	EA_cen	0,29	0,13	0,30	2,19	0,03	0,28	0,26	0,75	1,34
	CulE_Cen	0,16	0,13	0,16	1,20	0,23	0,16	0,14	0,77	1,30
	CE_EA_C	0,27	0,13	0,24	2,07	0,04	0,27	0,24	0,97	1,03
a. Dependent Variable: MShare										

The above moderated regression summary indicates that the model is statistically significant (p = 0,001), with adjusted R2 = 0.201 as shown in **Error! Reference source not found.** above. There was homoscedasticity, as assessed by Breusch pagan test shown in Table 48. There was no evidence of multi-collinearity as the tolerance and variance inflation factors (VIF) were >0.1 and <10 respectively shown in **Error! Reference source not found.**. The test for normality of residuals indicated with the Kolmogorov-Smirnov test, that the data is not normally distributed with same result achieved with the Shapiro Wilk-test. The moderator variable CE_EA_C was found to be statistically significant (p = 0.044) with a coefficient of 0.245.

E.3.5: Moderated regression between DOS, EA and the dependent variable Market Share

Table 70: Model summary for moderated regression for DOS-EA-Market Share

Model Summary[b]									
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.442[a]	0,195	0,152	0,736	0,195	4,520	3	56	0,007

a. Predictors: (Constant), DOS_EA_cen, DOS_cen, EA_cen
b. Dependent Variable: MShare

Table 71: Model co-efficients and significance for DOS-EA-Market Share .

Coefficients[a]										
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.			Collinearity Statistics	
		B	Std. Error	Beta			Partial	Part	Tolerance	VIF
1	(Constant)	3,60	0,11		32,41	0,00				
	EA_cen	0,31	0,14	0,32	2,23	0,03	0,29	0,27	0,69	1,44
	DOS_cen	0,15	0,15	0,15	1,04	0,30	0,14	0,12	0,70	1,43
	DOS_EA_cen	0,14	0,17	0,10	0,86	0,39	0,11	0,10	0,99	1,01
a. Dependent Variable: MShare										

E.3.6: Moderated regression between DI, EA and the dependent variable Market Share

Table 72: Model summary for moderated regression for DI-EA-Market Share

Model Summary[b]									
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.476[a]	0,227	0,186	0,721	0,227	5,480	3	56	0,002
a. Predictors: (Constant), DI_EA_cen, DI_cen, EA_cen									
b. Dependent Variable: MShare									

Table 73: Model co-efficients and significance for DI-EA-Market share

Coefficients[a]										
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.			Collinearity Statistics	
		B	Std. Error	Beta			Partial	Part	Tolerance	VIF
1	(Constant)	3,55	0,11		31,67	0,00				
	EA_cen	0,27	0,15	0,27	1,82	0,07	0,24	0,21	0,60	1,66
	DI_cen	0,18	0,14	0,20	1,33	0,19	0,18	0,16	0,61	1,65
	DI_EA_cen	0,23	0,14	0,20	1,65	0,10	0,22	0,19	0,99	1,01
a. Dependent Variable: MShare										

Appendix E.4: Moderated regression DV, Profit.

E.4.1: Moderated regression between DTE, EA and the dependent variable Profit.

Table 74: Model summary for moderated regression for DTE-EA-Profit

Model Summary[b]									
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df 1	df 2	Sig. F Change
1	.376[a]	0,141	0,095	0,711	0,141	3,076	3	56	0,035
a. Predictors: (Constant), TE_EA_C, TE_Cen, EA_cen									
b. Dependent Variable: Profit									

Table 75: Model co-efficients and significance for DTE-EA-Profit

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.			Collinearity Statistics	
		B	Std. Error	Beta			Partial	Part	Tolerance	VIF
1	(Constant)	3,68	0,10		38,29	0,00				
	EA_cen	0,29	0,12	0,32	2,42	0,02	0,31	0,30	0,89	1,12
	TE_Cen	0,11	0,11	0,12	0,94	0,35	0,13	0,12	0,90	1,11
	TE_EA_C	0,01	0,13	0,01	0,09	0,93	0,01	0,01	0,99	1,01
a. Dependent Variable: Profit										

E.4.2: Moderated regression between DTS, EA and the dependent variable Profit.

