Gordon Institute of Business Science
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The relationship between digitised dynamic capabilities and successful digital transformation during times of dramatic social change

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ABSTRACT

The quantitative research detailed in this document studied the impact of dramatic social change [DSC] on the relationship between digitised dynamic capabilities [DDC] and successful digital transformation [SDT] within a South African context. While there has been ample academic theory examining dynamic capabilities [DC] as a strategic response to rapid technological change, the 2020 COVID-19 epidemiological crisis introduced a new context worthy of study. In examining DSC's moderating effect on the various aspects of DDC, the study hoped to make a small contribution towards understanding the specific organisational competencies that support SDT in times of dramatic, external, change. In addition to the above, the research sought to operationalise those processes and routines that were hypothesised to measure distinct sub-capabilities within the multi-dimensional construct of DDC.

KEYWORDS

Dynamic capabilities; digitised dynamic capabilities; digital transformation; COVID-19; dramatic social change.

DECLARATION

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

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ABBREVIATIONS

CM	centre mean
CDO	chief digital officer
DC	dynamic capabilities
DDC	digitised dynamic capabilities
DSC	dramatic social change
DSN	digital sensing (capabilities)
DSZ	digital seizing (capabilities)
DT	digital transformation
DTF	digital transforming (capabilities)
EFA	exploratory factor analysis
ICT	information communications and technology
IoT	Internet of things
IT	information technology
IV	interaction variable
KMO	Kaisen-Meyer-Olkin (measure of sampling adequacy)
SDT	successful digital transformation
Sig	significance probability (also known as p-value)

CHAPTER 1 : INTRODUCTION TO RESEARCH PROBLEM

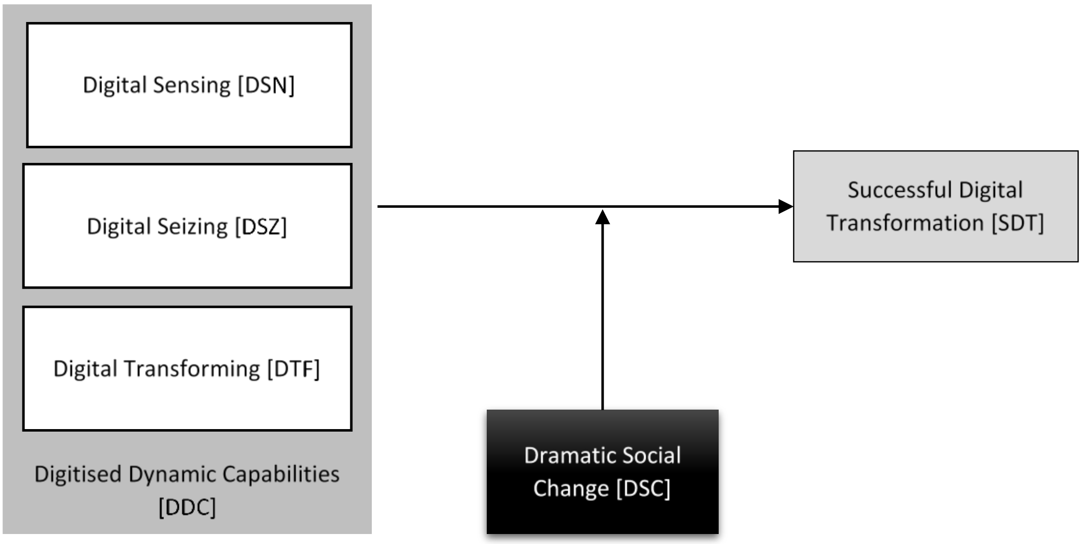

Figure 1: Theoretical model and constructs

Research Problem:	The relationship between digitised dynamic capabilities and successful digital transformation during times of dramatic social change

1.1. INTRODUCTION

On the 23rd of March 2020, South African President, Cyril Ramaphosa, announced a national lockdown in response to the COVID-19 epidemic (Ramaphosa, 2020). This unprecedented measure, aimed at containing the disease's spread (Ramaphosa, 2020), had an unforeseen consequence on South African firms: an immediate urgency to adopt digital technology (Dwolatzky & Harris, 2020; Gabriel, 2020; Goldstruck, 2020). This “new normal” (Patel-Carstairs & Burgess, 2020; Cable News Network [CNN], 2020), increased the drive for digital transformation [DT], as businesses rapidly tried to accommodate a remote workforce, along with changing consumer purchasing behaviours and demands (Botes, 2020; Bogoshi, 2020; Courie, 2020; Dwolatzky & Harris, 2020). Moreover, this crisis was expected to irrevocably influence and shape organisational change and business processes well into the future (Botes, 2020; Bogoshi, 2020; Courie, 2020).

The COVID-19 epidemic accelerated the DT paradigm (Dwolatzky & Harris, 2020; Gabriel, 2020; Goldstruck, 2020), forcing businesses to tap into new possibilities unlocked by technology platforms, and rewarding those that were successful with a skilled and "digitally capable" workforce (Botes, 2020; Courie, 2020). Although the full economic and social impact of the lockdown was yet to be measured, it had become evident that different sectors were responding to this transformative challenge in diverse ways, with some managing better than others (Dwolatzky & Harris, 2020; Sanders, 2020; Weidemann, 2020).

Of concern was the perception that, before the advent of COVID-19, many South African firms struggled with DT, falling behind their comparable counterparts in other countries (Geissbauer, Lübben, Schrauf, & Pillsbury, 2018; Wright, 2019). The region seemingly had difficulty in connecting strategic, technological, operational, and human-resource capabilities with a comparatively lower level of investment and growth in digital technologies and ecosystems (Geissbauer et al., 2018). Although the business literature suggested that DT already featured as a strategic imperative on the leadership agenda (Hess, Matt, Wiesbock, & Benlian, 2016; Singh & Hess, 2017; Sebastian et al., 2017; Svahn, Lindgren, & Mathiassen, 2017), the COVID-19 crisis irrevocably shifted this into immediate focus and priority. However, based on the literature, even when senior leadership were motivated to support DT, they faced competing, often contradictory, concerns (Hess et al., 2016, Svan et al., 2017). In these disruptive environments, management needed to weigh the implementation of current competences (or capabilities) against the simultaneous development of new, digital, capabilities which, as Hess et al. (2016) and Svan et al. (2017) observed, had to be compatible with historic path dependencies.

Fortunately, the concept of dynamic, digitised, organisational capabilities – and how these are applied in response to various external disruptions – has sound academic foundations, introducing a more grounded research opportunity than suggested by the grey literature. The application of DC (Teece, 2007) within the context of the dramatic COVID-19 disruption could, therefore, offer a theoretical framework within which to study how different organisations respond to rapid technological change in their competitive environments (Di Stefano, Peteraf, & Verona, 2014; Teece, 2007; Teece, Pisano, & Shuen, 1997; Vial, 2019; Warner & Wäger, 2019).

Consequently, and as explored in the following sections, the research project outlined in this document attempted to define and execute a relevant, contextual, and empirical academic study which could identify, explain, and test the various organisational competencies that support DT.

1.2. RESEARCH PROBLEM AND PURPOSE

As detailed in the introduction to this chapter, the COVID-19 epidemiological crisis drastically accelerated the pace of digital disruption (Dwolatzky & Harris, 2020; Gabriel, 2020; Goldstruck, 2020). The resulting change in consumer behaviour and competition (Botes, 2020; Bogoshi, 2020; Courie, 2020; Dwolatzky & Harris, 2020) consequently informed the underlying research problem. In addition, it framed the (strategically relevant) question of how South African firms had adapted their existing DC (or lack thereof) in response to these unique external factors.

DC was defined by Teece (2007) and Teece et al. (1997) as the firm's ability to develop, combine, or reconfigure internal competencies in response to changes in the competitive environment. As highlighted by Teece (2007) and Teece et al. (1997), these capabilities are only successful if backed by the requisite organisational routines and management competencies. Therefore, argued Teece (2007), a clear distinction must be made between sub-capabilities and the main capabilities they support. Teece (2007) identified these sub-capabilities as the various processes, procedures, systems, and structures that support organisational competences. Building on the concept introduced by Teece (2007), Warner and Wäger (2019) further theorised that firms need DC grounded in digitised perspectives and sub-capabilities to implement transformative business models successfully. As the academic consensus seemed to propose, these business model transformations would ensure relevance in a disruptive digital environment (Karimi & Walter, 2015; 2016; Teece, 2018; Teece & Linden, 2017; Velu, 2017).

As a result, the research study hoped to operationalise and statistically validate a process model that reports the causal relationship between a specific system of digitised organisational capabilities, their associated sub-capabilities, and a successful DT strategy. In addition, it hoped to reflect on the veracity of the various mechanisms in periods of extreme disruption through the application of a moderated interaction variable. Within this context, the main research problem was thus defined as the relationship between DDC and SDT during times of DSC.

The succeeding sections briefly outline the research study's scope, along with the expected business and academic contributions, before concluding with an outline of the remaining chapters in the document.

1.2.1. Scope

The targeted respondents for this quantitative, post-positivist, research study included professionals, specialists, and consultants at incumbent South African firms who had actively participated in (or overseen) DT projects during the six months preceding the COVID-19 lockdown. The dataset used in the statistical analysis was collated from replies gathered through several collectors within the SurveyMonkey platform, using the survey instrument defined during the operationalisation of the Warner and Wäger (2019) qualitative process model. The reflective research study purposefully adopted a cross-sectional approach. It was deemed relevant to apply contextual perceptions, feedback, and insights applicable to this period of dramatic, external, social change. The study's theoretical scope was purposefully narrowed to the digitised constructs and subdimensions extracted from the Warner and Wäger (2019) process model. This focus served as a conceptual fit for the defined research problem and supported the research study's efforts to replicate and statistically validate the selected model within environments experiencing dynamic change.

In support of the above, the antecedents and academic literature for all associated constructs were consulted and reviewed, the outcome of which is detailed in the following chapter. Finally, the inherent methodological limitations, along with any research limitations – that became evident as the defined hypotheses were subjected to various statistical tests – have been considered within the research scope and are detailed within the relevant sections of this document.

1.2.2. Business rationale and potential contribution

The stated research problem was supported in the business literature by Singh and Hess (2017). They suggested that a firm's DT should extend beyond mere functional considerations and include, instead, a comprehensive and holistic set of activities that could be implemented to pursue those new opportunities that originate from digital disruption. From an academic perspective, Singh, Klarner, and Hess (2020) and Rogers (2016) argued that DT is, fundamentally, grounded in strategy and not technology, with the implication that senior management should explore ways to capitalise on disruptive business model transformations that seek to enhance customer needs and experiences. Equally, Vial (2019) observed how DT demands that strategy and associated changes to an organisation's structure, processes, and culture, are required to yield the capability to generate new paths for value creation.

Consequently, through statistical validation of the DDC process model developed by Warner and Wäger (2019), this research study sought to reveal those discrete organisational routines that either facilitate or impede the development of digitised capabilities for business model innovation through SDT. Furthermore, by applying operationalised aspects of the DDC process model to a quantitative scale with moderated interaction (Kump, Engelmann, Kessler, & Schweiger, 2018), the research aimed to validate the efficacy and impact of DDC as a strategic response for strategic business model renewal and digitisation in periods of extreme disruptive change.

1.2.3. Academic rationale and potential contribution

The study humbly sought to build on the existing academic theory in three ways. First, through testing relationships which have been the subject of previous theoretical studies, but which had not been validated in the specific context of the research study (Whetten, 1989). Whetten (1989) suggested that while these validations may not necessarily introduce new academic constructs, their contribution to theory-driven research were still important. Consequently, the research study hoped to make a small contribution to the review of mechanisms contained in Teece’s (2007) DC model. More specifically, it attempted to expand on the body of research that sought to understand the contribution of DDC (Warner & Wäger, 2019) – and their various sub-capabilities – to strategic business model innovation through DT at incumbent South African firms.

Secondly, the research study attempted a moderate level of theory building – as proposed by Colquitt and Zapata-Phelan (2007) – through the introduction of DSC (De la Sablonnière, 2017) as a new, substantive, moderator to existing relationships within the DDC process model (Battisti & Deakins, 2017; Nenonen & Storbacka, 2020; Ritter & Pedersen, 2020; Warner & Wäger, 2019). As a result, the study aimed to supplement the work of Warner and Wäger (2019) by adding an additional dimension to existing relationships. Through this addition, the study hoped to examine the potential impact of this new contextual construct on the existing theory, as recommended by Whetten (1989). This secondary contribution expanded on a research limitation identified by Warner and Wäger (2019), which concerned applying their model to broader research contexts. Warner and Wäger (2019) questioned whether their process model could be applied to an equivalent sample set of firms in dynamic (or volatile) environments. By applying the external moderator to the DDC process model (Warner & Wäger, 2019), the research hoped to transfer and validate the model's findings into a broader context.

Thirdly, Warner and Wäger (2019) noted that their theoretical model was grounded in qualitative methods, applied to extract meaning from the defined subset of digitised sub-capabilities and contingency factors rather than quantitative methods. Consequently, Warner and Wäger (2019) suggested that research that sought to operationalise their framework could result in a new understanding of DT's long-term impact in firms. To this end, the research study attempted a relatively high level of theory building (Colquitt & Zapata-Phelan, 2007) through the operationalisation of variables from the DDC process model. These variables would also be measured on a quantitative scale for statistical validation of DDC, its various subdimensions, and discrete indicators.

1.2.4. Document structure

The remaining chapters of this research project are structured as follows:

Chapter 2 This chapter draws on current, peer-reviewed, academic literature to expand upon and explore the theoretical underpinnings of the research study introduced in Chapter 1. It is presented as a structured theoretical analysis and follows the primary constructs identified in Figure 1. Finally, it attempts to confirm the theoretical need for the research study with conclusions grounded in evidence from the available literature.

Chapter 3 Following the literature review, this chapter outlines the conceptual, quantitative, model adopted for the research study, along with the associated hypotheses and sub-hypotheses that support the main research question. It also introduces the philosophy, ontology, epistemology, and measurement design adopted for the project before concluding with a brief introduction to the testing procedures adopted for the analysis and validation of the various propositions.

Chapter 4 Expanding on the concepts introduced in the previous chapter, this section details and defends the research methodology and design adopted for the study. It includes a full academic review of the population, sampling approach, unit of analysis, research instrument design, data collection, and data verification processes.

Chapter 5 This chapter presents the empirical data collected through the research instrument, along with the outcome and values from the various statistical tests, validations, and analytics performed on the collected dataset within IBM SPSS v26. It concludes with a brief overview of the results from the various hypotheses (and sub-hypotheses) tests against the obtained values from the previous sections of the chapter.

Chapter 6 This chapter discusses the results presented in the previous chapter in the context of the research questions and associated literature.

Chapter 7 The concluding chapter highlights the research's main findings, pulling the results together into a unified set of conclusions. It includes recommendations to stakeholders based directly on the findings; gives recommendations for future research; and suggests some managerial implications of the study outcomes.

CHAPTER 2 : LITERATURE REVIEW

2.1. INTRODUCTION

As introduced in the background to this research study, the strategic implications of the rapid drive for digitisation, thrust upon South African firms in the aftermath of the COVID-19 lockdown (Nenonen & Storbacka, 2020; Ritter & Pedersen, 2020), necessitated a deeper understanding of the various theoretical constructs within this context. The current academic theory surrounding DC, as they relate to DT, along with the variables that influence their successful development, needed to be considered. In addition, the academic antecedents for all related models, frameworks, and definitions had to be reviewed. The resulting analysis would ensure that the research methodology was constructed soundly, with appropriate operationalisation and measurement of the underlying mechanisms that initialise, facilitate, and impede DDC development for success in rapid DT during times of DSC.

In this chapter, the research study suggests an academically coherent DT definition to ensure consistency of application and contextual relevance. Next, the current literature on DC is discussed in the specific context of DT. The DSC construct (De la Sablonnière, 2017) is also explored, along with the various theoretical views on its societal and normative influences (Battisti & Deakins, 2017; Nenonen & Storbacka, 2020; Ritter & Pedersen, 2020). Then, to resolve some of the constraints and limitations cited for DC as a response to rapid DT, the DDC process model developed by Warner and Wäger (2019) is explored in more detail, including the underlying, digitised, sub-capabilities (i.e., subdimensions that support digital competencies). Finally, the chapter concludes with a brief overview of the theory advocating a quantitative DC scale (Kump et al., 2018) to support the DDC process model's operationalisation.

2.2. ANTECEDENTS

2.2.1. Definition of digital transformation

Warner and Wäger (2019) observed that senior executives across various industries are markedly inconsistent in their application of the term “digital transformation” throughout the fieldwork carried out for their study. Vial (2019) echoed this observation in his research, citing 28 different academic sources, collectively containing 23 unique definitions of the term. Vial (2019) decried the lack of conceptual clarity within various academic frameworks and theoretical models. From a strategic research perspective, this created challenges of its own, as the broad spectrum of activities that could be perceived to contribute to DT would make criterion-based comparison and validation difficult.

Although the implication of the above is that a gap exists in the literature, allowing for an extensive semantic analysis of the associated concepts so that an academically consistent definition could be derived, that was not the aim of this project. Instead, the study aligned itself with DT's contextual description as detailed in Warner and Wäger’s (2019) research.

Accordingly, the definition adopted for this research study described DT as “the use of new digital technologies, such as mobile, artificial intelligence, cloud, blockchain, and the Internet of things [IoT] … to enable major business improvements to augment customer experience, streamline operations, or create new business models” (Warner & Wäger, 2019, p. 326). Thus, the definition framed DT as a means of renewal, which leverages off technological advances to develop specific sets of capabilities that redefine business models, improve collaboration, and shake up the established culture (Warner & Wäger, 2019).

This view of pervasive technologies – converging to create and support new, innovative, strategic choices – echoed the contextual literature (Nambisan, Lyytinen, Majchrzak, & Song, 2017). Furthermore, it built on the literature that has highlighted the heightened volatility, complexity and uncertainty in the environment brought about by DT (Autio, Nambisan, Thomas, & Wright, 2018; Dattée, Alexy, & Autio, 2018). Finally, Warner and Wäger (2019) aligned the definition with earlier academic literature that conceptualised strategic transformation and innovation as continuous processes (Agarwal & Helfat, 2009; Tsoukas & Chia, 2002).

The following section, having adopted DT's definition detailed above, explains the relationship between this construct and DC, citing recent literature and academic views on the correlation between the successful execution of digitised change and the various capabilities proposed by Teece (2007).

2.2.2. Dynamic capabilities and digital transformation

The foundational literature made a clear distinction between DC and operational capabilities (Winter, 2003). Operational abilities, argued Helfat and Winter (2011), supported existing products or services, within an established customer base, using proven techniques. By contrast, DC were more focused on strategic change, aligning the organisational processes, culture, and business model with the demands of a changing environment (Zhara, Spaienza, & Davidsson, 2006; Teece, 2007). Equally, Vial (2019) posited that the DC perspective (Teece, 2007) continued to be a relevant and significant contributor within the academic discourse around competitive advantage. This was especially (as the current literature suggested) the case when considering the development of enduring competitive advantage in those environments characterised by rapid, external, technological change (Helfat & Raubitschek, 2018; Schilke, Hu, & Helfat, 2018; Vial, 2019; Yeow, Soh, & Hansen, 2018). In further support of this perspective, Teece (2007) in his seminal work detailed how DC enabled firms to innovate and adapt to changes in their environment through three primary mechanisms: sensing, seizing, and transforming. Each of these activities, argued Teece (2007), would allow firms to continually reconfigure (transform) their resources as they strategically identified and seized opportunities or identified and responded to threats.

Vial (2019) suggested an academic resonance between the conceptual foundations presented for both DC and DT. Vial (2019) submitted, alongside Warner and Wäger (2019), that the literature has positioned DT as a source of continuous change and disruption in a firm's competitive environment. As a result, firms' ability to deploy repeatable mechanisms that would ensure successful, sustained adaptation in the face of such technology-driven changes became an intriguing and essential research question. Ordinary capabilities could not, in isolation, describe how firms build and sustain competitive advantage in rapidly changing environments (Teece, 2007, 2014; Teece et al., 1997). In addition, as modern consumers have migrated to digital technologies, value networks have become broader and more complex (Vial, 2019). As a result, traditional, physical resources started to become comparatively less relevant than digital services and platforms (Vial, 2019) further limiting the strategic reach of ordinary (i.e., operational) capabilities (Helfat & Winter, 2011). In their earlier work, Helfat et al. (2009) described the impact of DC within firms as promoting “evolutionary fitness”, exhibited through the successful adaptation of DC to the contextual environment in which the firm operates. Thus, as suggested by Teece (2007) and Helfat et al. (2009), DC actively promoted and supported the achievement of high evolutionary fitness, enabling the firm to grow and thrive in times of rapid change. Seen against the accepted definition of DT outlined in the previous section, which focused on renewal and innovation, it may be concluded that the DC perspective aligned both conceptually and academically with DT's stated objectives.

Although the literature (Helfat et al., 2009; Teece, 2007, 2014; Teece et al., 1997; Vial, 2019) had soundly positioned DC as applicable to the context of external, technological, turbulence, a more in-depth understanding was required of the sub-capabilities that support DC. This insight was important, as the literature indicates that DC were driven in the performance of routines (Teece et al., 1997). These routines were expressed as repeatable patterns of interdependent actions (Eisenhardt & Martin, 2000; Feldman & Pentland, 2003; Kump et al., 2018; Vial, 2019) and anchored in the capability of individuals within the organisation (Helfat & Martin, 2015; Teece, 2007; Teece et al., 1997; Vial, 2019; Yeow et al., 2018). Vial (2019) further stressed that the efficacy of these routines, in the context of DT, was determined by a firm's ability to sense technological disruptions or opportunities, seize them through strategic responses and, finally, to reconfigure the impacted elements of their business model appropriately (Teece, 2007; 2014).

Of interest to this research study was the legitimacy of these mechanisms in the face of sudden, external, forced digitisation efforts. Within the research project's specific context, South African firms were challenged with immediate, universally applicable, and legally enforced constraints on their workforce, customer base, and distribution networks. Their ability to respond to these challenges, along with the contribution of those latent, expressed, or absent DC (as identified in the literature) lay at the heart of the research problem. As a result, the following sub-sections explore the theoretical antecedents for the various activities and mechanisms within DC. In addition, the broader processes and activities that support the development and maintenance of DC are considered (Schilke et al., 2018), along with an ongoing review of the academic contribution this framework supplies to the context of disruptive DT and change.