Table 76: Model summary for moderated regression for DTS-EA-Profit

Model Summary[b]									
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.383[a]	0,147	0,101	0,709	0,147	3,206	3	56	0,030
a. Predictors: (Constant), TS_EA_C, EA_cen, TS_Cen									
b. Dependent Variable: Profit									

Table 77: Model co-efficients and significance for DTS-EA-Profit

Coefficients[a]										
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.			Collinearity Statistics	
		B	Std. Error	Beta			Partial	Part	Tolerance	VIF
1	(Constant)	3,68	0,10		38,15	0,00				
	EA_cen	0,28	0,12	0,31	2,42	0,02	0,31	0,30	0,91	1,10
	TS_Cen	0,15	0,14	0,14	1,08	0,29	0,14	0,13	0,89	1,13

	TS_EA_C	0,02	0,17	0,02	0,12	0,90	0,02	0,01	0,97	1,04
a. Dependent Variable: Profit										

E.4.3: Moderated regression between LS, EA and the dependent variable Profit.

Table 78: Model summary for moderated regression for LS-EA-Profit

Model Summary[b]									
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.459[a]	0,211	0,168	0,682	0,211	4,981	3	56	0,004
a. Predictors: (Constant), LS_EA_C, EA_cen, LS_Cen									
b. Dependent Variable: Profit									

Table 79: Model co-efficients and significance for LS-EA-Profit

Coefficients[a]										
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.			Collinearity Statistics	
		B	Std. Error	Beta			Partial	Part	Tolerance	VIF
1	(Constant)	3,63	0,10		37,48	0,00				
	EA_cen	0,17	0,13	0,19	1,37	0,18	0,18	0,16	0,74	1,36
	LS_Cen	0,32	0,14	0,32	2,27	0,03	0,29	0,27	0,71	1,42
	LS_EA_C	0,20	0,14	0,18	1,45	0,15	0,19	0,17	0,92	1,09
a. Dependent Variable: Profit										

E.4.4: Moderated regression between DCE, EA and the dependent variable Profit.

Table 80: Model summary for moderated regression for DCE-EA-Profit

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.379[a]	0,144	0,098	0,710	0,144	3,136	3	56	0,032
a. Predictors: (Constant), CE_EA_C, CulE_Cen, EA_cen									
b. Dependent Variable: Profit									

Table 81: Model co-efficients and significance for DCE-EA-Profit

Coefficients[a]										
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.			Collinearity Statistics	
		B	Std. Error	Beta			Partial	Part	Tolerance	VIF
1	(Constant)	3,65	0,10		36,26	0,00				
	EA_cen	0,35	0,13	0,39	2,70	0,01	0,34	0,33	0,75	1,34
	CulE_Cen	-0,08	0,13	-0,09	-0,66	0,51	-0,09	-0,08	0,77	1,30
	CE_EA_C	0,10	0,13	0,09	0,73	0,47	0,10	0,09	0,97	1,03
a. Dependent Variable: Profit										

E.4.5: Moderated regression between Digital organisational structure, entrepreneurial agility and the dependent variable Profit.

Table 82: Model summary for moderated regression for DOS-EA-Profit

Model Summary[b]									
Model	R	R Square	Adjusted R Square	Std. Error of the	Change Statistics				

				Estimate					
					R Square Change	F Change	df 1	df 2	Sig. F Change
1	.362[a]	0,131	0,085	0,715	0,131	2,821	3	56	0,047
a. Predictors: (Constant), DOS_EA_cen, DOS_cen, EA_cen									
b. Dependent Variable: Profit									

Table 83: Model co-efficients and significance for DOS-EA-Profit

Coefficients[a]										
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.			Collinearity Statistics	
		B	Std. Error	Beta			Partial	Part	Tolerance	VIF
1	(Constant)	3,67	0,11		33,96	0,00				
	EA_cen	0,29	0,14	0,32	2,15	0,04	0,28	0,27	0,69	1,44
	DOS_cen	0,06	0,14	0,06	0,39	0,70	0,05	0,05	0,70	1,43
	DOS_EA_cen	0,05	0,16	0,04	0,29	0,77	0,04	0,04	0,99	1,01
a. Dependent Variable: Profit										

E.4.6: Moderated regression between Digital insights, entrepreneurial agility and the dependent variable Profit.

Table 84: Model summary for moderated regression for DI-EA-Profit

Model Summary[b]									
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				

					R Square Change	F Change	df1	df2	Sig. F Change
1	.371[a]	0,138	0,092	0,713	0,138	2,986	3	56	0,039
a. Predictors: (Constant), DI_EA_cen, DI_cen, EA_cen									
b. Dependent Variable: Profit									

Table 85: Model co-efficients and significance for DI-EA-Profit

Coefficients[a]										
		Unstandardized Coefficients		Standardized Coefficients	t	Sig.			Collinearity Statistics	
Model		B	Std. Error	Beta			Partial	Part	Tolerance	VIF
1	(Constant)	3,63	0,11		32,81	0,00				
	EA_cen	0,31	0,15	0,35	2,16	0,03	0,28	0,27	0,60	1,66
	DI_cen	0,01	0,14	0,01	0,07	0,95	0,01	0,01	0,61	1,65
	DI_EA_cen	0,11	0,14	0,10	0,82	0,42	0,11	0,10	0,99	1,01
a. Dependent Variable: Profit										

Appendix E.5: Moderation regression DV, ROI

E.5.1: Moderated regression between Digital Technology embeddedness, entrepreneurial agility and the dependent variable ROI.

Table 86: Model summary for moderated regression for DTE-EA- ROI

Model Summary[b]									
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change

1	.416[a]	0,173	0,129	0,770	0,173	3,913	3	56	0,013
a. Predictors: (Constant), TE_EA_C, TE_Cen, EA_cen									
b. Dependent Variable: ROI									

Table 87: Model co-efficients and significance for DTE-EA-ROI

Coefficients[a]										
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.			Collinearity Statistics	
		B	Std. Error	Beta			Partial	Part	Tolerance	VIF
1	(Constant)	3,71	0,10		35,61	0,00				
	EA_cen	0,39	0,13	0,39	3,04	0,00	0,38	0,37	0,89	1,12
	TE_Cen	0,05	0,12	0,05	0,41	0,68	0,06	0,05	0,90	1,11
	TE_EA_C	0,04	0,14	0,04	0,31	0,76	0,04	0,04	0,99	1,01
a. Dependent Variable: ROI										

E.5.2: Moderated regression between Digital Technology strategy, entrepreneurial agility and the dependent variable ROI.

Table 88: Model summary for moderated regression for DTS-EA-ROI

Model Summary[b]									
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.482[a]	0,232	0,191	0,742	0,232	5,645	3	56	0,002
a. Predictors: (Constant), TS_EA_C, EA_cen, TS_Cen									
b. Dependent Variable: ROI									

Table 89: Model co-efficients and significance for DTS-EA-ROI

Coefficients[a]										
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.			Collinearity Statistics	
		B	Std. Error	Beta			Partial	Part	Tolerance	VIF
1	(Constant)	3,71	0,10		36,75	0,00				
	EA_cen	0,33	0,12	0,33	2,70	0,01	0,34	0,32	0,91	1,10
	TS_Cen	0,30	0,14	0,26	2,09	0,04	0,27	0,24	0,89	1,13
	TS_EA_C	0,03	0,18	0,02	0,16	0,88	0,02	0,02	0,97	1,04
a. Dependent Variable: ROI										

E.5.3: Moderated regression between Leadership support, entrepreneurial agility and the dependent variable ROI.

Table 90: Model summary for moderated regression for LS-EA-ROI

Model Summary[b]									
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.499[a]	0,249	0,209	0,734	0,249	6,190	3	56	0,001
a. Predictors: (Constant), LS_EA_C, EA_cen, LS_Cen									
b. Dependent Variable: ROI									

Table 91: Model co-efficients and significance for LS-EA-ROI

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.			Collinearity Statistics	
		B	Std. Error	Beta			Partial	Part	Tolerance	VIF
1	(Constant)	3,63	0,10		34,88	0,00				
	EA_cen	0,27	0,14	0,27	1,96	0,05	0,25	0,23	0,74	1,36
	LS_Cen	0,29	0,15	0,27	1,95	0,06	0,25	0,23	0,71	1,42
	LS_EA_C	0,28	0,15	0,24	1,95	0,06	0,25	0,23	0,92	1,09
a. Dependent Variable: ROI										

E.5.4 Moderated regression between Digital culture embeddedness, entrepreneurial agility and the dependent variable ROI.