2.2.3. Sensing capabilities

Firms need sensing capabilities, as defined by Teece (2007), to continually scan the competitive landscape for disruptive changes, unexpected shifts in consumer behaviour or new technological trends (Birkinshaw, Zimmermann, & Raisch, 2016; Day & Schoemaker, 2016; Dong, Garbuio, & Lovallo, 2016; Giudici, Reinmoeller, & Ravasi, 2018; Helfat & Raubitschek, 2018; Loebbecke & Picot, 2015; Warner & Wäger, 2019). This construct was further expanded upon by Teece (2007), who detailed that these sensing activities should also include creative, learning, and interpretive dimensions. In a symbiotic fashion, these would enable the analysis of diverse sets of information and data about potential trends in the firm's ecosystem (Teece, 2007). From this, it may be asserted that these related tasks' multi-disciplinary nature demands engagement from all organisation levels and cannot be limited to senior management alone (Teece & Linden, 2017).

In support of these demands, the literature proposes both functional scenario planning (Helfat & Raubitschek, 2018; Teece, Peteraf, & Leih, 2016) and dynamic executive competences (Helfat & Peteraf, 2015). According to the literature, these potential measures could improve a firm's ability to sense and respond to unexpected technological trends (Helfat & Peteraf, 2015; Helfat & Raubitschek, 2018; Teece et al., 2016; Warner & Wäger, 2019). These approaches' analytical limitations did become apparent, though, when seen in the modern context of large-scale, real-time processing of predictive data by advanced digital infrastructure or business intelligence platforms (Ross, Sebastian, & Beath, 2017; Warner & Wäger, 2019). Agrawal, Gans, and Goldfarb (2017) expanded on these concerns, citing the rising trend of firms that increasingly rely on artificial intelligence to predict new trends, in the hope that the algorithmic capability seemingly resident in these applications will overcome the cognitive limits of human-based sensing activities.

However, irrespective of the prevalence, nature, and extent of automated, data-driven analytics in South African firms, the onset of COVID-19 and the resulting, national constraint on strategic alternatives would not likely have been foreseen by any of these platforms. Teece (2018) further highlighted the lag between business model innovation and technological capabilities, reflecting a dependency of these efforts on context, rather than technology. The COVID-19 crisis certainly shook the sensing paradigm to its core, as the immediate (and inescapable) context for all business was clear: successfully implement DT through a radical review of your business model or become immediately irrelevant.

Consequently, as the research study considered: Are sensing capabilities still significant contributors to SDT within the context of DSC? Or would the focus shift in these times of disruptive (and immediate) change to seizing activities? In the following section, the seizing construct is explored further, along with the criteria proposed by literature to support the rapidly changing demands of an environment such as the one framed in this research study.

2.2.4. Seizing capabilities

Teece (2007) theorised that firms should develop a set of seizing capabilities which allow experimentation with new business models, supporting decentralised boundaries and digital platforms. This, Teece (2007) argued, would be successful only if those firms fostered leadership characteristics with a low tolerance for hubris, deception, bias, and delusion. Day and Schoemaker (2016) supported Teece's (2007) assertions, stating that seizing capabilities should be experimental, using techniques such as rapid prototyping build to gain focus and commitment from stakeholders. In their study, Autio et al. (2018) also observed how DT had proved advantageous to entrepreneurial firms willing to experiment with radical business model innovations, adapting power relationships, intermediaries, and outputs of existing value chains in the pursuit of new opportunities.

However, what was evident from the prevailing academic discourse is that inertia could be a real and significant inhibitor to these seizing efforts (Birkinshaw, 2018; Rigby, Sutherland, & Takeuchi, 2016). Teece (2007; 2014) noted that path dependencies were the enemy of radical competency – destroying innovation and instead favouring those improvements that support competency enhancements. To overcome these limitations, the literature suggests that firms should adopt a more agile approach (traditionally seen as a software methodology), but this seemed to be more difficult in practice than the theory suggested (Birkinshaw, 2018; Rigby et al., 2016; Teece et al., 2016), as supported by the research problem under scrutiny in this report.

Teece et al. (2016) defined agility as a firm's capability in redirecting its available resources to those, higher-yield, value-creating activities most efficiently and effectively, as warranted by both internal and external circumstances. Expanding on this view, Warner and Wäger (2019) went on to suggest that those firms who leveraged off their information technology [IT] competencies reported an improved success rate in agile strategic responses, ranging from resource utilisation to more complex product development. This perspective built on Rigby et al.'s (2016) research, who observed that agile-related methodologies were spreading beyond IT to other corporate functions. However, Rigby et al. (2016) noted that many of these projects failed, as leaders were incapable of contextualising the success factors for agile, which included: flexible supply chains, alternative sourcing measures, organisational slack, and accessible innovation processes.

As with sensing mechanisms, seizing capabilities seem constrained by contextual issues and limited technological innovation processes which, as highlighted by Teece et al. (2016), are critical in preserving and enhancing strategic agility. Consequently, the question arises regarding the contribution that these agile seizing capabilities make in the face of disruptive DT, even more so when the context is radically and suddenly imposed on these firms. Perhaps, as per the literature, the value of agile seizing capabilities is strengthened by executing effective transformation capabilities (Birkinshaw, 2018).

2.2.5. Transforming capabilities

The literature indicates that, while sensing and seizing capabilities contributed respectively to the discovery and creation of opportunities, for firms to implement a DT strategy successfully, they needed transforming capabilities that fully exploited the potential advantages of strategic adaptation and innovation (Karimi & Walter, 2015; Teece & Linden, 2017). Accordingly, transforming capabilities are defined as an organisation's capacity to periodically transform aspects of their culture and business model in response to new threats or opportunities (Teece, 2007, Teece et al., 1997). Furthermore, as Day and Schoemaker (2016) observed, firms that exhibit the most successful transforming capabilities are those that adopt and cultivate an agile and entrepreneurial mindset, echoing the findings from Autio et al. (2018).

Transforming capabilities – and their impact on successful DT – seemed to be magnified in those firms that continuously renew their strategic assets and organisational structures in response to disruptive competitive forces (Agarwal & Helfat, 2009; Teece, 2014). Equally, the research suggested that firms evolutionarily deploy digital-centric technology to expand, adapt or abandon existing activities (Foss & Saebi, 2018; Kim & Min, 2015). This view was supported by Velu (2017), who noted that senior management often struggled with managing the resulting mismatch between their existing cognitive perception of established business models and the new economic reality.

What became evident from exploring the various theoretical antecedents to DC was that contextual constraints, lack of technological innovation, and cognitive bias all hampered business model innovation efforts. Of particular interest to this study was the correlation between these core theoretical concepts and firms' ability to respond to immediate, disruptive DT, as within the research project's stated context. This context, which has been expressed as DSC, is of conceptual and academic importance, along with the various theoretical constructs and societal implications it introduced. Hence, before moving on to the different, digitised, mechanisms recommended by Warner and Wäger (2019), the following section investigates the DSC construct, along with a brief introduction to its use as a moderator.

2.3. DRAMATIC SOCIAL CHANGE

The literature defines a crisis as an unstable situation, wherein a pivotal change is imminent (Ritter & Pedersen, 2020). If mismanaged, these situations could have a significant and detrimental impact on an organisation (Pedersen, Ritter, & Di Benedetto, 2020; Ritter & Pedersen, 2020). However, Ritter and Pedersen (2020) noted that crises might also introduce new opportunities, giving rise to new business models or value propositions. This notion of renewal, supported by a new set of capabilities that serve changing customer needs (Ritter & Pedersen, 2020), perfectly aligns the concept of “change” with DC, as explored in previous sections. In addition, as Ritter and Pedersen (2020) noted, the COVID-19 crisis highlighted the differences in various organisations’ levels of capabilities and preparedness, laid bare in their strategic response to the decisive change.

Further to the literary definition of a crisis, De la Sablonnière (2017) characterised the specific typology of DSC as “a situation where a rapid event leads to a profound societal transformation and produces a rupture in the equilibrium of the social and normative structures” (De la Sablonnière, 2017, p. 2). Additionally, De la Sablonnière (2017) identified the following four characteristics typically associated with DSC: 1) accelerated pace at which the change impacts the environment, 2) a rupture in the social structure and institutions, 3) a rupture in the normative structure, modifying core behaviours, and 4) a shared threat to cultural beliefs, values, and attitudes. In applying this definition (and its associated features) against the COVID-19 crisis, the literature seems to support DSC's construct as a valid moderator within the research project's scope. Also, through DSC's application to the research project, the study aligned with the organisational psychology perspective of social change (De la Sablonnière, 2017). This theoretical approach viewed DSC primarily from the viewpoint of organisational change, considering both the individual mindset and broader strategic responses to an external threat (Burke & Litwin, 1992; Reichers, Wanous, & Austin, 1997). Finally, the study adopted the functionalist theory of DSC, which assumes that society exists in a state of equilibrium (De la Sablonnière, 2017). Consequently, the theory states, when the equilibrium is threatened due to rapid, external events, adjustments are made within the observed institutions, along with a modification to behaviours and attitudes, so that a new state of equilibrium is achieved (De la Sablonnière, 2017).

These observable routines, actions, and strategic responses were measured within the survey instrument's output, attempting to statistically quantify the impact this construct has on the relationships between DDC and SDT. This moderator effect is described by Hair, Black, and Babin (2018) as occurring when a third independent variable (in this case, DSC) causes the relationship between the dependent variable (SDT) and the independent variables (DDC) to change. The viability of DSC within this context was thus justified, as the disruptive nature of the change was expected to impact the social structure and those individuals and organisations within it (De la Sablonnière, 2017).

Accordingly, the theoretical constructs described in this section were used in the definition of the substantive moderators (detailed in Chapter 3). Consideration was given to the expected redefinition of routines, norms, and habits that accompany DSC (De la Sablonnière, 2017), as expressed in the various mechanisms and sub-capabilities of the DDC process model. These assumptions are detailed in hypotheses four, five, and six, along with their associated sub-hypotheses.

As explained in this chapter's preceding sections, this research study sought to gain a deeper understanding of the broad constructs that surround DC and their support of DT. Thus, having explored the theoretical precursors to DDC, along with the proposed moderator, the subsequent section assesses, against the available academic literature, the theoretical relevance and empirical validity of the process model developed by Warner and Wäger (2019). This review includes aspects of the relevant frameworks, data structures and foundational concepts deployed by Warner and Wäger (2019), linking the findings back to both the literature presented and the context of the defined hypotheses.

2.4. THE DYNAMIC CAPABILITIES PROCESS MODEL

To address the various limitations of DC – as a strategic response to disruptive technological transformation – Warner and Wäger (2019) suggested that firms need to define and adopt more explicit, digitally focused DC. These, argued Warner and Wäger (2019), should be supported by clearly defined sub-capabilities that actively leverage technological advances to achieve enhanced levels of responsiveness and business model innovation. They posited this approach would inspire new value propositions and foster operational excellence (Warner & Wäger, 2019).

With this perspective in mind, the following sections revisit the conceptualisation of those mechanisms identified by Teece (2007; 2014) and Teece et al. (1997) in support of the successful execution of DC (i.e., sensing, seizing, and transforming). The sections also present a specific view on the digitisation of these artefacts by Warner and Wäger (2019). The additional context further substantiates the foundational routines to support DC for DT and details the theoretical aspects that the research study aimed to operationalise.

2.4.1. Digitised dynamic capabilities for digital transformation

Although ample academic consensus exists on the contribution of DC to a firm’s ability to sustain competitive advantage in digitally disruptive environments (Helfat & Raubitschek, 2018; Karimi & Walter, 2015; 2016; Schilke et al., 2018; Teece, 2007, 2014; 2018; Teece & Linden, 2017; Teece et al., 1997; Vial, 2019; Velu, 2017; Yeow et al., 2018), little research has examined the specific sub-capabilities, focused on DT, that support DC (Warner & Wäger, 2019). During their research, Warner and Wäger (2019) explored these “digitised” sub-capabilities through a multiple case study approach, which combined a broad scope of qualitative data, drawn from interviews with senior executives with experience in leading DT projects.

In a broader theoretical context, the prevailing data suggests that the successful development and execution of digitally-focused DC has already become a strategic imperative for a growing number of diverse firms, driven by the ubiquity of convergent, disruptive, digital technologies (Autio et al., 2018; Vial, 2019; Warner & Wäger, 2019; Yeow et al., 2018). Furthermore, the process of digitisation (i.e., the use of digital technologies and data to create revenue) has increasingly forced traditional organisations to adopt a more entrepreneurial approach and mindset (Autio et al., 2018; Vial, 2019; Warner & Wäger, 2019; Yeow et al., 2018). As a result, the environmental forces that preceded the COVID-19 crisis had already begun to foster a renewed drive by firms to build systems of digitised capabilities in response to external threats (Autio et al., 2018; Vial, 2019; Warner & Wäger, 2019; Yeow et al., 2018). As Warner and Wäger (2019) proposed, these threats were primarily introduced through the de-coupling and removal of traditional intermediaries in established value chains. Notably, this observation has become eerily perceptive in the aftermath of the COVID-19 crisis and its impact on conventional channels.

Figure 2 represents the final data structure constructed by Warner and Wäger (2019) and summarises the proposed interrelation (from left to right) between the discrete indicators (key activities), lower-order constructs, or subdimensions (sub-capabilities), and aggregate dimensions, or higher-order constructs (DDC), that support SDT. Their results, noted Warner and Wäger (2019), found that access to new, enabling, digital technologies and platforms (such as IoT, blockchain, and cloud-based solutions) challenged the traditional constraints inherent in DC, a view supported in the literature by Velu (2017) and Vial (2019). Consequently, these platforms allowed firms to scale their operations up (or down) at levels of efficacy, speed and cost that were simply not possible a decade earlier (Warner & Wäger, 2019). These findings directly supported the stated research problem and suggested a potential strategic contribution from the research project towards firms seeking to improve their responsiveness in the face of rapid, disruptive, digital change.

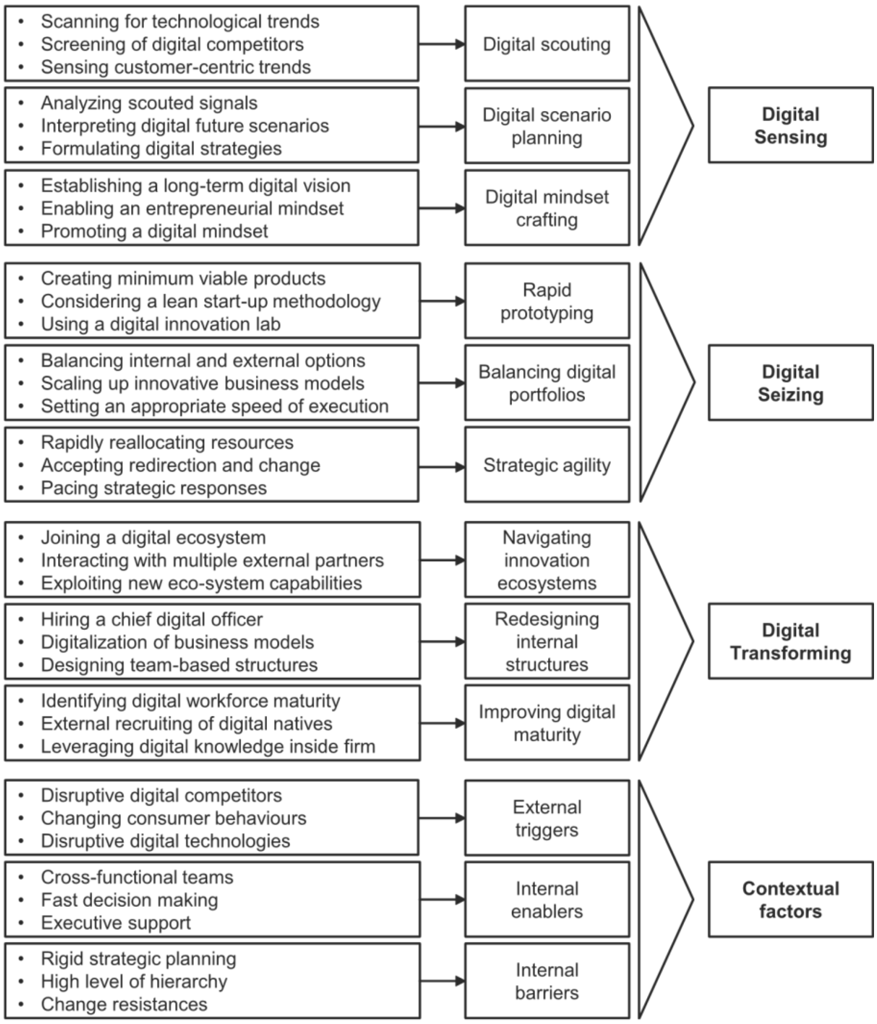

Figure 2: Data structure of DDC process model
Source: Warner & Wäger, 2019, p. 335

The discrete indicators (key activities) listed to the left of the model, represent the digitised routines and repeatable actions (Eisenhardt & Martin, 2000; Feldman & Pentland, 2003; Kump et al., 2018, Vial, 2019, Warner & Wäger, 2019) adopted for the study, operationalised into the associated survey instrument as measures for the DDC sub-capabilities (Teece, 2007, 2014; Warner & Wäger, 2019). Consequently, each subset of interdependent processes, as they relate to DDC (Helfat & Martin, 2015; Teece, 2007; Teece et al., 1997; Vial, 2019; Warner & Wäger, 2019; Yeow et al., 2018) would, in turn, determine the sub-capabilities of the respondents' firms to sense, seize, and transform in the face of technological disruption (Teece, 2007, 2014; Vial, 2019; Warner & Wäger, 2019). As the application of these constructs to the context of the study alluded to a new perspective of both DT and DC, a review was needed of each digitised sub-capability. Additionally, their contribution to SDT needed to be detailed, framed by Warner and Wäger (2019) within the context of a) business model renewal, b) collaborative approach renewal, and c) culture renewal (as can be seen in Figure 3).

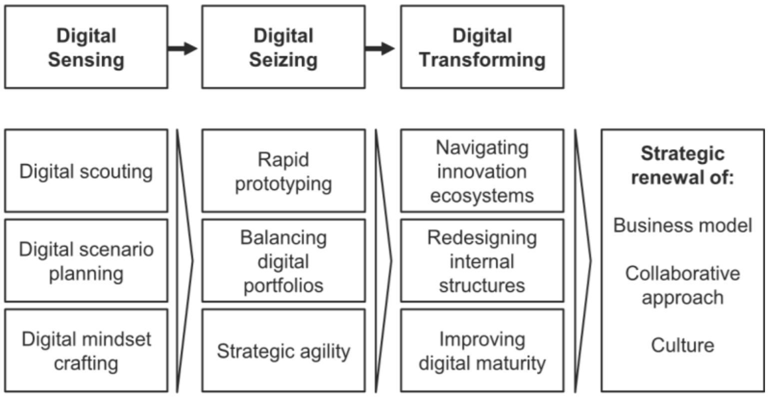

Figure 3: DDC for successful digital transformation
Source: Adapted from Warner & Wäger, 2019, p. 336

The following sub-sections thus briefly explore the findings presented by Warner and Wäger (2019) in support of their process model, along with a summary of each of the clusters associated with digital sensing, digital seizing, and digital transforming activities in support of SDT.

2.4.2. Building digital sensing capabilities

Warner and Wäger (2019) introduced the digital sensing cluster with an observation, from their data, that recent advancements in technology had significantly challenged the conventional approach to strategic planning. Their research suggested that new, digitised sub-capabilities needed to be developed within the sensing construct, centred explicitly around digital scenario planning and scouting (Warner & Wäger, 2019). They proposed that these would aid firms in their efforts to identify new technologies, customer preferences, and competitor trends as the traditional networks were simply no longer applicable (Warner & Wäger, 2019). This new approach included the use of technology hubs to identify technological trends, supported by data analytics and machine-learning to sense those disruptive developments that strategic planners traditionally struggled to predict (Birkinshaw et al., 2016; Day & Schoemaker, 2016; Dong et al., 2016; Giudici et al., 2018; Helfat & Raubitschek, 2018; Loebbecke & Picot, 2015; Warner & Wäger, 2019). In addition, a prominent theme emerged, defined by Warner and Wäger (2019) as digital mindset crafting. This sub-capability, supported by an entrepreneurial, digitally orientated culture forms an essential first step to any DT process (Autio et al., 2018; Day & Schoemaker; 2016; Warner & Wäger, 2019).

These findings were further supported by research which suggested that the current literature had not yet extensively acknowledged the development of digitised sensing sub-capabilities (Day & Schoemaker, 2016; Nambisan et al., 2017). Furthermore, the research from Warner and Wäger (2019) seems to resonate with academic consensus on the observable rise of both strategic planning competences (Dong et al., 2016) and scouting capabilities (Monteiro & Birkinshaw, 2017) within firms, in response to digital disruption. Finally, their observations around digital mindset crafting built on the classical principles of strategic thinking (Mintzberg, 1994) along with some emerging academic schools of thought around strategic thinking in the digital age (Kane, Palmer, Phillips, & Kiron, 2017).

Within the DSC context, the digital mindset proposed above seems to resonate with the stated research problem. As Warner and Wäger (2019) submitted, this sub-capability should result in an improved ability to respond rapidly in a digitally disruptive environment, a view supported in their findings. Importantly, they argued, a critical enabler for the sensing sub-capability lies in the firm's capability in fostering a cross-functional and entrepreneurial culture (Warner & Wäger, 2019). Finally, the evidence would suggest that the contribution of these specific, digitised sub-capabilities would be amplified in times of unprecedented change and disruption (Autio et al., 2018; Vial, 2019; Warner & Wäger, 2019; Yeow et al., 2018). Consequently, the digital sensing capability, along with its three sub-capabilities and discrete indicators, formed the foundation of the first hypothesis (and its sub-hypotheses) that the research study attempted to validate. Testing the consistency, validity, and correlation of the digital sensing variables (and their measures) preceded the validation of the moderating effect suggested in the research problem.

2.4.3. Building digital seizing capabilities

Business model innovation lies at the core of SDT, argued Warner and Wäger (2019), in their digital seizing cluster review. Their findings emphasised the importance of specific sub-capabilities, such as strategic agility and rapid prototyping (Birkinshaw, 2018; Rigby et al., 2016; Teece et al., 2016). These competencies allow firms to experiment with minimum viable products, responding to changing customer demands (Birkinshaw, 2018; Rigby et al., 2016; Teece et al., 2016; Warner & Wäger, 2019). Additionally, Warner and Wäger (2019) noted that investment in technologies that support rapid scaling, innovation, and acquisitions is vital. Not only would these investments facilitate speed of execution, but the underlying technology would empower firms to balance their new digital portfolios and achieve business model innovation (Peteraf, Stefano, & Verona, 2013; Vial, 2019; Warner & Wäger, 2019). With the emergence of radically new business models (e.g., servitisation or subscription-based), innovative revenue streams still have to be balanced against existing product (or service) offerings (Peteraf et al., 2013; Vial, 2019; Warner & Wäger, 2019).

Evident from the model proposed by Warner and Wäger (2019), however, is the growing importance of continuous review and redeployment of firms' resources. This sub-capability (framed within the theory of strategic agility) would serve firms well as they seek more efficient ways to respond to threats or opportunities (Warner & Wäger, 2019). As suggested in the literature, these competencies were amplified as disruptive DT became increasingly ubiquitous (Helfat & Raubitschek, 2018; Karimi & Walter, 2015; 2016; Schilke et al., 2018; Teece, 2018; Teece & Linden, 2017; Vial, 2019; Velu, 2017; Yeow et al., 2018). The findings of Warner and Wäger (2019) therefore aligned with academic consensus, along with the acknowledgement that strategic agility as a sub-capability is crucial to the successful innovation of business models, a view echoed by Birkinshaw (2018), Rigby et al. (2016) and Teece et al. (2016).

From the above, the digital seizing capability, along with its three sub-capabilities and discrete indicators, formed the foundation of the second hypothesis (and its sub-hypotheses). As with the previous hypothesis, testing the consistency, validity, and correlation of the digital seizing variables (and their measures) preceded the validation of the moderating effect on the various sub-capabilities. Then, the associated moderation interaction was to assess the possible magnification of several sub-capabilities within their contribution to SDT, as expressed within the context of rapid, immediate, and disruptive transformation.

2.4.4. Building digital transforming capabilities

Finally, the digital transforming cluster outlined by Warner and Wäger (2019) highlighted the importance of organisational culture, with specific reference to developing and improving upon the digital proficiencies of the firm’s personnel. In studying the process model's associated components, transformational leadership's contribution was evident, specifically in its support of collaboration and coordination for new business model development (Warner & Wäger, 2019). The findings further highlighted the need for leadership styles driven by purpose and not hierarchy (Warner & Wäger, 2019). For firms to successfully navigate the complexities inherent to DT, argued Warner and Wäger (2019), they need leadership that actively pursues disassociation with existing practices (i.e., historic path dependencies). If leaders want to adopt a digitised approach to DC, a renewed commitment to decentralised internal structures and digital capability-building has to take centre stage (Warner & Wäger; 2019). The research of Birkinshaw (2018) supports these observations, and echoes the need for updated, digitally focused governance processes that have a transformative effect on the collaborative activities and interactions in firms. Moreover, emerging schools of thought on the innovation of business models (Autio et al., 2018; Dattée et al., 2018; Nambisan et al., 2017) resonate with the importance of navigating innovation ecosystems (Warner & Wäger, 2019). Specifically, these digital networks include co-creation and collaboration opportunities with new partners, which accelerates the speed of innovation and new business model development (Autio et al., 2018; Dattée et al., 2018; Nambisan et al., 2017; Warner & Wäger, 2019)

In conclusion, Warner and Wäger (2019) argued, the very nature, scope, and purpose of DC are being influenced and changed by the prevalence of disruptive digital technologies. The strategic responses available to firms have allowed business model innovation in ways that were simply not possible before (Vial, 2019; Velu, 2017; Warner & Wäger, 2019; Yeow et al., 2018). Therefore, they proposed that firms adapt their digital transforming capabilities, with a clear emphasis on those technologies that facilitate rapid responses to market changes (Warner & Wäger, 2019). Additionally, improving the workforce's digital maturity has become an important area of focus alongside the introduction of these new technologies (Warner & Wäger, 2019). Whether through the active recruitment of external digital “natives” or continued capability-building programmes for existing staff, SDT depends on the workforce's overall maturity (Warner & Wäger, 2019). They concluded this sub-capability is critical in shifting the context for strategic change and DDC (Warner & Wäger, 2019), allowing for a more theoretically and empirically sound application of SDT.

This final perspective framed the third hypothesis, along with its associated sub-hypotheses. The consistency, validity, and correlation of the digital transforming sub-capabilities (and their measures) were tested, followed by the validation of DSC's moderating effect. The hypotheses referenced are detailed in Chapter 3, along with the expanded quantitative conceptual model that incorporates the theoretical constructs detailed in the preceding sections.

2.5. OPERATIONALISATION OF THE PROCESS MODEL

2.5.1. Background and rationale

Kump et al. (2018) noted that as they developed their own, quantitative DC scale, no other standardised scale existed for the measurement of DC. They found that this absence limited the comparability of empirical findings and impaired data-based theory development. Equally, Schilke et al. (2018) observed that many current DC studies were biased towards an empirical approach. While some academic literature had started to explore the application of proxies for DC research (Girod & Whittington, 2017), a third of publications still reported findings from survey studies (Kump et al., 2018).

From this, the research project inferred that a gap exists within the academic discourse for a standard scale of DDC, against which systematic empirical analysis may be introduced for the contextual subject matter. Kump et al. (2018) supported this view and argued that the absence of quantitative scales within the DC literature continues to limit the comparability of findings from the current base of (quantitative) studies. Besides, they stated, this gap implied a lack of research opportunities for academic meta-analyses that would improve conceptual clarity on the theoretical foundations of DC (Kump et al., 2018).

Finally, Clark and Watson (1995) established that a scale's development should have a well-established academic construct as its starting point. From this, argued Clark and Watson (1995), a systematic and multi-staged procedure could be followed to operationalise those sets of artefacts that most consistently reflect the construct. Schilke et al. (2018) posited that the most widely cited and acknowledged academic framework for DC was that of Teece (2007). In addition to this well-established construct, the research project adopted the digitised process model of Warner and Wäger (2019). This qualitative model contains academically supported artefacts, detailing the various higher-order constructs, lower-order constructs and discrete indicators that would aid in the composition and definition of a quantitative, digitised DC scale.

2.5.2. Implications of scale application for dynamic capabilities conceptualisation

In previous sections of the literature review, this research study presented the view, initially proposed by Eisenhardt and Martin (2000), that DC are expressed as routines. At first glance, this definition may contradict the view of DC as capacities (Teece et al., 1997) challenging their quantitative application and measurement. However, as Di Stefano et al. (2014) argued, these seemingly divergent academic views could be combined. Capacities are latent, stated Di Stefano et al. (2014), and only observable once they are actioned upon. In contrast, routines and their constituent elements were generally more observable (Di Stefano et al., 2014). Kump et al. (2018) supported this view and observed that DC were latent capacities, manifested in the outcomes of visible routines. Only through these routines could DC enable continuous and reliable strategic renewal (Peteraf et al., 2013; Di Stefano et al., 2014; Kump et al., 2018).

Of further relevance to this research study (and the associated research problem) was the perspective of DDC as they relate to highly dynamic environments. This was particularly pertinent as the research attempted to operationalise the capabilities and routines identified by Warner and Wäger (2019) in the context of rapid, disruptive DT. Peteraf et al. (2013) suggested that within the perspectives presented by Teece et al. (1997) and Eisenhardt and Martin (2000), DC in highly dynamic environments should take the shape of higher-order capabilities (e.g., continuous product innovation). This, Peteraf et al. (2013) said, would allow these higher-order capabilities to enable the development and deployment of lower-order capabilities, measured in the execution of behaviours and processes. Finally, Peteraf et al. (2013) recommended that these DC remain useful to the firm, even in rapidly changing market conditions.

2.6. CONCLUSION

Within the construct of DC, the preceding literature review suggested a framework of strategic competencies that could help answer how South African firms have adapted to the disruption of the COVID-19 crisis. While previous research alluded to the amplified external and disruptive influence on firms (Autio et al., 2018; Dattée et al., 2018), brought about by the sudden and unexpected flow of digitised products, services, and business models (Nambisan et al., 2017), none of these came close to predicting the current contextual implications. Consequently, this research study humbly rose to the challenge, deploying operationalised aspects of the DDC process model into a quantitative scale. Using the academic frameworks examined in the literature review, the research aimed to answer six main hypotheses. The first three hypotheses (along with their associated sub-hypotheses) comprised an attempt to explore and validate the correlation and measurement validity of the various subdimension and their related indicators. The remaining three main hypotheses (and sub-hypotheses) then had to report on the causal relationship between the subdimensions of DDC and SDT with an explicit reflection on the integrity and contribution of the various mechanisms in periods of DSC. These arguments, along with the ontology and epistemology adopted for the research project, are summarised in the following chapter.

CHAPTER 3 : RESEARCH HYPOTHESES

3.1. CONCEPTUAL MODEL AND HYPOTHESES

The research study attempted to operationalise the process model developed by Warner and Wäger (2019), which conceptualised those DDC that support SDT. Furthermore, the research introduced the concept of DSC (De la Sablonnière, 2017) as a moderator within the existing framework. In doing so, the replication study hoped to add value through empirical evidence that conceptualised and validated the multi-dimensional construct of DDC within dynamic environments. Additionally, it sought to examine the specific impact of DSC on the contextual contribution of each variable (or subdimension) to strategic renewal efforts in the pursuit of SDT. The overarching research question (which informed the study's purpose) was thus framed as: *What impact does DSC have on the relationship between DDC and SDT?*

Figure 4 represents the conceptual diagram of the hypothesised theoretical model adopted for the study and illustrates the various higher- and lower-order constructs included in the research study. Table 1 summarises the overall research design, methodology, proposed hypotheses, and sub-hypotheses that are discussed, analysed, and tested in the remainder of this report.

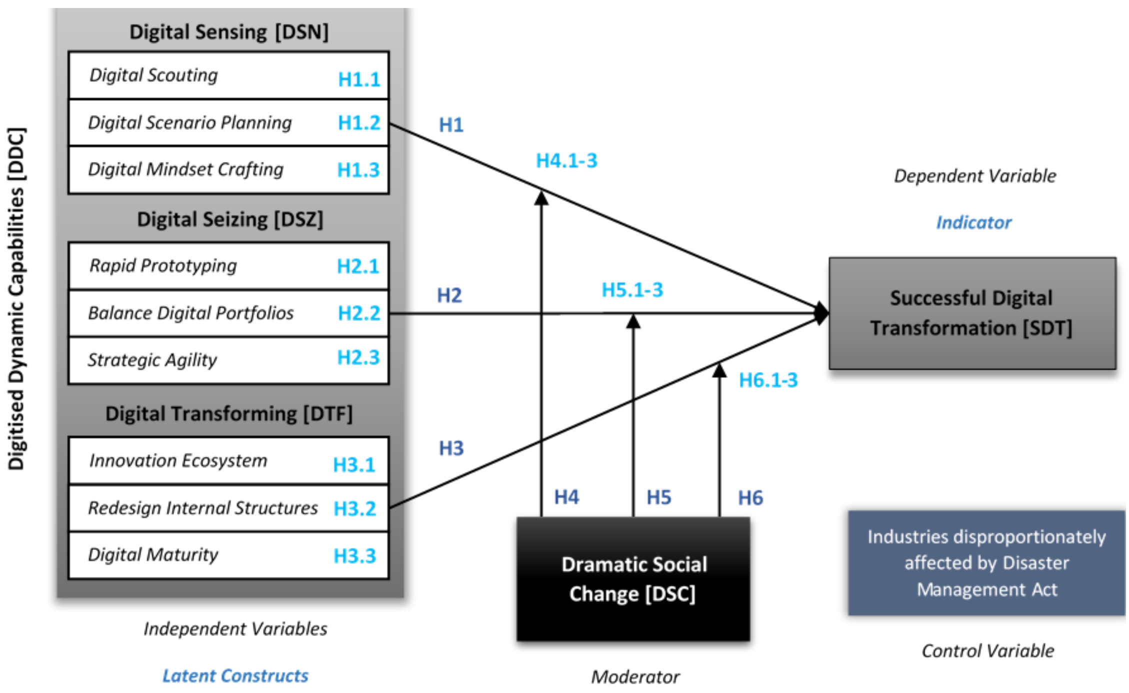

Figure 4: Conceptual model and hypotheses

Table 1: Research design and hypotheses

Research problem:	The relationship between dynamic capabilities and successful digital transformation during times of dramatic social change.
Research question:	What impact does dramatic social change have on the relationship between digitised dynamic capabilities and successful digital transformation?
Sub-question:	What are the various routines and processes that may be used to predict or measure the subdimensions of digitised dynamic capabilities?
Key words:	Dynamic capabilities; digitised dynamic capabilities; digital transformation; dramatic social change; process model
Analysis:	Quantitative – Statistical analysis using **IBM SPSS Statistics v26**
Ontology and epistemology:	Causal | Empirical realist | Objective | Post-positivist | Nomothetic philosophy Replication study: dynamic capabilities process model (Warner & Wäger, 2019)
Measurement design:	Reflective – causality flows from the latent constructs to the indicator
Time frame:	Cross-sectional study
Data collection:	Observational | Self-administered | Online | Survey questionnaire 7-Point Likert scale using SurveyMonkey
Control variable:	Industries disproportionately affected by Disaster Management Act: Tobacco | Alcohol | Commercial Airlines | Travel | Hotel & Hospitality
Hypothesis 1	The contribution of the higher-order construct: **digital sensing** towards the dependent variable: **successful digital transformation**, can be measured through three distinct subdimensions: 1) **digital scouting**, 2) **digital scenario planning**, and 3) **digital mindset crafting**
Sub-Hypothesis 1.1	The lower-order construct (subdimension) of **digital scouting** can be measured through three discrete operationalised indicators: 1) scanning for technological trends, 2) screening of digital competitors, and 3) sensing customer-centric trends
Sub-Hypothesis 1.2	The lower-order construct (subdimension) of **digital scenario planning** can be measured through three discrete operationalised indicators: 1) analysing scouted signals, 2) interpreting digital future scenarios, and 3) formulating digital strategies
Sub-Hypothesis 1.3	The lower-order construct (subdimension) of **digital mindset crafting** can be measured through three discrete operationalised indicators: 1) establishing a long-term digital vision, 2) enabling an entrepreneurial mindset, and 3) promoting a digital mindset
Hypothesis 2	The contribution of the higher-order construct **digital seizing** towards the dependent variable: **successful digital transformation**, can be measured through three distinct subdimensions: 1) **rapid prototyping**, 2) **balance digital portfolios**, and 3) **strategic agility**
Sub-Hypothesis 2.1	The lower-order construct (subdimension) of **rapid prototyping** can be measured through three discrete operationalised indicators: 1) create minimum viable products, 2) a lean start-up methodology, and 3) using a digital innovation lab
Sub-Hypothesis 2.2	The lower-order construct (subdimension) of **balance digital portfolios** can be measured through three discrete operationalised indicators: 1) balance internal and external options, 2) scaling up innovative business models, and 3) set up appropriate speed of execution
Sub-Hypothesis 2.3	The lower-order construct (subdimension) of **strategic agility** can be measured through three discrete operationalised indicators: 1) rapidly reallocating resources, 2) accept redirection and change, and 3) pacing strategic responses

Hypothesis 3	The contribution of the higher-order construct **digital transforming** towards the dependent variable: **successful digital transformation,** can be measured through three distinct subdimensions: 1) **innovation ecosystems**, 2) **redesign internal structures**, and 3) **improve digital maturity**
Sub-Hypothesis 3.1	The lower-order construct (subdimension) of **innovation ecosystems** can be measured through three discrete operationalised indicators: 1) joining digital ecosystem, 2) interact with multiple external partners, and 3) exploit new ecosystem capabilities
Sub-Hypothesis 3.2	The lower-order construct (subdimension) of **redesign internal structures** can be measured through three discrete operationalised indicators: 1) hiring a Chief Digital Officer, 2) digitise business models, and 3) design team-based structures
Sub-Hypothesis 3.3	The lower-order construct (subdimension) of **improve digital maturity** can be measured through three discrete operationalised indicators: 1) identify digital workforce maturity, 2) external recruiting of digital natives, and 3) leverage digital knowledge inside firm
Hypothesis 4	The strength of the relationship between the higher order construct: **digital sensing** and the dependent variable: **successful digital transformation**, is moderated by **dramatic social change**.
Sub-Hypothesis 4.1	The strength of the contribution that the subdimension: **digital scouting** has to the dependent variable: **successful digital transformation** is moderated by **dramatic social change**.
Sub-Hypothesis 4.2	The strength of the contribution that the subdimension: **digital scenario planning** has to the dependent variable: **successful digital transformation** is moderated by **dramatic social change**.
Sub-Hypothesis 4.3	The strength of the contribution that the subdimension: **digital mindset crafting** has to the dependent variable: **successful digital transformation** is moderated by **dramatic social change**.
Hypothesis 5	The strength of the relationship between the higher order construct: **digital seizing** and the dependent variable: **successful digital transformation** is moderated by **dramatic social change**.
Sub-Hypothesis 5.1	The strength of the contribution that the subdimension: **rapid prototyping** has to the dependent variable: **successful digital transformation** is moderated by **dramatic social change**.
Sub-Hypothesis 5.2	The strength of the contribution that the subdimension: **balance digital portfolios** has to the dependent variable: **successful digital transformation** is moderated by **dramatic social change**.
Sub-Hypothesis 5.3	The strength of the contribution that the subdimension: **strategic agility** has to the dependent variable: **successful digital transformation** is moderated by **dramatic social change**.
Hypothesis 6	The strength of the relationship between the higher order construct: **digital transforming** and the dependent variable: **successful digital transformation**, is moderated by **dramatic social change**.
Sub-Hypothesis 6.1	The strength of the contribution that the subdimension: **innovation ecosystems** has to the dependent variable: **successful digital transformation** is moderated by **dramatic social change**.
Sub-Hypothesis 6.2	The strength of the contribution that the subdimension: **redesign internal structures** has to the dependent variable: **successful digital transformation** is moderated by **dramatic social change**.
Sub-Hypothesis 6.3	The strength of the contribution that the subdimension: **improve digital maturity** has to the dependent variable: **successful digital transformation** is moderated by **dramatic social change**.

Source: Author's own research study

As shown in Table 1, while the primary focus of the research study centred on exploring the possibility of a moderated relationship between DDC and SDT, the operationalisation of the qualitative model by Warner and Wäger (2019) introduced some compelling sub-hypotheses for analysis. Specifically, the operationalised structure (outlined in Figure 4) inferred that each of the higher-order constructs – which constitute DDC – may be measured through three lower-order constructs (or subdimensions). Additionally, the model suggested that these subdimensions, in turn, consist of distinct indicators, which could all be accommodated in the research instrument design. Finally, DSC's moderating effect defined the concluding sub-hypotheses considered for the study, along with an attempt to assess the interactive impact of this third independent variable on the latent constructs and their subdimensions (Hair et al., 2018).

To test the various hypotheses (and sub-hypotheses), the research study used the statistical results to validate the "alternative" hypotheses (as listed in Table 1) against the possible, opposite, null hypotheses – where no relationships or lower-order constructs exist (Zikmund, Babin, Carr, & Griffin, 2010). The various statistical validations are detailed in the succeeding chapter, with the outcome discussed as part of the research results presented in Chapter 5. The choice of methodology, population, sampling size, and measurements summarised in Table 1 are outlined, explored, and validated in the chapter to follow.

CHAPTER 4 : RESEARCH DESIGN AND METHODOLOGY

4.1. INTRODUCTION

This chapter details the overall design, philosophy, and strategy adopted for the research study, along with the academic foundations and rationale for decisions made regarding the methodological, structural, analytical, and measurement concepts adopted (or adapted) for the project.

Building on the concepts introduced in the previous chapter, the methodological and ontological considerations are outlined in more detail, with subsequent sections expanding on the population definition, measurement instrument design, and data collection process. The overview includes an introduction of the operationalisation dictionary and consistency matrix, before concluding with a review of the adopted methodology's limitations.

4.2. CHOICE OF RESEARCH METHODOLOGY AND DESIGN

4.2.1. Philosophical foundations

The research study adopted an empirical realist ontology (Sousa, 2010) deploying induction and deduction in its various hypotheses and sub-hypotheses (which assumed cause-and-effect relationships), as depicted in Figure 1. In support of this approach, the post-positivist approach (Creswell & Creswell, 2018; Sousa, 2010) viewed the associated constructs (and their relationships) as a set of measurable, quantifiable, and observed phenomena.

The suitability of a post-positivist methodology, in the context of DC (Teece, 2007; Teece et al., 1997), was further endorsed by the research of Kump et al. (2018). DC, argued Kump et al. (2018), might be regarded as a multi-dimensional construct, reflected in the interrelated capacities of sensing, seizing, and transforming. Furthermore, Kump et al. (2018) posited that DC may be viewed as a set of latent capacities, manifested in observable routines and associated outcomes.

This perspective aligned directly with the post-positivist philosophy – in which causes are observed to (arguably) determine effects or outcomes (Creswell & Creswell, 2018; Sousa, 2010). By applying empirical research within a predefined population, the study hoped to measure and quantify the underlying effects on the variables through a process of inductive generalisation (Sousa, 2010). In doing so, the resulting study built on the principal tenet underpinning the post-positivist approach – in that it attempted to predict and explain the theoretical phenomena associated to the research question (Sousa, 2010).

Thus, the research question identified in this research study reflects the post-positivist need (Creswell & Creswell, 2018; Sousa, 2010) to identify and test the underlying causes (DDC) which influence the outcome (SDT). Furthermore, the study supports a reductionist approach in reducing the core theoretical concepts into a discrete set of higher-order constructs: digital sensing, digital seizing, and digital transforming, that each underpins the six main hypotheses (Creswell & Creswell, 2018; Sousa, 2010).

Finally, the research's nomothetic philosophy was highlighted in its design as a replication study (Sousa, 2010), in which the constructs of the original study (Warner & Wäger, 2019) were repeated within a different context. The validity of these findings were measured through the application of quantitative techniques and statistical analysis.

4.2.2. Methodological fit

The quantitative nature of the research is supported by Creswell and Creswell (2018), who described quantitative research as testing objective theories by examining relationships between variables. The proposed correlation research design (Creswell, 2014; Creswell & Creswell, 2018; Sousa, 2010) complemented the stated research question, its associated hypotheses, and sub-hypotheses.

Consequently, the study tested the impact, contribution, and outcomes of changes to operationalised variables from the DDC process model of Warner and Wäger (2019) against the primary dependent variable, SDT, in the context of DSC. This approach echoed the contextual relevance of correlational design, as described by Creswell (2014), in applying a correlation statistic to measure the degree of association between two or more variables.

To further validate the quantitative approach's methodological fit, the researcher applied the archetypes defined by Edmondson and McManus (2007) to assess each of the criteria associated with the research study. The data (Table 2) seemed to support the underlying research question, along with its associated constructs and hypotheses. Accordingly, the alignment of the proposed conceptual model (Figure 1) within the context of "mature theory", as defined by Edmondson and McManus (2007), validated the selection of a quantitative approach for the research study outlined in this report.