Table 92: Model summary for moderated regression for DCE-EA-ROI

Model Summary[b]									
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.470[a]	0,221	0,179	0,748	0,221	5,297	3	56	0,003
a. Predictors: (Constant), CE_EA_C, CulE_Cen, EA_cen									
b. Dependent Variable: ROI									

Table 93: Model co-efficients and significance for DCE-EA-ROI

Coefficients[a]										
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.			Collinearity Statistics	
		B	Std. Error	Beta			Partial	Part	Tolerance	VIF
1	(Constant)	3,64	0,11		34,30	0,00				

	EA_cen	0,32	0,14	0,32	2,36	0,02	0,30	0,28	0,75	1,34
	CulE_Cen	0,11	0,14	0,11	0,84	0,40	0,11	0,10	0,77	1,30
	CE_EA_C	0,25	0,14	0,22	1,80	0,08	0,23	0,21	0,97	1,03
a. Dependent Variable: ROI										

E.5.5: Moderated regression between Digital organisational structure, entrepreneurial agility and the dependent variable ROI.

Table 94: Model summary for moderated regression for DOS-EA-ROI

Model Summary[b]									
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.463[a]	0,214	0,172	0,751	0,214	5,080	3	56	0,004
a. Predictors: (Constant), DOS_EA_cen, DOS_cen, EA_cen									
b. Dependent Variable: ROI									

Table 95: Model co-efficients and significance for DOS-EA-ROI

Coefficients[a]										
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.			Collinearity Statistics	
		B	Std. Error	Beta			Partial	Part	Tolerance	VIF
1	(Constant)	3,63	0,11		32,03	0,00				
	EA_cen	0,31	0,14	0,31	2,21	0,03	0,28	0,26	0,69	1,44
	DOS_cen	0,16	0,15	0,15	1,06	0,29	0,14	0,13	0,70	1,43
	DOS_EA_cen	0,25	0,17	0,17	1,45	0,15	0,19	0,17	0,99	1,01
a. Dependent Variable: ROI										

E.5.6: Moderated regression between Digital insights, entrepreneurial agility and the dependent variable ROI.

Table 96: Model summary for moderated regression for DI-EA-ROI

Model Summary[b]									
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.462[a]	0,213	0,171	0,751	0,213	5,055	3	56	0,004
a. Predictors: (Constant), DI_EA_cen, DI_cen, EA_cen									
b. Dependent Variable: ROI									

Table 97: Model co-efficients and significance for DI-EA-ROI

Coefficients[a]										
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.			Collinearity Statistics	
		B	Std. Error	Beta			Partial	Part	Tolerance	VIF
1	(Constant)	3,61	0,12		30,90	0,00				
	EA_cen	0,44	0,15	0,44	2,89	0,01	0,36	0,34	0,60	1,66
	DI_cen	-0,06	0,14	-0,06	-0,42	0,68	-0,06	-0,05	0,61	1,65
	DI_EA_cen	0,24	0,15	0,20	1,68	0,10	0,22	0,20	0,99	1,01
a. Dependent Variable: ROI										

Appendix F: Ethical clearance

MastersResearch2020 <MBAResearch2020@gibssa.mail.onmicrosoft.com>
to me

Gordon Institute of Business Science
University of Pretoria

Ethical Clearance Approved

Dear Luke Venkatesan,

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.

Figure 12: Ethical clearance

Appendix G: Consent form

Questions Responses 75

Section 1 of 7

The effect of Entrepreneurial Agility and Digital Maturity on Firm Performance in digital transformation of organizations.

Dear Sir/Madam,

I am currently a student at the University of Pretoria's Gordon Institute of Business Science and completing my research in partial fulfillment of an MBA.

I am conducting research on the effect of an organization's entrepreneurial agility (which describes an organizations affinity for radical or aggressive change) and digital maturity on their firm performance for organizations that have commenced with digital transformation initiatives. To that end, you are asked to complete a survey questionnaire. This will help us better understand these relationships and should take no more than 8 minutes of your time. Your participation is voluntary, and you can withdraw at any time without penalty. All responses will be treated as confidential, where participation is anonymous and only aggregated data will be reported. By completing the survey, you indicate that you voluntarily participate in this research. If you have any concerns, please contact my supervisor or me. Our details are provided below.

Researcher name: Luke Venkatesan
Email: 18361359@mygibs.co.za
Phone: +27 60 961 8498

Research Supervisor: Dr Manoj Chiba`
Email: ChibaM@gibs.co.za
Phone: +27 11 771 4000

Figure 13: Consent form