Table 2: Archetype of methodological fit

Prior theory & research	**MATURE STATE** – established prior theory and research for all key constructs: Dynamic capabilities, digitised dynamic capabilities, and dramatic social change
Research question	Focused hypotheses relating to existing constructs
Type of data collected	Quantitative data, with focused measures where extent or amount is meaningful
Data collection methods	Survey designed to be systematically coded and quantified Obtaining data from a population that measures the extent of salient constructs
Constructs and measures	Rely heavily on existing constructs and measures
Goal of data analysis	Formal hypotheses testing
Data analysis methods	Statistical inference Standard statistical analysis
Theoretical contribution	A supported theory that may add specificity, new mechanisms, or new boundaries to existing theories

Source: Adapted from Edmondson and McManus, 2007

4.2.3. Measurement model

Coltman, Devinney, Midgley, and Venaik (2008) highlighted the importance of distinguishing between formative and reflective measures when selecting a measurement model for a piece of research. They argued this decision could significantly influence the researcher's ability to ultimately assign meaningful relationships in their structural model (Coltman et al., 2008).

As can be seen in Figure 4, the research study established a structural relationship (Borsboom, Mellenbergh, & Van Heerden, 2003; 2004) by statistically relating the latent, unobserved constructs (DDC) to the observed indicator of these constructs (SDT). The resulting statistical co-variation allowed for a quantitative argument expressed as if indicator "Y" is influenced by variations in latent construct "X", external changes that affect X could therefore be observed in indicator Y (Coltman et al., 2008). Through the application of these relational validations, the research study, therefore, assumed a reflective relationship between the constructs and indicator, with causality that flowed from the latent constructs to the indicator (Coltman et al., 2008).

4.2.4. Research design – Data collection methodology

Research design is described by Creswell and Creswell (2018) as the logic bridging data collection and the resulting conclusions derived from the research questions. From a quantitative perspective, longitudinal (multiple periods) and cross-sectional (single point in time) approaches constitute the two primary data collection methodologies (Rindfleisch, Malter, Ganesan, & Moorman, 2008).

Rindfleisch et al. (2008) argued that, while longitudinal surveys reduce validity threats such as common method variance and causal inference, a cross-sectional approach may be more appropriate in certain circumstances. Specifically, the research from Rindfleisch et al. (2008) highlighted that the cross-sectional approach is most apt for research that examines concrete and externally-oriented constructs, which are firmly entrenched in theory. Inversely, the longitudinal approach is most applicable where the events' time-based aspects are apparent, with a low likelihood of intervening events adversely impacting the study's outcome (Rindfleisch et al., 2008).

Informed by the empirical realist ontology of the research, this paper posits that DC were a continuous and non-transient phenomenon within the context of DSC (Teece, 2007; Teece et al., 1997). Accordingly, it was inferred that a cross-sectional approach was most suited, academically, for the research study. This was supported by the recommendation of Rindfleisch et al. (2008), as the measurement of the concrete variable (DC) was entrenched in academic theory (Battisti & Deakins, 2017), influenced by an external temporal construct (DSC). In addition, this recommendation considered the risk of more long-term, intervening structures, powers, and contingencies (social, economic, political) that may have skewed the research if a longitudinal study was carried out post the events of COVID-19 (Rindfleisch et al., 2008).

4.3. POPULATION

4.3.1. Selection

The research's population selection followed a purposeful approach, targeting professionals, specialists, and consultants from incumbent South African firms who have been involved in projects relating to DT efforts amid the 2020 COVID-19 epidemiological crisis. This broadly supported the research gap identified in the Warner and Wäger's (2019) study, which questioned whether the process model they developed could be applied to an equivalent sample set of firms in dynamic or volatile environments.

In addition to Warner and Wäger's (2019) contextual validation, the human capital within the proposed population was judged to represent their familiarity and involvement with DT projects (Helfat & Peteraf, 2015; Warner & Wäger, 2019). Furthermore, this approach allowed the population group to be more homogenous, with minimum variation in data collection methods. Finally, this approach ensured consistency in the responses collected, with more comparable and reliable data (Helfat & Peteraf, 2015).

4.3.2. Sampling

Due to the size of the proposed population, probability sampling was not possible, as it would have been difficult to obtain a complete list or sampling frame of all individuals within the population (Creswell & Creswell, 2018; Tyrer & Heyman, 2016; Zikmund et al., 2010). Consequently, this paper adopted a non-probability sampling methodology (Creswell & Creswell, 2018; Tyrer & Heyman, 2016, Zikmund et al., 2010).

In support of the above, a judgment (or purposive) sampling approach was followed, with the researcher selecting an initial sample-set of members – based on appropriate characteristics that were validated through demographic data collected from the survey instrument (Creswell & Creswell, 2018; Tyrer & Heyman, 2016; Zikmund et al., 2010). The researcher targeted individuals from his professional networks, associations, LinkedIn groups, and circles of influence to define a purposeful sample that met the study's objectives, consisting of 108 suitable participants that matched the predefined criteria. Participants were judged to represent the defined population as they were typical of the population (Helfat & Peteraf, 2015), with responses that would contribute to answering the research question.

To further increase the total number of replies, the research study adopted a snowball methodology as a secondary sampling technique (Creswell & Creswell, 2018; Zikmund et al., 2010). In this non-probability approach, the 108 targeted individuals (selected during the purposeful process described above) were used to obtain additional respondents that met the selection criteria, through a process of referral (Creswell & Creswell, 2018; Zikmund et al., 2010). This was achieved by asking each recipient in the initial study to forward the survey link to other professionals within their respective personal networks.

4.3.3. Unit of analysis

DC, argued Kump et al. (2018), constitute organisational routines and are not isolated to individuals. Therefore, the survey instrument developed for this study measured the associated variables at an organisational level, rather than individual attitudes and outcomes. Correspondingly, the unit of analysis for the research study was contextualised as outputs from incumbent South African firms and their strategic responses to DT in times of DSC. This causally related to the source of data collected by the research.

4.4. MEASUREMENT AND DATA INSTRUMENTS

4.4.1. Measurement instrument

In the execution of the research hypotheses, a survey-based measurement scale was deployed in the form of a self-administered online questionnaire (included in Appendix A), developed using the operationalisation of capabilities specifically related to DT. In addition, the primary measurement instrument developed for the study did not follow a dichotomous structure but adopted, instead, a continuous approach (i.e., a seven-point Likert scale). In doing so, the survey questionnaire (Appendix A) allowed for more variations in the descriptors of dynamic capability configurations, supporting the research of Barreto (2010).

The proposed design aligned with the quantitative, correlational approach outlined in previous sections of this chapter – it used the data collected to generalise (from a sample) to a defined population (Fowler, 2009). It was accepted that the proposed design would prove suitable for the stated hypotheses, as the operationalised variables were measured using a set of predefined questions (Barreto, 2010; Creswell & Creswell, 2018). Finally, the study asserted the developed scale's psychometric quality through cross-validation of the factor structure found in the exploratory factor analysis.

4.4.2. Operationalisation dictionary

Zikmund et al. (2010) suggested that the research problem definition should inform the measured concepts, allowing researchers to identify the corresponding scales that determine a variance in the concept. This study attempted to identify those scales that correspond to the variances with the core concept of DDC through a process of operationalisation. Equally, in the design of its instrument, the research project attempted to determine those relevant correspondence rules that indicate the relationship between values on the scale and the associated values of the underlying DDC (Zikmund et al., 2010).

Furthermore, the process model's multi-dimensional nature (Figure 1) provided a more complete, academically sound account of the concept (Warner & Wäger, 2019). It detailed multiple higher-order constructs, lower-order constructs, and indicators that would be used as a foundation to define the various constructs associated with DDC (Zikmund et al., 2010).

The digitised constructs (and their associated measurement variables) included in the final scale were accordingly (primarily) sourced from the process model (Figure 1) developed by Warner and Wäger (2019) and integrated as contextual, operationalised aspects in the instrument. The operational definitions for the associated variables are detailed in Appendix B. The table (Appendix B) represents the various concept definitions and their associated operational definitions, used in the scale development to measure the variables that determine the multiple constructs associated with the research question, hypotheses, and sub-hypotheses.

4.5. DATA COLLECTION

4.5.1. Data collection tool

The primary collection tool took the form of an online, self-administered, survey questionnaire distributed through SurveyMonkey and allowed for variations on the various descriptors using a seven-point Likert scale, ranging from "Strongly disagree" [1] to "Strongly agree" [7] for all interval data (Creswell & Creswell, 2018). SurveyMonkey was deemed an appropriate tool for the research study, as the platform had been used for comparative research within the same academic context (Creswell & Creswell, 2018).

The questionnaire (Appendix A) contained 35 questions in total. There were four ordinal items, using answers from either a radio-button or pre-populated drop-down box, and 31 interval items that relate to the construct variables or hypotheses, which used the Likert scale to supply answers. It was expected that the survey would take around seven minutes to complete per respondent.

4.5.2. Informed consent from participants

As stipulated by the ethical guidelines, an informed consent letter was required to safeguard both GIBS and the researcher from possible legal action. Consequently, this was deliberately included in the design of the survey. While no (digital) signatures were captured, the first ordinal question in the instrument was constructed in a way that the resulting answer from the participant would signal agreement. In addition, logic was applied within the SurveyMonkey design that immediately took any participants who declined the informed consent statement to the last page of the survey, which thanked them for their time and did not record any further responses.

The first question (signalling informed consent from the participant) was worded as follows:

This research aims to validate the various organisational capabilities that contribute to successful digital transformation, as well as the impact on these efforts by dramatic, *external, social change (such as the COVID-19 epidemiological crisis). The resulting data will contribute to the body of knowledge seeking to understand the localised impact of COVID-19 on digital transformation projects in South African firms and should take around seven minutes of your time to complete.*

Your participation in this survey is voluntary, and you can withdraw at any time without penalty. In addition, your participation is completely anonymous and only aggregated data will be included in the final report. By completing the survey, you indicate that you voluntarily participate in this research. If you have any concerns, please contact either myself or my supervisor, using the contact details supplied.

4.5.3. Pre-testing of the questionnaire

Pre-testing of the instrument was carried out to confirm validity, reliability, expected time to complete, and clarity of questions (Creswell & Creswell, 2018; Zikmund et al., 2010). The pre-testing involved distributing the survey link and introductory mail to a small pilot group of ten individuals, who all met the population criteria (including the appointed research supervisor). One-on-one interviews were conducted with the pilot group respondents to incorporate any constructive critique into the questionnaire's design and layout (before distribution to the larger population).

From the initial responses, several small changes and amendments were made to the instrument. First, the wording of the introductory mail was revised, as the feedback indicated that the broader context and strategic rationale for the study were not clear enough. In addition, the wording of the informed consent statement was amended, based on a recommendation from the supervisor. Finally, the most extensive changes were focused on using the "tooltip" function within SurveyMonkey to add definitions for several technical terms used to describe indicators or specific measurements. While the questions remained unchanged, this useful feedback was incorporated as many of the non-technical respondents from the pilot group indicated that they struggled to contextualise the more obscure references (e.g., digital innovation lab, innovation ecosystem, etc.).

Once these changes had been applied, the questionnaire was distributed to an additional five respondents (who were not included in the original pilot group). Based on their feedback, the changes were deemed to have positively impacted the instrument's integrity and clarity and incorporated into the final questionnaire.

4.5.4. Data collection process

Once ethical clearance had been received, a brief introductory email was distributed to the 108 participants in the declared purposeful sample. This email served as advance notice of the survey and highlighted the importance of their contributions (and perspectives) to the research study. The communication included a high-level introduction to the stated research problem and a summary of the context and strategic value of the research being completed. The message included an invitation to contact the researcher for additional clarification around the stated research context.

Two days later, the finalised questionnaire was distributed to the 108 recipients, which again highlighted the importance of their contribution and provided more detail around the business rationale for the associated research study. Included in the email was a link to the online (SurveyMonkey) survey, an overview of the number of questions included, as well as the expected time to complete. The invitation highlighted the participant's confidentiality, along with the voluntary nature of the engagement and finally, an invitation to forward the study to other participants that met the defined criteria.

Following the email distribution, the researcher personally contacted (through phone calls, WhatsApp messages, or separate emails) each of the recipients to individually request their participation and actively requesting distribution of the survey to their respective professional (and personal) networks. The research result statistics detailed in the following chapter highlight this approach's success as a remarkably high percentage of the purposeful sample did ultimately submit answers for the survey. The snowball approach also seemed to pay dividends, with multiple replies being recorded on SurveyMonkey beyond the distribution group's initial demographics.

In parallel to the initiatives mentioned above, the content (from the message to the purposeful sample group) was used to launch several targeted campaigns on LinkedIn. These efforts extended to invitations for participation within at least eight special interest DT and technology leadership groups or forums within the platform. Disappointingly, the response rate through LinkedIn was extremely low, despite an intensified effort during the closing week of the survey. This final campaign, which used an updated call-to-action message, stressed the upcoming deadline alongside a sincere request for broader participation to gain deeper insight into the research question.

Lastly, in the week before the closure date, a final email was sent to the original distribution group (along with a few additional respondents that had reached out to the researcher personally from the snowballing technique). As with the LinkedIn campaign, this message confirmed the upcoming deadline for the survey, thanked all recipients who had completed the survey for their time, and invited those that had not yet completed the questionnaire to contribute their valued perspective to the research study.

4.5.5. Response rate and desired sample size

At the outset of the research study, an initial minimum sample size totalling around 250 (usable) responses had been set as the objective. This would allow the resulting dataset to fall well within the minimum threshold (200 respondents) for confirmatory factor analysis and structural equation modelling as specified by Beavers et al. (2013), Hair et al. (2018), and Zikmund et al. (2010) respectively. Consequently, the data collection process aimed to collect at least 300 responses, as this would allow for those replies ultimately excluded from the sample, following the various data validation and cleaning exercises (Hair et al., 2018).

However, despite several intensive efforts across multiple channels, only 209 total responses were ultimately collected during the time frame set for data collection. While the overall response rate to email-based invitations was comparatively good – driven through extensive one-on-one engagement with each of the initial recipients – the initial objective had not been met within the available time frame. The smaller sample size was compounded by a comparatively disappointing response rate from various social media engagements. Had there been more time available to accommodate more engaging or interactive campaigns (e.g., partnering with DT thought leaders for access to their networks), the results may have been more positive. However, during the collection process, each of the individuals approached to explore this alternative cited the difficulties around COVID-19 as a severe restriction on their ability to link the survey to workshops or webinars within the limited time frame.

Ultimately, the final sample set was still well within the minimum acceptable sample size of 127 for multiple regression with three independent variables, as stipulated by Knofczynski and Mundfrom (2008). In addition, Beavers et al. (2013) argued that, for datasets less than 200, exploratory factor analysis is perfectly suitable for the reliable assessment of multi-dimensional relationships. As a result, the collected responses were deemed to be statistically appropriate, and the survey was closed at the projected date so that sufficient time remained for the required analysis to be documented.

4.5.6. Data storage and retention

All survey data collected as part of the research study will be retained for a minimum period of ten years, stored in a secure folder within the researcher’s personal Microsoft

OneDrive file repository, password-secured with two-factor authentication. Anonymity was ensured as no personally identifiable information was gathered or recorded in the research instrument (survey questionnaire).

4.6. DATA ANALYSIS APPROACH

4.6.1. Control variable

Control variables are defined as those that researchers include in their design to eliminate alternative explanations or reduce error (Becker, 2005; Schwab, 2004). Within the final conceptual model (Figure 1), the researcher included a control variable using experimental design (Becker, 2005). A predefined variable was identified, which would exclude selected responses from the final sample used for statistical analysis.

More specifically, the context of this study implied that selected industries (or markets) were so severely impacted by the restrictions of the National Disaster Act – invoked in the aftermath of the COVID-19 crisis in South Africa – that their efforts in respect to DDC were externally constrained (Becker, 2005; Schwab, 2004). These outliers risked skewing the results, giving an incorrect view of the studied relationships (Becker, 2005). Industries excluded from the statistical analysis extended to firms that fell under the following categories: Tobacco; Alcohol; Commercial Airlines; Travel; Hotel and Hospitality.

4.6.2. Data cleaning

Once the final dataset had been assembled, a process of data cleaning was followed, as recommended by Hair et al. (2018), to ensure the veracity of all relevant dimensions and their associated responses. These steps, which are detailed in the following chapter, reviewed the following characteristics: confirmation of consent, usability, population fit, and completeness (Hair et al., 2018). Any responses deemed to violate the conditions for validity were excluded from the sample – which was exported from SurveyMonkey for statistical analysis within the IBM SPSS application.

4.6.3. Statistical analysis of data

As detailed in the consistency matrix (Appendix C), the results of the research study included both descriptive statistics (used to characterise the data) and detailed inferential assessments (used to test the hypotheses and sub-hypotheses), following the recommendations of Field (2018), Hair et al. (2018), and Zikmund et al. (2010). In doing so, the study hoped to present a statistically grounded validation of both the operationalised research instrument and its associated hypotheses.

The descriptive statistics included the means, standard deviations, and ranges of scores for all variables utilised. The study made use of Cronbach's alpha to validate internal consistency of scales for all lower-order subdimensions, along with Pearson's correlation to assess construct validity (Field, 2018; Hair et al., 2018; Zikmund et al., 2010). Furthermore, factor analysis was employed to pursue dimension reduction per construct, supported by scrutiny of the Kaisen-Meyer-Olkin [KMO] measure of sampling adequacy and Bartlett's test of sphericity (Field, 2018; Hair et al., 2018; Zikmund et al., 2010).

Finally, multiple linear regression was employed to assess the various relationships between the multi-dimensional independent variables and the dependent variable (Field, 2018; Hair et al., 2018; Zikmund et al., 2010). The analyses included adjusted R^2 values, combined with multi-level model interpretation to identify the impact on the strength of these relationships by the contextual moderator variables (Field, 2018; Hair et al., 2018; Zikmund et al., 2010).

4.7. STRATEGIES TO ENSURE THE VERACITY OF DATA

The research study considered five potential threats to internal validity, as amended from Creswell and Creswell (2018). Consequently, the following section explores the broader context and strategies employed within the study to mitigate these identified risks.

4.7.1. Internal threat to validity: History

Particularly prevalent to the research problem associated with the study, this threat relates to external events that unduly influence the research outcome beyond the experiment's boundaries (Creswell & Creswell, 2018). In mitigation of this threat, the study aimed to ensure that all participants in the sample had shared experience of the research problem and hypotheses, limiting responses to a population that had been involved in DT efforts during the COVID-19 crisis.

4.7.2. Internal threat to validity: Selection

This threat relates to selecting participants that, if not remediated, can predispose responses to specific outcomes (Creswell & Creswell, 2018). In answer to this threat, the research study ensured that participants' selection was randomised (within the population) so that characteristics or unwarranted prejudices to specific outcomes were equally distributed over the sample set.

4.7.3. Internal threat to validity: Compensatory rivalry

Should participants feel that their responses will be publicly or directly compared to the output of others, they may compensate and provide false or misleading information relating to the variables being measured in the scale (Creswell & Creswell, 2018), as they do not wish to be represented as having failed at the competencies being measured in the study. In response to this threat, the study ensured all responses' anonymity, with no details recorded or distributed that may identify specific organisations or individuals. All data were anonymised at the stated unit of analysis with no distinguishing data presented at any time.

4.7.4. External threat to validity: Interaction of setting

Creswell and Creswell (2018) defined this threat as the inability of researchers to transfer their data to other settings due to the study's characteristics and context. In response to this threat, the research study grounded its theoretical and academic constructs in process models and scales that had been validated in settings other than the research being conducted. In answering the research problem (and hypotheses), this research aimed to expand on applying the data beyond the settings first applied to these constructs.

4.7.5. Statistical conclusion validity

Statistical conclusion validity threats arise, stated Creswell and Creswell (2018), when researchers inadvertently draw erroneous inferences from the data collected. Creswell and Creswell (2018) noted that this risk was heightened by breaching statistical assumptions and insufficient statistical power. To counter this threat, the research study reported on the definition and measures of all applicable variables (as detailed in Appendix B).

4.8. METHODOLOGICAL LIMITATIONS

One major limitation of the research study is its exclusion of smaller firms that do not have appointed specialists, consultants, senior managers, or executives who oversee DT projects. Although this was done to ensure statistical and contextual correlation to the model being tested in the hypotheses, there is an opportunity to expand to research beyond the scope mentioned in this paper. Specifically, it could be extended to include those small-to-medium sized businesses in the formal (and informal) sectors that were severely impacted by COVID-19, with digital initiatives driven by the business owners themselves. Many of these smaller businesses would not have had access to the same resources, strategic mechanisms, and larger incumbent firms' competences. As a result, their corresponding application of those capabilities detailed in this study would make for an interesting and relevant contribution to the study of these variables in the context of disruptive change. Furthermore, by expanding the population's scope, these demographics could be incorporated into the survey instrument, opening the door for more in-depth, comparative analytics between various industries and sectors, or businesses of different sizes and ages.

Another limitation, inherent to the research study's quantitative nature, is that the survey questionnaire, with a subset of standardised questions, will produce results without the additional insights, commentary and detail that support the broader contextual scope of the responses. As a result, a qualitative replication study, using the same process model, may provide more exploratory detail as to incumbent firms' various strategic responses, supplying further validation of the framework.

The cross-sectional nature of the research study could, arguably, be improved upon when considered within the scope of a longitudinal alternative. In doing so, researchers can investigate the various antecedents for DT success that preceded the COVID-19 crisis and confirm the continued (long-term) success of any initiatives launched during times of DSC.

As the snowballing technique was used, a percentage of responses gathered during the data collection process may prove to be invalid, as participants who fall outside the defined population may have submitted answers to the survey. While the demographic data gathered by the research instrument would eliminate these invalid responses from the final analysis, it does imply that a significant percentage of the total responses could be disqualified from the final sample.

The non-probability approach adopted for the research study implies that participants that fell outside the researcher's personal or professional network may have been under-represented in the final data. Consequently, using a set of randomised respondents from a more clearly defined, accredited, third-party database could improve the representative sample obtained in comparative research.

Finally, as COVID-19 is a global phenomenon, the hypotheses proposed in this research could be applied to a broader geographical context in future, with respondents from other regions or countries contributing to the validation of the identified variables and relationships.

CHAPTER 5 : RESEARCH RESULTS

5.1. INTRODUCTION

This chapter presents the results from data gathered from the various SurveyMonkey collectors, configured to amass responses for the questionnaire associated with this research study. In addition, the output from the various, sequential, statistical tests and analytical processes – which were executed on IBM SPSS v26 – is presented in summary form, with all relevant auxiliary detail included in the appendices of this paper. In support of these results, the chapter articulates the various methods and techniques applied, along with their academic foundations.

The first two sections summarise the various demographic data, alongside the re-coding and data preparation (Hair et al., 2018) that was carried out, using the responses (and underlying data) in consideration. The succeeding sections then explore each construct's descriptive statistics before presenting the outcome of various tests for construct validity, instrument reliability, dimension reduction, and normality. The final analyses focus on linear regression, with the chapter concluding with a brief overview of these results compared against the stated hypotheses (and sub-hypotheses).

5.2. DEMOGRAPHICS AND SAMPLE SIZE

The survey responses were collected over four weeks, spanning between the 30th of September 2020 and the 30th of October 2020. Of the 211 responses that were received for the survey, 82.5% (174 responses) were gathered during the first week, with the remaining trickling in during the second half of October. Despite several campaigns on social media platforms (such as LinkedIn), only eight responses were captured from these collectors, with most of the survey results (203 in total) originating from the web link that was distributed on e-mail. Overall, the 211 responses had an 85% completion rate and participants took, on average, 05m:44s to complete the 35 questions in the survey (Source: SurveyMonkey).

Table 3: Informed consent [control variable] – Respondent answers

I agree to voluntarily participate in the survey		
Answer Choices	Responses	
Yes	99,05%	209
No	0,95%	2
	Answered	**211**
	Skipped	**0**

Source: Adapted from SurveyMonkey output, author’s own research study

Of the 211 respondents, two declined the informed consent question (as can be seen in Table 3) and were immediately taken to the last page of the survey (by the logic built within SurveyMonkey), thanking them for their time. Their responses were not considered for the analyses and brought the total sample down to 209.

Of the remaining dataset, ten respondents in total – despite accepting the informed consent statement – did not record an answer for any of the other 34 questions and were therefore excluded from the analysis, implying that the sample size totalled 199.

Table 4: Industry description [control variable] – Respondent answers

Which of the following best describes the industry your company operates in?		
Answer choices	Responses	
ICT Hardware and Software (Distribution, Development, Manufacture, Sales, or Support)	29,15%	58
Mining, Agriculture or Forestry	15,58%	31
Banking, Insurance or Financial Services	14,57%	29
Professional Services (Consulting, Legal, Outsourcing, etc.)	7,54%	15
Internet Service Provider, Data Infrastructure or Telecommunications	6,03%	12
Industrials (Construction, Manufacturing, etc.)	4,02%	8
Transport or Logistics	3,02%	6
Retail or Commerce (incl. Wholesale)	3,02%	6
Education (Primary or High School)	3,02%	6
Tertiary Education (Academy, Business School, College or University)	3,02%	6
Other	3,02%	6
Public Service or State-Owned-Enterprise	2,01%	4
Healthcare or Medical Professional	1,51%	3
Media and Advertising	1,01%	2
Real Estate, Rental or Leasing	1,01%	2
Scientific or Technical services	1,01%	2
Hotel, Hospitality, Food or Leisure Travel**	0,50%	1
Aviation or Commercial Airline**	0,50%	1
Entertainment	0,50%	1
Alcohol or Tobacco Industry**	0,00%	0
	Answered	**199**

**Control Variable: Industries disproportionately affected by the Disaster Management Act

Source: Adapted from SurveyMonkey output, author's own research study

Of the 199 respondents, most replies (29.15%) originated from within the Information Communications and Technology [ICT] Sector. This was expected, as the industry represents the formal professional network of the researcher. Similarly, the Mining (15.58%) and Banking (14.57%) responses constitute the second and third largest sources, respectively, of replies and are reflective, once again, of the expanded professional network of the researcher. The remaining industries represented in the study can be seen detailed in Table 4. Notably, from the 199 responses, two fell within the defined control variable that had been identified for the study (as highlighted in Table 4). These replies were excluded from the final sample used for statistical analysis, following the literary precedent of implementing a control using experimental design (Becker, 2005). With the exclusion of these responses, the total sample was adjusted to 197.

Of the 197 replies, 48.23% of responses were from senior managers or executives, with a further 24.37% from middle management or specialists (Table 5). While the population defined for this research study did extend beyond these roles, the high representation of executive- and senior-level respondents should imply a more in-depth insight into the various strategies and activities that support DDC, as suggested by Helfat and Peteraf (2015).

Table 5: Current role in company [demographic] – Respondent answers

Which of the following best describes your current role in your company?		
Answer choices	Responses	
Senior Management / Business Unit Manager	25,89%	51
Middle Management / Specialist	24,37%	48
Director / Senior (C-suite) Executive	22,34%	44
Consultant	6,60%	13
Supervisor / Team Lead	6,09%	12
Other	4,57%	9
Self-employed / Partner	4,57%	9
Project (or Programme) Manager	4,06%	8
Middle Management	1,02%	2
Supervisor / Team Lead	0,51%	1
	Answered	**197**

Source: Adapted from SurveyMonkey output, author's own research study

Finally, while the initial distribution list for the survey followed a purposive sampling approach (Creswell & Creswell, 2018; Tyrer & Heyman, 2016; Zikmund et al., 2010), a secondary sampling technique called snowballing (Creswell & Creswell, 2018; Zikmund et al., 2010) was employed to elicit broader responses. This non-purposeful process of referral (Creswell & Creswell, 2018; Zikmund et al., 2010) does run the risk that participants, who do not fall within the defined population, participate in the survey. A question was included in the survey to confirm the respondent's involvement in DT projects to counter this threat. The results (as can be seen in Table 6) highlighted a further 48 replies that fell outside the scope of the defined parameters. While disappointing to exclude such a large percentage (26.62%) of the survey data from the final analysis, the pursuit of statistical integrity demanded that the final sample size was reduced to 149.

Table 6: Involvement in digital transformation projects [population] – Respondent answers

Have you personally been involved with, or overseen, one or more digital transformation projects over the last 6 months?		
Answer choices	Responses	
Yes	75,38%	149
No	24,62%	48
	Answered	**197**

Source: Adapted from SurveyMonkey output, author's own research study

5.3. DATA RE-CODING AND PREPARATION

Once the dataset (containing the final population of 149 respondents) had been exported from SurveyMonkey, it became apparent that the site's default templates had inverted the standard coding used for Likert scale replies – with positive replies now rated lowest and negative replies highest.

To ensure consistency with the anticipated statistical analysis that was to follow, the researcher re-coded the data in line with the normative defaults for Likert scale data (Creswell & Creswell, 2018), as per the results displayed in Table 7. The re-coded dataset was then imported into IBM SPSS v26 so that the remaining data preparation could be completed.

Table 7: Likert scale answer re-coding

7-point Likert scale answer	Rating BEFORE re-coding	Rating AFTER re-coding
Strongly Agree	1	7
Agree	2	6
Somewhat Agree	3	5
Neither Agree nor Disagree	4	4
Somewhat Disagree	5	3
Disagree	6	2
Strongly Disagree	7	1

Source: Adapted from SurveyMonkey output, author's own research study

As a first step, the researcher deleted any columns containing personally identifiable information (i.e., NAME, SURNAME, and IP ADDRESS). While the survey had been configured for anonymity (and therefore collected no data to populate within these columns), these were irrelevant to the required analytics and removed from the dataset.

Next, the researcher used the “variable view” function in SPSS to change the measure against all Likert scale items to “Scale” from “Nominal”, as well as ensuring that there were two decimal places defined for all associated variables (Field, 2018; Hair et al., 2018; Zikmund et al., 2010). In addition, the “Name” and “Label” fields were updated against all variables to ensure consistency with the questionnaire and to add descriptive markers for each item (as that would aid in the upcoming analysis).

Finally, the researcher reviewed the completeness of the answers within the final sample (Hair et al., 2018). Of the total responses, seven were found to have completed less than 50% of the 35 questions (respondents 47, 66, 91, 110, 116, 126, and 132). As these replies are deemed to be invalid (Creswell & Creswell, 2018; Hair et al., 2018; Zikmund et al., 2010) they were deleted from the dataset, reducing the sample size to 142.

A final, single, respondent was found to have answered 20 out of the 35 questions (57%) and, using the guidelines from Hair et al. (2018), the blank fields for this reply were completed using the mean values from other respondents in the same industry and with the same professional role, as defined within the demographics of the survey.

5.4. DESCRIPTIVE STATISTICS

Descriptive statistics are often used to present data in a meaningful and straightforward way (Creswell & Creswell, 2018). The added intent is to highlight patterns or high-level insights (such as variability or central tendencies). While no additional conclusions should be drawn from this initial statistical testing, it can help, as a first step, to describe and organise the respective variables included in the research study (Creswell & Creswell, 2018).

Consequently, the mean and standard deviations were calculated for all the constructs and their variables using SPSS, as can be seen in Table 8 (which contains the unidimensional moderators and dependent variable) and Table 9 (which details values for each of the discrete indicators measured on the scale).

Table 8: Descriptive statistics – Moderators and dependent variable

	N	Minimum	Maximum	Mean	Std. Deviation
MODERATOR_SENSE	142	2,00	7,00	6,47	0,94
MODERATOR_SEIZE	142	2,00	7,00	5,63	1,37
MODERATOR_TRANSF	142	1,00	7,00	6,22	1,06
SUCCESS_DT	142	1,00	7,00	5,60	1,24

Source: Adapted from IBM SPSS v26 data export, author's own research study

Table 9: Descriptive statistics – Multi-dimensional independent variables

	N	Minimum	Maximum	Mean	Std. Deviation
SENSE_1 SCOUTING	142	2,00	7,00	5,97	1,01
SENSE_2 SCOUTING	142	1,00	7,00	5,51	1,29
SENSE_3 SCOUTING	142	1,00	7,00	5,70	1,20
SENSE_4 SCENARIO PLANNING	142	1,00	7,00	5,41	1,23
SENSE_5 SCENARIO PLANNING	142	1,00	7,00	5,51	1,08
SENSE_6 SCENARIO PLANNING	142	2,00	7,00	5,64	1,15
SENSE_7 DIGITAL MINDSET CRAFTING	142	1,00	7,00	5,69	1,35
SENSE_8 DIGITAL MINDSET CRAFTING	142	1,00	7,00	5,48	1,44
SENSE_9 DIGITAL MINDSET CRAFTING	142	1,00	7,00	5,88	1,15
	N	Minimum	Maximum	Mean	Std. Deviation
SEIZE_1 RAPID PROTOTYPING	142	1,00	7,00	4,89	1,44
SEIZE_2 RAPID PROTOTYPING	142	2,00	7,00	5,38	1,23
SEIZE_3 RAPID PROTOTYPING	142	1,00	7,00	4,51	1,62
SEIZE_4 BALANCE DIGITAL PORTFOLIO	142	2,00	7,00	5,22	1,22
SEIZE_5 BALANCE DIGITAL PORTFOLIO	142	2,00	7,00	5,08	1,40
SEIZE_6 BALANCE DIGITAL PORTFOLIO	142	2,00	7,00	4,67	1,38
SEIZE_7 STRATEGIC AGILITY	142	2,00	7,00	5,03	1,43
SEIZE_8 STRATEGIC AGILITY	142	1,00	7,00	5,12	1,45
SEIZE_9 STRATEGIC AGILITY	142	2,00	7,00	5,26	1,21
	N	Minimum	Maximum	Mean	Std. Deviation
TRANSF_1 INNOVATION ECOSYSTEM	142	1,00	7,00	4,91	1,66
TRANSF_2 INNOVATION ECOSYSTEM	142	2,00	7,00	5,41	1,30
TRANSF_3 INNOVATION ECOSYSTEM	142	2,00	7,00	5,10	1,36
TRANSF_4 REDESIGN INT STRUCTURES	142	1,00	7,00	4,56	2,04
TRANSF_5 REDESIGN INT STRUCTURES	142	2,00	7,00	5,76	1,20
TRANSF_6 REDESIGN INT STRUCTURES	142	1,00	7,00	5,30	1,43
TRANSF_7 IMPROVE DIGITAL MATURITY	142	1,00	7,00	4,98	1,58
TRANSF_8 IMPROVE DIGITAL MATURITY	142	1,00	7,00	4,82	1,65
TRANSF_9 IMPROVE DIGITAL MATURITY	142	1,00	7,00	5,36	1,32

Source: Adapted from IBM SPSS v26 data export, author's own research study

5.5. CONSTRUCT VALIDITY

As the research study set out to operationalise a multi-dimensional qualitative model for understanding DDC, the resulting quantitative conceptual model contained three higher-order constructs as independent variables: digital sensing [DSN], digital seizing [DSZ], and digital transforming [DTF] which each, in turn, contained three subdimensions. In the resulting survey (Appendix A), these subdimensions were measured by three questions each (totalling nine questions, per higher-order construct).

Consequently, validating that the subsets of questions measure the concepts associated with them became an important next step from a statistical analytics perspective (Hair et al., 2018). In addition, establishing construct validity allowed further analysis of these subdimensions with a higher confidence factor once correlation had been established (Hair et al., 2018). To achieve this objective, construct validity was assessed using the bivariate correlation function in SPSS (Field, 2018; Hair et al., 2018) for each of the subdimensions and their questions.

The "Transform – Compute" variable function of SPSS was used to calculate the SUM of each subdimension and their associated questions (labelled as ITEM_TOTAL for each variable). These were then fed into the bivariate correlation function in SPSS along with their subset of three questions (Field, 2018). The consolidated results, along with their Pearson's correlation scores, are displayed in the summarised tables. Full details of the SPSS results are included in Appendix D.

Table 10: Construct validity – Higher-order construct: Digital sensing

		ITEM_TOTAL DIGITAL SCOUTING	SENSE_1 DIGITAL SCOUTING	SENSE_2 DIGITAL SCOUTING	SENSE_3 DIGITAL SCOUTING
ITEM_TOTAL	Pearson Correlation	**1**	**.81****	**.87****	**.86****
	Sig. (2-tailed)		**.00**	**.00**	**.00**
		ITEM_TOTAL SCENARIO PLANNNING	SENSE_4 SCENARIO PLANNING	SENSE_5 SCENARIO PLANNING	SENSE_6 SCENARIO PLANNING
ITEM_TOTAL	Pearson Correlation	**1**	**.88****	**.92****	**.91****
	Sig. (2-tailed)		**.00**	**.00**	**.00**
		ITEM_TOTAL DIGITAL MINDSET CRAFTING	SENSE_7 DIGITAL MINDSET CRAFTING	SENSE_8 DIGITAL MINDSET CRAFTING	SENSE_9 DIGITAL MINDSET CRAFTING
ITEM_TOTAL	Pearson Correlation	**1**	**.75****	**.84****	**.82****
	Sig. (2-tailed)		**.00**	**.00**	**.00**

******Significant Correlation at the 0.01 level (two-tailed)

Source: Adapted from IBM SPSS v26 data export, author's own research study

From the results for the higher-order construct: DSN (Table 10), the data confirmed that each of the questions displays a significant correlation (at the 0.01 level, two-tailed), with the calculated total for their specific subdimension (Field, 2018; Hair et al., 2018). Validity was thus established for each of the three subdimensions of DSN and their related subset of questions – as they were all individually and significantly correlated to their total item score (Hair et al., 2018).

Similarly, from the results for the higher-order construct DSZ (Table 11), the data confirmed that each of the questions displays a significant correlation (at the 0.01 level, two-tailed), with the calculated total for their specific subdimension (Field, 2018; Hair et al., 2018). Validity was thus established for each of the three subdimensions of DSZ and their related subset of questions – as they were all individually and significantly correlated to their total item score (Hair et al., 2018).

Table 11: Construct validity – Higher-order construct: Digital seizing

		ITEM_TOTAL RAPID PROTOTYPING	SEIZE_1 RAPID PROTOTYPING	SEIZE_2 RAPID PROTOTYPING	SEIZE_3 RAPID PROTOTYPING
ITEM_TOTAL	Pearson Correlation	**1**	**.78****	**.74****	**.82****
	Sig. (2-tailed)		**.00**	**.00**	**.00**
		ITEM_TOTAL BALANCE DIGITAL PORTFOLIO	SEIZE_4 BALANCE DIGITAL PORTFOLIO	SEIZE_5 BALANCE DIGITAL PORTFOLIO	SEIZE_6 BALANCE DIGITAL PORTFOLIO
ITEM_TOTAL	Pearson Correlation	**1**	**.83****	**.89****	**.87****
	Sig. (2-tailed)		**.00**	**.00**	**.00**
		ITEM_TOTAL STRATEGIC AGILITY	SEIZE_7 STRATEGIC AGILITY	SEIZE_8 STRATEGIC AGILITY	SEIZE_9 STRATEGIC AGILITY
ITEM_TOTAL	Pearson Correlation	**1**	**.85****	**.87****	**.85****
	Sig. (2-tailed)		**.00**	**.00**	**.00**

****Significant Correlation at the 0.01 level (two-tailed)

Source: Adapted from IBM SPSS v26 data export, author's own research study

Finally, from the results for the higher-order construct DTF (Table 12), the data confirmed that each of the questions displays a significant correlation (at the 0.01 level, two-tailed), with the calculated total for their specific subdimension (Field, 2018; Hair et al., 2018). Validity was thus established for each of the three subdimensions of DTF and their related subset of questions – as they were all individually and significantly correlated to their total item score (Hair et al., 2018).

Table 12: Construct validity – Higher-order construct: Digital transforming

		ITEM_TOTAL INNOVATION ECOSYSTEM	TRANSF_1 INNOVATION ECOSYSTEM	TRANSF_2 INNOVATION ECOSYSTEM	TRANSF_3 INNOVATION ECOSYSTEM
ITEM_TOTAL	Pearson Correlation	1	**.89****	**.83****	**.86****
	Sig. (2-tailed)		**.00**	**.00**	**.00**
		ITEM_TOTAL REDESIGN INT STRUCTURES	TRANSF_4 REDESIGN INT STRUCTURES	TRANSF_5 REDESIGN INT STRUCTURES	TRANSF_6 REDESIGN INT STRUCTURES
ITEM_TOTAL	Pearson Correlation	1	**.81****	**.76****	**.76****
	Sig. (2-tailed)		**.00**	**.00**	**.00**
		ITEM_TOTAL IMPROVE DIGITAL MATURITY	TRANSF_7 IMPROVE DIGITAL MATURITY	TRANSF_8 IMPROVE DIGITAL MATURITY	TRANSF_9 IMPROVE DIGITAL MATURITY
ITEM_TOTAL	Pearson Correlation	1	**.85****	**.82****	**.80****
	Sig. (2-tailed)		**.00**	**.00**	**.00**

****Significant Correlation at the 0.01 level (two-tailed)

Source: Adapted from IBM SPSS v26 data export, author's own research study

Although validity had now been confirmed by analysing each subdimension, a further test of the instrument was needed to confirm its accuracy, as is explored in the next section.

5.6. INSTRUMENT RELIABILITY

In addition to establishing construct validity, the scale's reliability must be tested, as this reflects the ability of the measure (questionnaire) to consistently reflect the construct associated with those questions when used under similar conditions (Field, 2018; Hair et al., 2018). Combining reliability with construct validity – when measuring an instrument – will ensure more consistent and accurate results, argued Hair et al. (2018).

The most common tool used to measure scale reliability is Cronbach's alpha (Field, 2018). For this research study, the standardised version of the equation was used, which calculates correlations to determine a correlation-matrix between the items on the scale (Field, 2018). The reliability statistics for each of the 27 independent variable questions on the scale (grouped per subdimension, three questions each) were calculated in IBM SPSS, with the results summarised in Table 13. Reliability was then assessed by comparing each of the computed values from SPSS against the minimum Cronbach's alpha value for reliability, set at 0.7 for non-exploratory research (Field, 2018; Hair et al., 2018). As the results displayed in this report are reported with two decimal places, the reliability threshold was displayed as > .65. Full details of the SPSS results are included in Appendix D.

From the results (Table 13), all subdimensions passed the test for reliability (Field, 2018; Hair et al., 2018), except for the three items associated with Redesign Internal Structures. For this subset of questions, the Cronbach's alpha was calculated as .64, which fell below the minimum threshold. After consulting the "Item-Total Statistics" table in SPSS (Field, 2018), it was evident that deleting the first question in the scale that measured this subdimension (Question DTF4, Appendix A) would increase the Cronbach's alpha to 0.71 (Field, 2018). This item was removed, and the reliability test was executed for a second time on the reduced set of two items, with a resulting score of .71. Consequently, all items passed the reliability test.

Table 13: Instrument reliability – Cronbach's alpha scores per construct subdimension

Higher-order construct	Sub-dimension	Cronbach's alpha	> .65	Number of items
Digital Sensing	Digital Scouting	***.80***	YES	3
	Scenario Planning	***.89***	YES	3
	Digital Mindset Crafting	***.72***	YES	3
Digital Seizing	Rapid Prototyping	***.68***	YES	3
	Balancing Digital Portfolio	***.82***	YES	3
	Strategic Agility	***.81***	YES	3
Digital Transforming	Innovation Ecosystem	***.82***	YES	3
	Redesign Internal Structures	***.71***	YES	**2 ****
	Improve Digital Maturity	***.76***	YES	3

******Item (Question DTF4) deleted as Cronbach's alpha fell below .65 and re-calculated on two remaining items

Source: Adapted from IBM SPSS v26 data export, author's own research study

5.7. FACTOR ANALYSIS AND DIMENSION REDUCTION

The higher-order constructs contained within the proposed conceptual model for the research study lend themselves, upon the first inspection, to a (recommended) confirmatory factor analysis (Hair et al., 2018, Beavers et al., 2013). However, the final sample size of the population forced the researcher to reconsider this approach. As argued by Beavers et al. (2013), for a dataset smaller than 200 responses, the underlying mathematics of the confirmatory factor analysis was simply not robust enough for reliable results. Consequently, an exploratory factor analysis [EFA] was selected for analysing the underlying patterns associated with those multi-dimensional relationships defined for the study (Hair et al., 2018). Using EFA, the data would indicate whether the associated patterns and relationships between the variables would allow the results to be condensed into a smaller set of components (Hair et al.,2018).

To calculate the relevant scores for each subset of questions, the associated variables were grouped and loaded, sequentially, into the "Dimension reduction" function in SPSS, with an extraction based on Eigenvalues greater than one, using varimax rotation (Field, 2018; Hair et al., 2018). The results are displayed in Table 14, with full details included in Appendix D.

Table 14: Factor analysis – KMO and Bartlett's scores per construct subdimension

Higher-order construct	Sub-dimension	KMO	Bartlett' s Sig.	Sig. < .05	Components extracted	Eigenvalues cumulative % of variance
Digital Sensing	Digital Scouting	*.71*	.00	YES	1	71.96%
	Scenario Planning	*.73*	.00	YES	1	82.10%
	Digital Mindset Crafting	*.65*	.00	YES	1	64.90%
Digital Seizing	Rapid Prototyping	*.67*	.00	YES	1	61.15%
	Balancing Digital Portfolio	*.71*	.00	YES	1	74.13%
	Strategic Agility	*.71*	.00	YES	1	73.56%
Digital Transforming	Innovation Ecosystem	*.72*	.00	YES	1	74.01%
	Redesign Internal Structures	*.50*	.00	YES	1	78.19%
	Improve Digital Maturity	*.69*	.00	YES	1	68.31%

Source: Adapted from IBM SPSS v26 data export, author's own research study

First, the results (Table 14) indicated that all construct subdimensions scored a KMO measure of sampling adequacy higher than .50. By implication, the sample size was adequate for factor analysis (Field, 2018; Hair et al., 2018). In addition, the significance probability [Sig.] value for Bartlett's test of sphericity was calculated as less than .05 for all the construct subdimensions. The aforementioned (statistically significant) result against all the constructs confirmed that sufficient correlation existed for the EFA to proceed (Field, 2018; Hair et al., 2018). Finally, the "Component Matrix" from SPSS showed that single component was successfully extracted for each subdimension included in the analysis (Field, 2018).

Based on the EFA results, a single composite index could now be created for the various constructs (Hair et al., 2018). Using the “Transform – Compute” variable function in SPSS, the mean value was calculated for each of the subdimensions and their associated items (Field, 2018). The resulting composite values would be used for all further analyses (Hair et al., 2018).

5.8. NORMALITY TESTS

Zikmund et al. (2010) stated that, when multiple regression is used on a dataset for statistical analysis, normal distribution is not required. However, before the final regression statistics were calculated in this study, a normality test was done to ensure that no significant deviations existed in the data, potentially skewing the results (Hair et al., 2018). Consequently, the “Explore” function was used in SPSS to test for normal distribution on the newly created composite indices (Field, 2018).

From the resulting analysis, two exceptions were highlighted. First, on the composite index for Scenario Planning, the boxplot (Figure 5) highlighted a single response (respondent 8) that was flagged as significantly deviating from the mean (Field, 2018; Hair et al., 2018). This outlier was deleted (taking the sample size to 141), and the normality test was run again. While overall normality of distribution was still not achieved, no further significant deviations were highlighted for this index.

Similarly, the boxplot associated with the composite index for Digital Mindset Crafting (Figure 6) highlighted two substantial deviations from the mean: respondents 69 and 36 (Field, 2018; Hair et al., 2018). These two outliers were deleted (taking the sample size to 139), and the normality test was run again. While overall normality of distribution was still not achieved, no further significant deviations were highlighted for this index.

The remaining results for each composite index, along with their comparison against the Shapiro-Wilk test for differences from a normal distribution (Hair et al., 2018) are summarised in Table 15. The Histograms and Normal Q-Q Plots for each composite index are included in Appendix D.

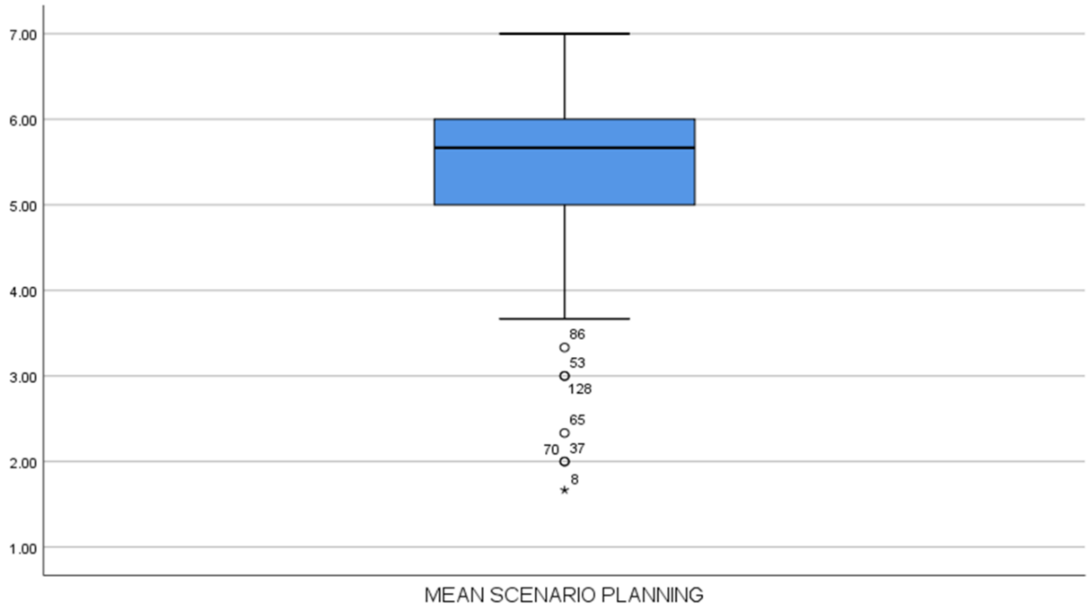

Figure 5: Boxplot for composite index: Scenario planning
Source: Exported from IBM SPSS v26, author's own research study

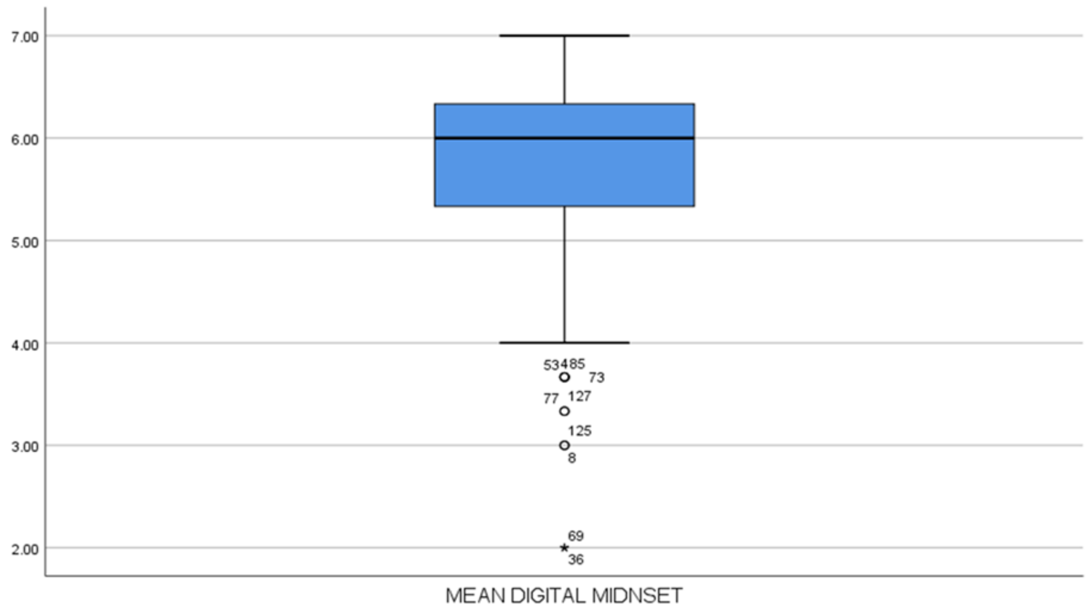

Figure 6: Boxplot for composite index: Digital mindset crafting
Source: Exported from IBM SPSS v26, author's own research study

Using the results from Table 15, it was evident that for most composite indices (except Rapid Prototyping), normality was violated – as the Shapiro-Wilk Sig. values were less than .05 (Hair et al., 2018). However, as Zikmund et al. (2010) reported, this was not a concern for multiple linear regression, as the test is considered robust.

Table 15: Normality – Data distribution using Shapiro Wilk Sig. score per composite index

Higher order construct	Sub-dimension composite index	Shapiro Wilk Sig.	Sig. > .05	Mean	Std deviation	N
Digital Sensing	Digital Scouting	.00	NO	5.79	0.88	139
	Scenario Planning	.00	NO	5.60	0.91	139
	Digital Mindset Crafting	.00	NO	5.75	0.96	139
Digital Seizing	Rapid Prototyping	.06	YES	4.98	1.05	139
	Balancing Digital Portfolio	.01	NO	5.05	1.09	139
	Strategic Agility	.01	NO	5.19	1.12	139
Digital Transforming	Innovation Ecosystem	.00	NO	5.19	1.20	139
	Redesign Internal Structures	.00	NO	5.58	1.10	139
	Improve Digital Maturity	.01	NO	5.12	1.12	139

Source: Adapted from IBM SPSS v26 data export, author's own research study

5.9. CENTRED MEAN AND INTERACTION VARIABLES

Before the analyses around regression could be executed, one final round of data preparation was required, as briefly outlined in this section.

First, a process of standardisation was followed for all independent variables, calculating the centred mean for the composite index of each (Hair et al., 2018). These mean-centring calculations would ensure that no multicollinearity existed within the independent variables (Field, 2018; Hair et al., 2018), with the resulting values used in the subsequent creation of moderator interactions.

Secondly, the process was repeated for all three independent moderator variables, with the intent to eliminate multicollinearity from these unidimensional observations (Hair et al., 2018). The mean-centred values for all variables were calculated using the "Transform – Compute" variable function in SPSS and deducted the mean values from each composite item (Field, 2018; Hair et al., 2018). The high-level detail of these calculations is listed in Table 16.

Once the centred mean values had been calculated, the final step in this process involved the creation of the interaction variables that would be used in the regression tests. This was achieved by using the "Transform – Compute" variable function in SPSS to multiply the new centred mean values for each independent variable by the centred mean value of their associated unidimensional moderators. (Field, 2018; Hair et al., 2018).

Table 16: Variable compute – Centred mean of composite indices and moderators

Higher-order construct	Sub-dimension	SPSS composite index name	SPSS numeric expression	Composite index mean
Digital Sensing	Digital Scouting	NEW_SCOUTING	MINUS	5.79
	Scenario Planning	NEW_SCEN_PLAN	MINUS	5.60
	Digital Mindset Crafting	NEW_DIG_MIND	MINUS	5.75
Digital Seizing	Rapid Prototyping	NEW_RAP_PRO	MINUS	4.98
	Balancing Digital Portfolio	NEW_BAL_DIG	MINUS	5.05
	Strategic Agility	NEW_STR_AGI	MINUS	5.19
Digital Transforming	Innovation Ecosystem	NEW_INN_ECO	MINUS	5.19
	Redesign Internal Structures	NEW_RED_INT	MINUS	5.58
	Improve Digital Maturity	NEW_IMP_DIG	MINUS	5.12
Construct	Dimension	SPSS variable name	SPSS numeric expression	Variable mean
Moderators	Digital Sensing Moderator	MD1	MINUS	6.47
	Digital Seizing Moderator	MD2	MINUS	5.63
	Digital Transform Moderator	MD3	MINUS	6.23

Source: Adapted from IBM SPSS v26, author's own research study

Having concluded this data transformation process, the analytics' final step – computing the linear regression for each interaction variable – could be completed. The following section details these test results before concluding the chapter with a brief overview of these results against the stated hypotheses.

5.10. MULTIPLE LINEAR REGRESSION

The linear model is seen as the most versatile statistical model for analysing relationships between one or more predictor variables and their outcome variable (Field, 2018; Hair et al., 2018). Multiple regression analysis expands on the general linear model to assess the relationship between a single dependent variable and multiple independent variables (Hair et al., 2018). This section summarises the predictive and comparative analytics executed on the research data (using multiple linear regression) and represents the most significant result-set for the assessment of the predictive and moderating relationships outlined in the research.

The SPSS regression analysis used for the research study calculated an individual weighting for each set of (mean-centred) independent variables (Field, 2018; Hair et al., 2018). These weightings were expressed as the adjusted R^2, or correlation coefficient, to maximise the level of statistical prediction (Field, 2018; Hair et al., 2018). Consequently, with multicollinearity eliminated in the previous centred mean calculations, it was estimated that these weights would more accurately indicate each independent variable's relative contribution to the overall prediction (Field, 2018; Hair et al., 2018).

In addition, the weightings facilitated multi-level model interpretation (Hair et al., 2018). From the research data, the moderators' comparative influence would be established using the output from two predictive models (Field, 2018; Hair et al., 2018). As the first model contained the predicted contribution of the mean-centred construct, this was then evaluated against the second model (for each subdimension) which included the interaction value of the moderated variable (Field, 2018; Hair et al., 2018). Finally, the SPSS analysis included measuring the ANOVA statistical test for the overall model fit (Field, 2018; Hair at el., 2018). The complete detail of the output is included in Appendix D.

From the results for the three independent variables that constitute the higher-order construct of DSN (Table 17), the data suggested a significant, individual contribution to the dependent variable by each of the three (mean-centred) subdimensions. The Sig. F. change values for each measurement fell below the .05 threshold, further supporting the observation (Field, 2018; Hair et al., 2018).

By contrast, the data seemed to indicate that the sensing moderator variable had no statistically significant influence on the relationship's strength for any of the DSN independent variables. This was reflected in the Sig. F. change values for the second set of moderated variables, which all exceeded the minimum of .05 (Field, 2018; Hair et al., 2018). The assessment was further supported by the multi-level model comparison, which reported no increase in the strength of the predictor when the adjusted R^2 contribution was considered in the second model iterations (Field, 2018; Hair et al., 2018). Encouragingly, the independent variables did all achieve statistically acceptable levels of model fit, falling below the ANOVA Sig. value threshold of 0.05 (Field, 2018; Hair et al., 2018).

Table 17: Linear regression – Digital sensing subdimensions against dependent variable

Predictors Centred mean [CM] and interaction values [IV]	Model	Adjusted R square	Contributor Sig. F. change < 0.05	Model 1 vs Model 2 Adjusted R square	Model fit ANOVA Sig. < 0.05
CM Digital Scouting	1	.12	.00	Decrease	.00
CM Digital Scouting IV Digital Scouting	2	.11	.96		.00
CM Scenario Planning	1	.14	.00	No Change	.00
CM Scenario Planning IV Scenario Planning	2	.14	.22		.00
CM Digital Mindset Crafting	1	.12	.00	No Change	.00
CM Digital Mindset Crafting IV Digital Mindset Crafting	2	.12	.15		.00

Source: Adapted from IBM SPSS v26 data export, author's own research study

In a similar vein, the results for the three independent variables that constitute the higher-order construct of DSZ (Table 18) also suggested a significant, individual contribution to the dependent variable by each of the three (mean-centred) subdimensions. As before, the Sig. F. change values for each measurement fell below the .05 threshold, further supporting the observation (Field, 2018; Hair et al., 2018).

Table 18: Linear regression – Digital seizing subdimensions against dependent variable

Predictors Centred mean [CM] and interaction values [IV]	Model	Adjusted R square	Contributor Sig. F. change < 0.05	Model 1 vs Model 2 Adjusted R square	Model fit ANOVA Sig. < 0.05
CM Rapid Prototyping	1	.05	.01	No Change	.00
CM Rapid Prototyping IV Rapid Prototyping	2	.05	.31		.01
CM Balance Digital Portfolio	1	.13	.00	No Change	.00
CM Balance Digital Portfolio IV Balance Digital Portfolio	2	.13	.31		.00
CM Strategic Agility	1	.20	.00	Decrease	.00
CM Strategic Agility IV Strategic Agility	2	.19	.65		.00

Source: Adapted from IBM SPSS v26 data export, author's own research study

As with the previous subdimension, the data again found that the seizing moderator variable had no statistically significant influence on this relationship's strength for any of the independent variables associated with DSZ. This was reflected in the Sig. F. change values for the second set of moderated variables, which all exceeded the minimum of .05 (Field, 2018; Hair et al., 2018).

The multi-level model comparison further supported this determination, as it reported no increase in the strength of the predictor when the adjusted R^2 contribution was considered in the second model (Field, 2018; Hair et al., 2018). The independent variables for this subdimension all achieved statistically acceptable model fit levels, falling below the ANOVA Sig. value threshold of 0.05 (Field, 2018; Hair et al., 2018).

Finally, the data for the three independent variables that constitute the higher-order construct of DTF (Table 19) also suggested a significant, individual contribution to the dependent variable by each of the three (mean-centred) subdimensions. The Sig. F. change values for each measurement fell below the .05 threshold, further supporting the observation (Field, 2018; Hair et al., 2018).

Table 19: Linear regression – Digital transforming subdimensions against dependent variable

Predictors *Centred mean [CM] and interaction values [IV]*	Model	Adjusted R square	Contributor Sig. F. change < .05	Model 1 vs Model 2 Adjusted R square	Model fit ANOVA Sig. < .05
CM Innovation Ecosystem	1	.04	.01	Increase	.01
CM Innovation Ecosystem IV Innovation Ecosystem	2	.05	.07		.01
CM Redesign Int Structures	1	.08	.00	Increase	.00
CM Redesign Int Structures IV Redesign Int Structures	2	.10	.02		.00
CM Improve Digital Maturity	1	.06	.00	Increase	.00
CM Improve Digital Maturity IV Improve Digital Maturity	2	.08	.05		.00

Source: Adapted from IBM SPSS v26 data export, author's own research study

For moderated interaction, the predictive statistics for DTF proved to be more compelling. The seizing moderator variable's results displayed the most statistically significant influence within the dataset, as recorded in the Sig. F. change values for each moderation interaction variable (Table 19). The assessment was, seemingly, supported by the multi-level model comparison, which reflected increased strength of the predictor

– applying the adjusted R^2 contribution in model 2 – for each of the subdimensions (Field, 2018; Hair et al., 2018).

When considering the threshold (of < .05) for the contributor statistic, however, only one moderation interaction achieves a statistically acceptable level, that of Redesign Internal Structures (Field, 2018; Hair et al., 2018). As with the previous subdimensions, the independent variables did all achieve statistically acceptable levels of model fit, falling below the ANOVA Sig. value threshold of 0.05 (Field, 2018; Hair et al., 2018).

5.11. RESULTS FOR HYPOTHESES TESTS

In the pursuit of robust validation and testing of the defined hypotheses, the research study adopted the null hypothesis methodology (Zikmund et al., 2010). Using this approach, the results of the various statistical analytics were applied to assess the null and alternative hypotheses for each assumption within the scope of the research study (Appendix C).

Consequently, the following sections each detail the various hypotheses, along with their null and alternative state, before assessing the results of each against the output obtained from the various statistical processes. Sequentially, each set of sub-hypotheses is listed first, along with the criteria for their null and alternative states, followed by the associated statistics, using the values presented in the preceding sections of this chapter. While the distinct values are not repeated in the assessments, the various outcomes of the analytics are used to qualify the resulting acceptance (or rejection) of the alternative hypotheses. Finally, the main hypothesis associated to the category of sub-hypotheses is presented, assessed both on its own merit as well as the outcome of the individual results from the subdimensions and indicators associated to that construct.

The implications of the various hypotheses tests, along with the consequence of the outcome on the main research question, are discussed at length in the following chapter.

5.11.1. Hypothesis 1 (and sub-hypotheses H1.1 – H1.3)

Sub-hypothesis 1.1	**H1.1**	The lower-order construct of digital scouting can be measured through three discrete operationalised indicators

Null hypothesis	**$H_0$1.1**	No correlation exists between the discrete indicators for digital scouting, and they do not measure the associated construct consistently
Alternative hypothesis	**$H_1$1.1**	Correlation exists between the discrete indicators for digital scouting, and they do measure the associated construct consistently
Results **H1.1**	Null hypothesis rejected **Alternative hypothesis accepted** Significant correlation at the 0.01 level, two-tailed Instrument reliability confirmed against all three items Factor analysis confirmed dimensionality	

Sub-hypothesis 1.2	**H1.2**	The lower-order construct of digital scenario planning can be measured through three discrete operationalised indicators
Null hypothesis	**$H_0$1.2**	No correlation exists between the discrete indicators for digital scenario planning, and they do not measure the associated construct consistently
Alternative hypothesis	**$H_1$1.2**	Correlation exists between the discrete indicators for digital scenario planning, and they do measure the associated construct consistently
Results **H1.2**	Null hypothesis rejected **Alternative hypothesis accepted** Significant correlation at the 0.01 level, two-tailed Instrument reliability confirmed against all three items Factor analysis confirmed dimensionality	
Sub-hypothesis 1.3	**H1.3**	The lower-order construct of digital mindset crafting can be measured through three discrete operationalised indicators
Null hypothesis	**$H_0$1.3**	No correlation exists between the discrete indicators for digital mindset crafting, and they do not measure the associated construct consistently

Alternative hypothesis	**$H_1$1.3**	Correlation exists between the discrete indicators for digital mindset crafting, and they do measure the associated construct consistently
Results **H1.3**	Null hypothesis rejected **Alternative hypothesis accepted** Significant correlation at the 0.01 level, two-tailed Instrument reliability confirmed against all three items Factor analysis confirmed dimensionality	

Hypothesis 1	**H1**	The contribution of the higher-order construct: DSN towards the dependent variable: SDT, can be measured through three distinct subdimensions
Null hypothesis	**$H_0$1**	No correlation exists between the subdimensions of DSN, and they do not measure the associated constructs consistently
Alternative hypothesis	**$H_1$1**	Correlation exists between the subdimensions of DSN, and they do measure the associated constructs consistently
Results **H1**	Null hypothesis rejected **Alternative hypothesis accepted** Significant correlation for all subdimensions of DSN Instrument reliability confirmed for all subdimensions of DSN Factor analysis confirmed dimensionality for all subdimensions of DSN	

5.11.2. Hypothesis 2 (and sub-hypotheses H2.1 – H2.3)

Sub-hypothesis 2.1	**H2.1**	The lower-order construct of rapid prototyping can be measured through three discrete operationalised indicators
Null hypothesis	**$H_0$2.1**	No correlation exists between the discrete indicators for rapid prototyping, and they do not measure the associated construct consistently

Alternative hypothesis	**$H_1$2.1**	Correlation exists between the discrete indicators for rapid prototyping, and they do measure the associated construct consistently
Results **H2.1**	Null hypothesis rejected **Alternative hypothesis accepted** Significant correlation at the 0.01 level, two-tailed Instrument reliability confirmed against all three items Factor analysis confirmed dimensionality	
Sub-hypothesis 2.2	**H2.2**	The lower-order construct of balance digital portfolios can be measured through three discrete operationalised indicators
Null hypothesis	**$H_0$2.2**	No correlation exists between the discrete indicators for balance digital portfolios, and they do not measure the associated construct consistently
Alternative hypothesis	**$H_1$2.2**	Correlation exists between the discrete indicators for balance digital portfolios, and they do measure the associated construct consistently
Results **H2.2**	Null hypothesis rejected **Alternative hypothesis accepted** Significant correlation at the 0.01 level, two-tailed Instrument reliability confirmed against all three items Factor analysis confirmed dimensionality	
Sub-hypothesis 2.3	**H2.3**	The lower-order construct of strategic agility can be measured through three discrete operationalised indicators
Null hypothesis	**$H_0$2.3**	No correlation exists between the discrete indicators for strategic agility, and they do not measure the associated construct consistently
Alternative hypothesis	**$H_1$2.3**	Correlation exists between the discrete indicators for strategic agility, and they do measure the associated construct consistently

Results **H2.3**	Null hypothesis rejected **Alternative hypothesis accepted** Significant correlation at the 0.01 level, two-tailed Instrument reliability confirmed against all three items Factor analysis confirmed dimensionality	

Hypothesis 2	**H2**	The contribution of the higher-order construct: DSZ towards the dependent variable: SDT, can be measured through three distinct subdimensions
Null hypothesis	**$H_0$2**	No correlation exists between the subdimensions of DSZ, and they do not measure the associated constructs consistently
Alternative hypothesis	**$H_1$2**	Correlation exists between the subdimensions of DSZ, and they do measure the associated constructs consistently
Results **H2**	Null hypothesis rejected **Alternative hypothesis accepted** Significant correlation all subdimensions of DSZ Instrument reliability confirmed for all subdimensions of DSZ Factor analysis confirmed dimensionality for all subdimensions of DSZ	

5.11.3. Hypothesis 3 (and sub-hypotheses H3.1 – H3.3)

Sub-hypothesis 3.1	**H3.1**	The lower-order construct of innovation ecosystems can be measured through three discrete operationalised indicators
Null hypothesis	**$H_0$3.1**	No correlation exists between the discrete indicators for innovation ecosystems, and they do not measure the associated construct consistently
Alternative hypothesis	**$H_1$3.1**	Correlation exists between the discrete indicators for innovation ecosystems, and they do measure the associated construct consistently

Results **H3.1**	Null hypothesis rejected **Alternative hypothesis accepted** Significant correlation at the 0.01 level, two-tailed Instrument reliability confirmed against all three items Factor analysis confirmed dimensionality	

Sub-hypothesis 3.2	**H3.2**	The lower-order construct of redesign internal structures can be measured through three discrete operationalised indicators
Null hypothesis	**$H_0$3.2**	No correlation exists between the discrete indicators for redesign internal structures, and they do not measure the associated construct consistently
Alternative hypothesis	**$H_1$3.2**	Correlation exists between the discrete indicators for redesign internal structures, and they do measure the associated construct consistently
Results **H3.2**	Null hypothesis rejected **Alternative hypothesis conditionally accepted** – after discrete indicators were reduced to two (to achieve minimum threshold for Cronbach's alpha) **Amended sub-hypothesis:** The lower-order construct of redesign internal structures can be measured through **two** discrete operationalised indicators Significant correlation and instrument reliability confirmed against two items Factor analysis confirmed dimensionality against two items	

Sub-hypothesis 3.3	**H3.3**	The lower-order construct of improve digital maturity can be measured through three discrete operationalised indicators
Null hypothesis	**$H_0$3.3**	No correlation exists between the discrete indicators for improve digital maturity, and they do not measure the associated construct consistently

Alternative hypothesis	**$H_1$3.3**	Correlation exists between the discrete indicators for improve digital maturity, and they do measure the associated construct consistently
Results **H3.3**	Null hypothesis rejected **Alternative hypothesis accepted** Significant correlation at the 0.01 level, two-tailed Instrument reliability confirmed against all three items Factor analysis confirmed dimensionality	

Hypothesis 3	**H3**	The contribution of the higher-order construct: DTF towards the dependent variable: SDT, can be measured through three distinct subdimensions
Null hypothesis	**$H_0$3**	No correlation exists between the subdimensions of DTF, and they do not measure the associated construct consistently
Alternative hypothesis	**$H_1$3**	Correlation exists between the subdimensions of DTF, and they do measure the associated construct consistently
Results **H3**	Null hypothesis rejected **Alternative hypothesis accepted** Significant correlation all subdimensions of DTF Instrument reliability confirmed for all subdimensions of DTF Factor analysis confirmed dimensionality for all subdimensions of DTF	

5.11.4. Hypothesis 4 (and sub-hypotheses H4.1 – H4.3)

Sub-hypothesis 4.1	**H4.1**	The strength of the relationship between the subdimension digital scouting and the dependent variable: SDT, is moderated by DSC
Null hypothesis	**$H_0$4.1**	There is no moderation effect on the contribution of the independent variable digital scouting to the dependent variable by the DSN moderator

Alternative hypothesis	**$H_1$4.1**	There is statistically significant moderation on the contribution of the independent variable digital scouting to the dependent variable by the DSN moderator
Results **H4.1**	**Null hypothesis accepted** Alternative hypothesis rejected Significant contribution to dependent variable by CM values of each item DSN moderator variable had no statistically significant moderating effect Multi-level model comparison reported **decrease** in moderated interaction Independent variables achieved model-fit using ANOVA values	
Sub-hypothesis 4.2	**H4.2**	The strength of the relationship between the subdimension digital scenario planning and the dependent variable: SDT, is moderated by DSC
Null hypothesis	**$H_0$4.2**	There is no moderation effect on the contribution of the independent variable digital scenario planning to the dependent variable by the DSN moderator
Alternative hypothesis	**$H_1$4.2**	There is statistically significant moderation on the contribution of the independent variable digital scenario planning to the dependent variable by the DSN moderator
Results **H4.2**	**Null hypothesis accepted** Alternative hypothesis rejected Significant contribution to dependent variable by CM values of each item DSN moderator variable had no statistically significant moderating effect Multi-level model comparison reported **no change** in moderated interaction Independent variables achieved model-fit using ANOVA values	

Sub-hypothesis 4.3	**H4.3**	The strength of the relationship between the subdimension digital mindset crafting and the dependent variable: SDT, is moderated by DSC
Null hypothesis	**$H_0$4.3**	There is no moderation effect on the contribution of the independent variable digital mindset crafting to the dependent variable by the DSN moderator
Alternative hypothesis	**$H_1$4.3**	There is statistically significant moderation on the contribution of the independent variable digital mindset crafting to the dependent variable by the DSN moderator
Results **H4.3**	**Null hypothesis accepted** Alternative hypothesis rejected Significant contribution to dependent variable by CM values of each item DSN moderator variable had no statistically significant moderating effect Multi-level model comparison reported **no change** in moderated interaction Independent variables achieved model-fit using ANOVA values	

Hypothesis 4	**H4**	The strength of the relationship between the higher-order construct: DSN and the dependent variable: SDT, is moderated by DSC
Null hypothesis	**$H_0$4**	There is no moderation effect on the contribution of the higher-order construct DSN to the dependent variable SDT by the DSN moderator
Alternative hypothesis	**$H_1$4**	There is statistically significant moderation on the contribution of the higher-order construct DSN to the dependent variable SDT by the DSN moderator

Results **H4**	**Null hypothesis accepted** Alternative hypothesis rejected Significant contribution to dependent variable by each subdimension DSN moderator variable had no statistically significant moderating effect Independent variables all achieved model-fit using ANOVA values

5.11.5. Hypothesis 5 (and sub hypotheses H5.1 – H5.3)

Sub-hypothesis 5.1	**H5.1**	The strength of the relationship between the subdimension rapid prototyping and the dependent variable: SDT, is moderated by DSC
Null hypothesis	**$H_0$5.1**	There is no moderation effect on the contribution of the independent variable rapid prototyping to the dependent variable by the DSZ moderator
Alternative hypothesis	**$H_1$5.1**	There is statistically significant moderation on the contribution of the independent variable rapid prototyping to the dependent variable by the DSZ moderator

Results **H5.1**	**Null hypothesis accepted** Alternative hypothesis rejected Significant contribution to dependent variable by CM values of each item DSZ moderator variable had no statistically significant moderating effect Multi-level model comparison reported **no change** in moderated interaction Independent variables achieved model-fit using ANOVA values

Sub-hypothesis 5.2	**H5.2**	The strength of the relationship between the subdimension balance digital portfolios and the dependent variable: SDT, is moderated by DSC

Null hypothesis	**$H_0$5.2**	There is no moderation effect on the contribution of the independent variable balance digital portfolios to the dependent variable by the DSZ moderator
Alternative hypothesis	**$H_1$5.2**	There is statistically significant moderation on the contribution of the independent variable balance digital portfolios to the dependent variable by the DSZ moderator
Results **H5.2**	**Null hypothesis accepted** Alternative hypothesis rejected Significant contribution to dependent variable by CM values of each item DSZ moderator variable had no statistically significant moderating effect Multi-level model comparison reported **no change** in moderated interaction Independent variables achieved model-fit using ANOVA values	

Sub-hypothesis 5.3	**H5.3**	The strength of the relationship between the subdimension strategic agility and the dependent variable: SDT, is moderated by DSC
Null hypothesis	**$H_0$5.3**	There is no moderation effect on the contribution of the independent variable strategic agility to the dependent variable by the DSZ moderator
Alternative hypothesis	**$H_1$5.3**	There is statistically significant moderation on the contribution of the independent variable strategic agility to the dependent variable by the DSZ moderator
Results **H5.3**	**Null hypothesis accepted** Alternative hypothesis rejected Significant contribution to dependent variable by CM values of each item DSZ moderator variable had no statistically significant moderating effect	

	Multi-level model comparison reported **decrease** in moderated interaction Independent variables achieved model-fit using ANOVA values	
Hypothesis 5	**H5**	The strength of the relationship between the higher order construct: DSZ and the dependent variable: SDT, is moderated by DSC
Null Hypothesis	**$H_0$5**	There is no moderation effect on the contribution of the higher-order construct DSZ to the dependent variable SDT by the DSZ moderator
Alternative Hypothesis	**$H_1$5**	There is statistically significant moderation on the contribution of the higher-order construct DSZ to the dependent variable SDT by the DSZ moderator
Results **H5**	**Null hypothesis accepted** Alternative hypothesis rejected Significant contribution to dependent variable by each subdimension DSZ moderator variable had no statistically significant moderating effect Independent variables all achieved model-fit using ANOVA values	

5.11.6. Hypothesis 6 (and sub hypotheses H6.1 – H6.3)

Sub-hypothesis 6.1	**H6.1**	The strength of the relationship between the subdimension innovation ecosystems and the dependent variable: SDT, is moderated by DSC
Null hypothesis	**$H_0$6.1**	There is no moderation effect on the contribution of the independent variable innovation ecosystems to the dependent variable by the DT moderator
Alternative Hypothesis	**$H_1$6.1**	There is statistically significant moderation on the contribution of the independent variable innovation ecosystems to the dependent variable by the DTF moderator

Results **H6.1**		**Null hypothesis accepted** Alternative hypothesis rejected Significant contribution to dependent variable by CM values of each item DTF moderator variable had no statistically significant moderating effect Multi-level model comparison reported **increase** in moderated interaction, but model 2 failed to meet adjusted R^2 threshold for significance Independent variables achieved model-fit using ANOVA values
Sub-hypothesis 6.2	**H6.2**	The strength of the relationship between the subdimension redesign internal structures and the dependent variable: SDT, is moderated by DSC
Null hypothesis	**$H_0$6.2**	There is no moderation on the contribution strength of the independent variable redesign internal structures to the dependent variable by the DTF moderator
Alternative hypothesis	**$H_1$6.2**	There is statistically significant moderation on the contribution strength of the independent variable redesign internal structures to the dependent variable by the DTF moderator
Results **H6.2**		Null hypothesis rejected **Alternative hypothesis accepted** Significant contribution to dependent variable by CM values of each item DTF moderator variable had statistically significant moderating effect Multi-level model comparison reported **increase** in contribution strength Independent variables achieved model-fit using ANOVA values

Sub-hypothesis 6.3	**H6.3**	The strength of the relationship between the subdimension digital maturity and the dependent variable: SDT, is moderated by DSC
Null hypothesis	**$H_0$6.3**	There is no moderation on the contribution strength of the independent variable digital maturity to the dependent variable by the DTF moderator
Alternative hypothesis	**$H_1$6.3**	There is statistically significant moderation on the contribution strength of the independent variable digital maturity to the dependent variable by the DTF moderator
Results **H6.3**	**Null hypothesis accepted** Alternative hypothesis rejected Significant contribution to dependent variable by CM values of each item DTF moderator variable had no statistically significant moderating effect Multi-level model comparison reported **increase** in moderated interaction, but model 2 failed to meet adjusted R^2 threshold for significance Independent variables achieved model-fit using ANOVA values	

Hypothesis 6	**H6**	The strength of the relationship between the higher order construct: DTF and the dependent variable: SDT, is moderated by DSC
Null hypothesis	**$H_0$6**	There is no moderation effect on the contribution of the higher-order construct DTF to the dependent variable SDT by the DTF moderator
Alternative hypothesis	**$H_1$6**	There is statistically significant moderation on the contribution of the higher-order construct DTF to the dependent variable SDT by the DTF moderator

Results **H6**	**Null hypothesis accepted** Alternative hypothesis rejected Although single subdimension (redesign internal structures) achieved statistically significant moderation, this was not sufficient for the higher-order construct to reflect an overall moderation interaction from the DTF moderator variable Significant contribution to dependent variable by each subdimension DSC moderator had no statistically significant moderating effect overall Independent variables all achieved model-fit using ANOVA values

CHAPTER 6 : DISCUSSION OF RESULTS

6.1. INTRODUCTION

Following the detailed output of the various statistical results presented in the previous chapter, the focus of this chapter is on the theoretical (and research) implications of these findings. Specifically, the succeeding sections attempt to analyse the six main hypotheses (and their supporting sub-hypotheses) along with a discussion on whether the assumptions detailed in these items were either confirmed or contradicted by the results of the research study. The strategic and academic implications of these results are then discussed in the final chapter, along with any limitations that were identified in either the survey instrument or methodology.

The research study had two main objectives, as expressed in the defined research questions and their six hypotheses (Chapter 3). First, the study attempted to validate the digitised indicators (i.e., processes and routines) that were hypothesised to measure distinct sub-capabilities (i.e., statistical subdimensions) within the multidimensional construct of DDC (hypotheses 1 to 3). These discrete indicators had been operationalised within the quantitative scale used in the research project. Furthermore, their associated assumptions were detailed in the sub-hypotheses associated with each of the three higher-order constructs of DDC. The results obtained from SPSS would thus act as confirmatory and statistical validation of these purported relationships, along with the accuracy with which they measured their specific subdimensions within DDC.

Following on these foundational constructs, the primary research problem was addressed in the second set of hypotheses (hypotheses 4 through to 6) which sought to validate the proposed moderation of DSC on each of the subdimensions, as they related to SDT. Building on the assumptions outlined in hypotheses 1 to 3, the second set of hypotheses was structured around the relative impact of the (three) contextual, unidimensional moderators on each subdimension. In doing so, the study hoped to illuminate any relative, discrete, and dimension-specific insights that could support the arguments outlined in the literature.

Consequently, the analysis of this chapter was structured around the two main objectives, as outlined above. The chapter examines the correlations between the various subdimensions and their indicators, before moving on to a discussion of the moderation interaction expressed in the linear regression tests. However, per introduction, a brief discussion is presented on the demographic results, followed by a review of responses to the dependent variable question, as these outcomes would have a bearing on later findings.

6.2. DEMOGRAPHIC RESULTS

Apart from the control variable (question: COV2, Appendix A) and population validation (question: DEM02, Appendix A), the research methodology had not intended to assess or statistically analyse any of the remaining demographic variables contained within the research instrument. However, two noteworthy insights needed to be highlighted for consideration in the discussions to follow.

First, of the survey responses, 29.15% originated from the ICT sector, with an additional 6.03% from the internet service provider and telecommunications space. Accordingly, possible bias may exist within the resulting data (Creswell & Creswell, 2018; Zikmund et al. 2010), as a disproportionate percentage of replies (35.18%) were supplied by respondents at firms within the technology space. The contribution of IT-driven transformation within the context of SDT is well documented in both current and foundational literature (Teece & Linden, 2017; Vial, 2019; Zuboff, 1988). Consequently, the resulting insights – gathered from firms grounded in IT-centric business models – may imply a significant bias in both the responses and the impact on SDT. Secondly, other bias (albeit to a lesser extent) may be inferred from the second and third largest contributors to the survey (15.58% and 14.57% respectively) coming from the mining and banking industries.

As the purposeful sample was targeted within the researcher's network of contacts, these results were not unexpected, considering that the three sectors represented those industries that the researcher interacted with most in his profession. It should serve, however, as a contextual consideration when interpreting the results from the survey instrument. In addition, these constraints should inform the recommendations and research limitations detailed in the concluding chapter.

6.3. DEPENDENT VARIABLE: SUCCESSFUL DIGITAL TRANSFORMATION

For the question that measured SDT (question: SDT1, Appendix A), the data reflected an unexpected measure of skewness (Field, 2018; Hair et al., 2018). By illustration, 59.39% of respondents indicated that their DT projects had been a success (Agree and Strongly Agree on Likert scale), with only 4.57% of replies showing failed execution (Disagree and Strongly Disagree). The remaining 36.04% of respondents fell within the mid-range of the scale. The data were thus indicative of a (disproportionally?) high level of success in SDT. These results implied two important considerations, with a potential limitation that had to be explored before the analysis of the hypotheses was carried out.

Based on the previous section's discussion, the first assumption could be that the reportedly higher success rate in SDT was attributable to the representation of IT-centric businesses (Vial, 2019; Teece & Linden, 2017). Although this could be construed as reflective of possible bias within the data, further insight into the various constructs and dimensions that support SDT would be required to confirm this assertion. In addition, to ensure conclusion validity (Creswell & Creswell, 2018) and avoid incorrect inferences, the researcher had to guard against drawing conclusions from a single response. Differing interpretations of the underlying construct, along with contextual factors, or flawed measurement of the variable, may all have had an influence on the outcome (Creswell & Creswell, 2018; Field, 2018; Hair et al., 2018, Zikmund et al., 2010). A deeper analysis of the construct and its associated definitions was, therefore, be needed. This requirement introduced the second, and arguably more relevant, implication for the research study.

Zikmund et al. (2010) recommended that the decision for researchers between a single- or multi-dimensional measure was informed by three considerations: 1) complexity of the issue, 2) whether individual attributes form a collective stimulus, and 3) the numbers of dimensions in the construct. Zikmund et al. (2010) highlighted that multi-item measures could easily be subjected to more intensive tests and validations, as deemed necessary in the analysis of responses to the SDT variable. In hindsight, it alludes to a flawed approach adopted by the researcher to measure the construct of SDT in a single question. While the implication for the proposed survey instrument (and scale) was concerning, the remediation would be explored in the final chapter. More relevant was the theoretical and analytical implications on the results, and their implied constraints on the hypotheses tests.

The link between successful transformative efforts and business model innovation is well established in the literature (Foss & Saebi, 2018; Karimi & Walter, 2015; 2016; Loebbecke & Picot, 2015; Ritter & Pedersen, 2020; Teece, 2018; Teece & Linden, 2017; Velu, 2017), and should have been incorporated into a multi-item perspective of SDT within the survey instrument. In their research on DDC, Warner and Wäger (2019) further expanded SDT within the context of three attributes: 1) business model renewal, 2) collaborative approach renewal, and 3) culture renewal, which would have added additional perspectives and opportunities for analysis, had they been considered for operationalisation. However, the reality was that these observations only became apparent when a more in-depth analysis of the SDT dependent variable was not accessible within the final stages of the research study. While the researcher deemed it important to state this limitation upfront, the resulting assessment of the various hypotheses had to be carried out within the single dimension for the dependent variable, as expressed in the survey. Whether the limitation would adversely impact the results remained to be seen, as discussed later in this chapter.

6.4. SUBDIMENSION CORRELATION AND CONSTRUCT VALIDITY

The next section discusses the data in relation to the first three hypotheses, which had set out to answer the sub-question outlined for the research study: what are the various routines and processes that may be used to predict or measure the subdimensions of DDC? This sub-question, which supported the primary research question, sought to understand the various higher-order constructs (aggregate dimensions), lower-order constructs (subdimensions), and discrete indicators (Hair et al., 2018) that constitute DDC, as suggested by the prevailing literature. The resulting evaluation had a solid academic grounding, as Teece (2007; 2014; 2018) and Teece et al. (1997) highlighted the strategic importance of understanding the sub-capabilities that support DC, along with their organisational routines and management practices. Using the various subdimensions suggested in the DDC process model (Warner & Wäger, 2019), the research study attempted to validate the multiple correlations and multi-item constructs against the data, the results of which are detailed below.

In addition to the above, the first three hypotheses (and nine sub-hypotheses) would serve to pursue a crucial objective: that of operationalising various aspects of the DDC process model. While only a small contribution to DC and DDC's overall constructs, a positive outcome could introduce the first steps towards the development of a quantitative scale to measure DDC.

6.4.1. Factor analysis and dimension reduction results

To avoid repetition and unnecessary verbosity in discussing the results, common outcomes and shared conclusions are presented upfront. Specifically, results from the EFA analysis against all the lower-order constructs were all consistent and encouraging. The calculated values for both the KMO measure and Bartlett’s test (of sphericity) reflected a combined validation of the underlying relationships between all variables (Hair et al., 2018) – as each subdimension fell within the acceptable statistical significance levels (Field, 2018; Hair et al., 2018). Each of the subdimensions loaded against a single component during factor extraction, supported by the cumulative percentage of variance from the Eigenvalues (Field, 2018; Hair et al., 2018).

The implication of these results was encouraging from both a methodological and theoretical perspective. First, it supported the research project's conceptual model and its objective to define a consistent DDC scale (Kump et al., 2018). The statistical analysis confirmed that the underlying measures all consistently reflected the constructs (Clark & Watson, 1995) and verified the veracity of the quantitative, observable routines to reflect the DDC subdimensions (Peteraf et al., 2013; Di Stefano et al., 2014; Kump et al., 2018; Warner & Wäger, 2019).

Theoretically, the results added to the growing body of academic consensus around the contribution of inter-related DC to strategic renewal in the face of digitised, technology-focused disruption (Helfat & Raubitschek, 2018; Karimi & Walter, 2015; 2016; Schilke et al., 2018; Teece, 2007; 2014; 2018; Teece & Linden, 2017; Teece et al., 1997; Vial, 2019; Velu, 2017; Yeow et al., 2018). In addition, the factor analysis conceptually supported the view of expanded DDC proposed by Warner and Wäger (2019). Further, it supported the literature suggesting that more digitised competencies – that collectively contribute to strategic responses in dynamic environments – had become ubiquitous across a diverse set of firms (Autio et al., 2018; Vial, 2019; Warner & Wäger, 2019; Yeow et al., 2018). Finally, the results made a small contribution to the ongoing validation of the DC construct, supporting the work by Teece (2007; 2014; 2018) and Teece et al. (1997), with added quantitative evidence for the correlation between primary capabilities and their associated sub-capabilities in disruptive digital environments (Karimi & Walter, 2015; 2016; Teece, 2018; Teece & Linden, 2017; Velu, 2017). For a more granular review of each subdimension, along with the assumptions contained in their hypotheses, the following sections discuss each in more detail.

6.4.2. Hypothesis 1: Digital sensing

The first hypothesis sought to validate the three lower-order constructs (subdimensions) that support DSN (Day & Schoemaker, 2016; Nambisan et al., 2017; Teece, 2007; Warner & Wäger, 2019), along with their individual, observable measures (as defined in each of the three sub-hypotheses). The first subdimension, digital scouting, confirmed a statistically significant correlation between the three operationalised questions that were theorised to measure the construct. These three routines, expressed as 1) scanning for technological trends, 2) screening of digital competitors, and 3) sensing customer-centric trends, were shown to be significantly correlated, supporting the academic literature that reported on the rise of scouting capabilities in response to digital disruption (Monteiro &

Birkinshaw, 2017). In addition, the statistical findings validated the various routines recommended by Warner and Wäger (2019) for firms more acutely to develop their sensing capabilities.

Alongside digital scouting, the literature suggests an observable rise in technology-centric strategic planning competences (Dong et al., 2016; Warner & Wäger, 2019). This view was supported by the second sub-hypothesis findings, which explored the various indicators for digital scenario planning. The argument listed these as 1) analysing scouted signals, 2) interpreting digital future scenarios, and 3) formulating digital strategies. As with the previous subdimension, a significant correlation was found, along with construct validity, amongst all the items. The findings thus validated the use of new, innovative networks to identify customer trends, along with the use of technology hubs and data analytics, as suggested by the prevailing literature (Birkinshaw et al., 2016; Day & Schoemaker, 2016; Dong et al., 2016; Giudici et al., 2018; Helfat & Raubitschek, 2018; Loebbecke & Picot, 2015; Warner & Wäger, 2019). Additionally, the findings supported the view that these activities would collectively aid and support the efforts to identify new technologies, trends, and preferences (Warner & Wäger, 2019).

Finally, the results validated the third sub-hypothesis of DSN, which identified the three indicators for the subdimension: digital mindset crafting as 1) establishing a long-term digital vision, 2) enabling an entrepreneurial mindset, and 3) promoting a digital mindset. These findings further endorsed the view of digital mindset crafting as a prominent and emerging, set of routines, focused on the development of an entrepreneurial, digitally-orientated culture (Autio et al., 2018; Day & Schoemaker; 2016; Ritter & Pedersen; 2020; Warner & Wäger, 2019). The processes, supported by their statistically significant correlations, add to the literary consensus on strategic thinking in the digital age (Kane et al., 2017), along with their contribution to the development of a cross-functional and entrepreneurial culture (Ritter & Pedersen; 2020; Warner & Wäger, 2019).

Consequently, the results for each sub-hypothesis informed the acceptance of the alternative hypothesis for H1. The digitised sub-capabilities all accurately and consistently measured the associated construct of DSN. This finding answered the call from the literature to examine and validate a set of DSN sub-capabilities (Day & Schoemaker, 2016; Nambisan et al., 2017). Finally, these findings heralded the first small step towards developing a quantitative scale for DDC (Kump et al., 2018), in that correlations for each of the subdimensions were found to be statistically valid.

6.4.3. Hypothesis 2: Digital seizing

The second hypothesis sought to validate the three lower-order constructs (subdimensions) that support DSZ (Birkinshaw, 2018; Rigby et al., 2016; Warner & Wäger, 2019), along with their individual, observable measures (as defined in each of the three sub-hypotheses). The first DSZ subdimension, rapid prototyping, confirmed a statistically significant correlation between the three operationalised questions that were theorised to measure the construct. These three routines, expressed as 1) create minimum viable products, 2) a lean start-up methodology, and 3) using a digital innovation lab, were shown to be significantly correlated, validating the rapid prototyping routines, as recommended by Warner and Wäger (2019), that enabled strategic responses to the threats and opportunities of disruptive DT (Helfat & Raubitschek, 2018; Karimi & Walter, 2015; 2016; Schilke et al., 2018; Teece, 2018; Teece & Linden, 2017; Vial, 2019; Velu, 2017; Yeow et al., 2018). Specifically, the findings validated the contribution of the various activities that allowed firms to experiment with minimum viable products in response to changing customer demands (Birkinshaw, 2018; Rigby et al., 2016; Teece et al., 2016; Warner & Wäger, 2019).

The activities that enable firms to balance their various digital portfolios, as suggested in the literature, was an important aspect to consider with the emergence of radical new business models (Peteraf et al., 2013; Vial, 2019; Warner & Wäger, 2019). Accordingly, the second sub-hypotheses measured this subdimension through three indicators 1) balancing internal and external options, 2) scaling up innovative business models, and 3) setting up appropriate speed of execution. The resulting validity of this construct, as exhibited in the correlation statistics, therefore supports the theoretical assertions, along with the relationship between scaling up innovative revenue streams while balancing existing product (or service) offerings (Peteraf et al., 2013; Vial, 2019; Warner & Wäger, 2019). Additionally, the findings supported the view that these digitised activities would collectively facilitate speed of execution through a strategic application of technology (Warner & Wäger, 2019).

Finally, the results validated the third sub-hypothesis, which identified the three indicators for the subdimension: strategic agility as 1) rapidly reallocating resources, 2) accept redirection and change, and 3) pacing strategic responses. The findings endorsed the prevailing academic consensus around the construct of strategic agility (Birkinshaw, 2018; Rigby et al., 2016; Teece et al., 2016) along with the nature of these inter-related activities in support of continuous review and reallocation of resources (Rigby et al., 2016; Teece et al., 2016; Warner & Wäger, 2019). Additionally, the results support Rigby et al.'s (2016) observation that agile methodologies were becoming more pervasive, with companies adopting the various processes, techniques, and inter-related activities in their pursuit of supply chain innovation and organisational flexibility.

Consequently, the results for each sub-hypothesis informed the acceptance of the alternative hypothesis for H2. The digitised sub-capabilities all accurately and consistently measured the associated construct of DSZ. Finally, it heralded an additional, minor contribution towards developing a quantitative scale for DDC (Kump et al., 2018), in that correlations for each of the subdimensions were found to be statistically valid.

6.4.4. Hypothesis 3: Digital transforming

The third hypothesis sought to validate those lower order constructs (subdimensions) that support the construct of DTF (Autio et al., 2018; Birkinshaw, 2018; Dattée et al., 2018; Nambisan et al., 2017; Teece et al., 2016; Warner & Wäger, 2019), along with their individual, observable measures (as defined in each of the three sub-hypotheses). The first subdimension, innovation ecosystems, confirmed a statistically significant correlation between the three operationalised questions that were theorised to measure the construct. These three routines, expressed as 1) joining digital ecosystems, 2) interacting with multiple external partners, and 3) exploiting new ecosystem capabilities, were shown to be significantly correlated, supporting literature that expressed the need for updated governance processes which transformed the collaborative activities within firms (Birkinshaw, 2018). In addition, these highly correlated routines were in support of new schools of thought around business model innovation, which focused on digital networks that allow co-creation and collaboration opportunities with new partners, accelerating the speed of innovation and new business model development (Autio et al., 2018; Birkinshaw, 2018; Dattée et al., 2018; Nambisan et al., 2017; Warner & Wäger, 2019). Finally, these correlations supported the assertion that the prevalence of disruptive digital technologies was influencing the scope and purpose of DC, with new sets of activities that sought to empower business model innovation in previously unexplored ways (Vial, 2019; Velu, 2017; Warner & Wäger, 2019; Yeow et al., 2018).

Of particular interest to the research study were the results from the second sub-hypothesis of DTF. The subdimension: redesign internal structures, was measured through the following three indicators: 1) hire a chief digital officer [CDO], 2) digitise business models, and 3) design team-based structures. However, this was the only alternative hypothesis that needed to be conditionally accepted, after one of the items caused the subset of routines to fall below the cut-off point for the Cronbach's alpha value. Using the reliability item statistics as a reference, deleting the first item (hiring a

CDO) would significantly improve the measures' reliability, taking the overall score to 0.71. Conversely, the same scores indicated that the remaining two indicators reflected a high correlation with the construct. Consequently, within the selected sample, the activity of appointing a CDO did not seem to measure the associated construct in any statistically significant way.

While unexpected within the DDC process model context, this perspective did have some precursors in the literature. Singh et al. (2020) noted that despite the increasing number of firms appointing CDO to accelerate DT, few studies have examined their specific role and contribution. In addition, posited Singh et al. (2020), several challenges face CDOs, chief amongst which are the lack of horizontal coordination mechanisms within organisations, limiting alignment efforts. As a result, as suggested by Singh et al. (2020), it may simply be that there is little or no clarity on the design parameters required within organisations that would facilitate SDT initiatives by CDOs. From the findings of the study, this view seems to be supported by the data.

Finally, the results validated the third sub-hypothesis of DTF, which identified the three indicators for the subdimension: improve digital maturity as 1) identify digital workforce maturity, 2) external recruiting of digital natives, and 3) leverage digital knowledge inside firm. These results supported the literature that viewed routines dedicated to developing and improving digital proficiencies as critical to DST (Vial, 2019; Velu, 2017; Warner & Wäger, 2019; Yeow et al., 2018). In addition, the processes, supported by their statistically significant correlations, add to the literary perspective on digitally-focused leadership, along with the critical contribution this has to transformative efforts (Autio et al., 2018; Birkinshaw, 2018; Dattée et al., 2018; Nambisan et al., 2017; Singh et al., 2020; Teece et al., 2016; Warner & Wäger, 2019).

Consequently, the results for each sub-hypothesis informed the acceptance of the alternative hypothesis for H3. The digitised sub-capabilities all accurately and consistently measured the associated construct of DTF. Finally, it represented a further contribution towards the development of a quantitative scale for DDC (Kump et al., 2018), in that correlations for each of the subdimensions were found to be statistically valid.

6.5. MODERATION INTERACTION PER SUBDIMENSION

Having successfully validated the construct validity and correlation between the various dimensions and the concepts they measured, the final section in this chapter discusses the data concerning the last three hypotheses. The assumptions contained within this final set of hypotheses supported the main research question: what impact does DSC have on the relationship between DDC and SDT? The research question, which supported the primary research problem, sought to validate the reliability of the mechanisms confirmed in the previous section in a new context. More specifically, it hoped to support, through the data, the moderating impact of DSC on these constructs and their relationship to SDT.

The moderation interaction was assessed against each of the DDC subdimensions to expand on the reported statistical analysis. In doing so, the resulting analysis hoped to qualify the literature, which suggested that the contribution of individual subdimensions was amplified during times of exceptional change and disruption (Warner & Wäger, 2019). The results for each subdimension (along with the three main hypotheses) are detailed below.

6.5.1. Linear regression and multi-level model results

As with the previous section, to avoid repetition in the discussion of the results, common outcomes and shared conclusions are presented upfront. Multiple linear regression (Field, 2018; Hair et al., 2018) was carried out against each independent variable's composite indices. Using the resulting correlation coefficient, or adjusted R^2 (Field, 2018; Hair et al., 2018), each dependent variable's relative contribution to the dependent variable was evaluated. These contributions were then assessed against a multi-level model, wherein the impact on the relationship between the variables by the moderator was established (Field, 2018; Hair et al., 2018). A shared outcome was observed from these results for hypotheses 4, 5, and 6, and the alternative hypotheses for all three rejected. It should be noted that a single subdimension (that of "redesign internal structures") did reflect a statistically significant moderated interaction within its sub-hypothesis. In addition, the higher-order construct of DTF exhibited higher levels of significance (from the adjusted R^2) than either of the remaining two constructs. Ultimately, however, most of the sub-hypotheses for this argument failed to meet the minimum thresholds for significance and, as a result, the main alternative hypothesis (H6) was rejected. Thus, the null hypothesis for each hypothesis (4, 5, and 6) was accepted, with the implication that the data could not statistically validate the impact of the new contextual construct (DSC) on the existing theory.

The inference from these results was significant from both a theoretical and methodological perspective. First, the theoretical implications needed to be considered. The findings, which reflected either little or no statistically significant impact by the context of the research study on SDT, directly contradicted consensus in both business sources (Botes, 2020; Bogoshi, 2020; Courie, 2020; Dwolatzky & Harris, 2020; Gabriel, 2020; Goldstruck, 2020) and academic literature (Battisti & Deakins, 2017; Nenonen & Storbacka, 2020; Ritter & Pedersen, 2020). The results were also at odds with the antecedents to DDC, which speculated on the adverse impact of disruptive, rapid technological change on the ability of firms to deploy DC in the reconfiguration of their business models (Helfat & Raubitschek, 2018; Schilke et al., 2018; Teece, 2007; 2014; Vial, 2019; Yeow et al., 2018). Additionally, as suggested in the literature, selected capabilities (along with their routines, processes, and behaviours) would be either be amplified or diminished during times of sudden, unexpected disruption (Birkinshaw, 2018; Foss & Saebi, 2018; Kim & Min, 2015; Velu, 2017). The research study's statistical data could not validate these assumptions, as the moderated interaction was not present in any of the accepted null hypotheses (Zikmund et al., 2010). As it seemed unlikely that the research project would contradict established academic theory and foundational observations, the more likely origin of these results pointed to the study's methodological aspects.

Despite the relative strategic (and academic) importance of understanding the impact of crises on business model changes, little research had been done in this respect ahead of the COVID-19 crisis (Ritter & Pedersen, 2020, Pedersen et al., 2020). Consequently, it may be argued, the specific academic constructs around dramatic, external changes had not, yet, been clearly defined within the specific context sought in the research study. The research study adopted the concept of DSC (De la Sablonnière, 2017), along with its associated perspectives and theories, as moderator. Thus, it may be inferred that this construct's sociological and psychological roots did not transfer well to a quantitative measurement of a complex management issue with multiple attributes and dimensions (Zikmund et al., 2010). Additionally, the researcher attempted to define specific moderators within the survey instrument within the context of the three aggregate dimensions (Questions: MOD1, MOD2, and MOD3 in Appendix A). However, the data would suggest that these unidimensional measurements, per higher-order construct, were not sufficient to measure and reflect the desired moderated interaction accurately. While suggested remedies for addressing a possible, alternative moderator is discussed in the last chapter of this document, other methodological considerations need to be weighed as potential sources of the failed hypotheses tests.

Two considerations remain. As outlined at the start of this chapter, the sample may have introduced bias into the responses gathered by the study (Zikmund et al., 2010). Consequently, the disproportionate representation of technology-based firms in the population may infer a higher level of preparedness (Ritter & Pedersen, 2020) for a sudden external crisis than firms without a strong technological predisposition (Teece & Linden, 2017; Vial, 2019). Notwithstanding, the prevailing theory would suggest that some, observable, influence is inevitable in the face of massive supply chain disruptions and customer preference shifts (Battisti & Deakins, 2017; Nenonen & Storbacka, 2020; Ritter & Pedersen, 2020). Furthermore, as detailed in Chapter 5, normality tests were executed, with statistically significant deviations from the mean eliminated from the sample before linear regression was run. While normality is not a prerequisite for linear regression (Zikmund et al., 2010), any adverse influence on the resulting tests (by these outliers) would have been eliminated. The null hypotheses accepted for each of the three propositions could thus not be accounted for, statistically or theoretically, through the influence of bias alone.

The final remaining source of the anomalous results points to the flawed approach, detailed in Section 6.3, around the decision to adopt a unidimensional measure for the dependent variable. Measuring the relationship between the multiple independent variables against a single dependent variable, the research study restricted (by design) the depth of analysis that could be carried out on the resulting dataset. Specific nuances, inferences, interpretations, or contextual influences that may have influenced the respondents' answers cannot be accounted for, nor could any statistical conclusions be drawn outside of the single measured variable.

In closing, irrespective of the limitations implied by the null hypotheses, the results from the multiple linear regression still produced some insightful and relevant statistics, worthy of further consideration and discussion. Specifically, the prediction contribution percentages and model fit for each of the constructs deserve some investigation, as these do represent a tangible contribution. Accordingly, the following sections briefly outline a more granular view of each subdimension's outcome before moving on to the document's final chapter.

6.5.2. Hypothesis 4: Digital sensing and successful digital transformation

Hair et al. (2018) argued that establishing model fit (i.e., statistically acceptable parameters of relationship and significance) was required before a researcher could make inferences from the data. Within the context of hypothesis 4, all DSN subdimensions were deemed as a good fit for the construct being measured, falling below the maximum ANOVA threshold (Field, 2018; Hair et al., 2018). Although the null hypothesis was accepted for hypothesis 4 – with no statistically relevant moderation observed in the model comparison – each subdimension's predictive analytics still produced results relevant to the literature.

Specifically, the weights calculated against each subdimension (using model one, with no moderated interaction) illustrated a combined contribution to the overall, dependent construct by the independent DSN variables of 40%. The subdimension contributions were 12% (digital scouting), 14% (digital scenario planning), and 12% (digital mindset crafting) respectively. The relative contribution of these variables to SDT would imply that the digitised, technology-centric, sensing routines, processes, and behaviours proposed by the literature were statistically relevant (Birkinshaw et al., 2016; Day & Schoemaker, 2016; Dong et al., 2016; Giudici et al., 2018; Helfat & Raubitschek, 2018; Loebbecke & Picot, 2015; Warner & Wäger, 2019). Additionally, the significant contribution (40%) to SDT observed in the data supported research which highlighted the strategic contribution of sensing capabilities in the face of disruptive changes, unexpected shifts in consumer behaviour, or new technological trends (Birkinshaw et al., 2016; Day & Schoemaker, 2016; Dong et al., 2016; Giudici et al., 2018; Helfat & Raubitschek, 2018; Loebbecke & Picot, 2015; Teece, 2018; Teece & Linden, 2017; Vial, 2019; Yeow et al., 2018; Warner & Wäger, 2019).

Finally, although some literature cited digital mindset crafting as a prominent capability (Warner & Wäger, 2019) – without which the first step of DT would not be possible (Autio et al., 2018; Day & Schoemaker; 2016) – the data suggested otherwise. Within the aggregate dimension of DSN, the contribution of this subdimension (12%) to SDT was equal to that of the other two subdimensions (12% and 14%). Although this alluded to the potential of some intriguing, additional hypotheses around the contextual contribution of this independent variable (within the population and broader circumstances of COVID-19), the null hypothesis inferred that no further assumptions could be made from this result.

6.5.3. Hypothesis 5: Digital seizing and successful digital transformation

As with the previous hypothesis, the results for hypothesis 5 reflected that all DSZ subdimensions were a good fit for the construct being measured, falling below the maximum ANOVA threshold (Field, 2018; Hair et al., 2018). Although the null hypothesis was also accepted for hypothesis 5 – with no statistically relevant moderation observed in the model comparison – the predictive analytics for each subdimension of DSZ still produced results relevant to the literature.

The weights calculated against each subdimension (using model one, with no moderated interaction) illustrated a combined contribution to the overall dependent construct by the independent DSZ variables of 38%. The subdimension contributions were 5% (rapid prototyping), 13% (balance digital portfolios), and 20% (strategic agility) respectively.

The relative contribution of the variables indicates that, within the sample, rapid prototyping did not contribute as much to SDT as the other subdimensions. Accordingly, the development of minimum viable products – in response to consumers' changing demands (Birkinshaw, 2018; Rigby et al., 2016; Teece et al., 2016; Warner & Wäger, 2019) – was not seen as a significant seizing capability by the respondents. These results are likely attributable to the sample's composition within the research study, with disproportionate representation from the ICT, mining, and banking sectors. These industries, composed of highly commoditised (i.e., standardised) products could, arguably, derive less strategic value from this specific subdimension that other, comparable, firms. Unfortunately, further analysis was not possible beyond this initial observation within the defined constraints listed for both the dependent variable and population.

Conversely, the subdimension of strategic agility reflected the highest individual contribution to SDT against all the subdimensions included in the analysis (a total of 20%). This substantial influence on the dependent variable supported the academic consensus on the strategic importance of strategic agility (Birkinshaw, 2018; Rigby et al., 2016; Teece et al., 2016; Warner & Wäger, 2019), particularly as a response to external, disruptive DT (Helfat & Raubitschek, 2018; Karimi & Walter, 2015; 2016; Schilke et al., 2018; Teece, 2018; Teece & Linden, 2017; Vial, 2019; Velu, 2017; Yeow et al., 2018). In addition, this result supports the view of Rigby et al. (2016) that agile methodologies had becoming increasingly relevant to firms and validated the argument from Warner and Wäger (2019) that an agile approach would improve a firm’s redirection of its available resources to higher-yield, value-creating activities (Teece et al., 2016).

6.5.4. Hypothesis 6: Digital transforming and successful digital transformation

Finally, the results for hypothesis 6 reflected that all DTF subdimensions were a good fit for the construct being measured, falling below the maximum ANOVA threshold (Field, 2018; Hair et al., 2018). The null hypothesis was accepted for hypothesis 6, despite a single dimension reflecting an observed moderation interaction, as the overall effect was not seen as significant for the main hypothesis. Even with no statistically relevant moderation reported, the analytics for each DTF subdimension still produced compelling results.

The weights calculated against each subdimension (using model one, with no moderated interaction) illustrated a combined contribution to the overall, dependent, construct by the independent DTF variables of 18%. The subdimension contributions were 4%

(innovation ecosystem), 8% (redesign internal structures), and 6% (improve digital maturity) respectively.

Notably, the aggregate dimension of DTF was the only construct to reflect increases in the predicted contribution of each subdimension to the dependent variable when the moderation variable was considered (within model two). Innovation ecosystems reflected an increase from 4% to 5%, while redesign internal structures increased from 8% to 10% and, finally, improve digital maturity went from 6% to 8%. Additionally, the adjusted R^2 contributors were statistically more significant than any other independent variable (when measured against each of the three DTF predictors, or subdimensions). Despite these higher values against the subdimensions, only a single moderated interaction passed the statistical test for moderation.

Possibly then, even within the null hypothesis, the data hinted at a measure of moderation within the results for DTF, supporting observations from more recent literature that explored management actions in the aftermath of COVID-19 (Ritter & Pedersen, 2020; Pedersen et al., 2020; Rapaccini, Saccani, Kowalkowski, Paiola, & Adrodegari, 2020). This was further borne out by the single subdimension to achieve statistically significant moderation, that of redesign internal structures. Pedersen et al. (2020) have argued that historic operational activities could not successfully respond to the COVID-19 crisis, in support of this finding. Instead, they posited that changes were needed, focused on interconnected processes and innovative, cooperative solutions (Pedersen et al., 2020). Rapaccini et al. (2020) cautioned that these changes should not imply abandoning the traditional work paradigm but require, instead, the introduction of remote collaboration tools and a result-orientated culture. These contemporary academic perspectives, supported by the statistical results for DTF, build on the work of Autio et al. (2018), Dattée et al. (2018), Nambisan et al. (2017), and Warner and Wäger (2019), which reflected the need for digital processes to transform collaborative activities and interactions in firms. Additionally, the single moderated interaction supported the assertions within DSC's functional theory (De la Sablonnière, 2017). From this perspective, institutions that found themselves amid sudden disruptions to normative structures would attempt modifications within their behaviours and attitudes to restore equilibrium (De la Sablonnière, 2017) – an observation supported by the DTF data.

6.6. FINAL OBSERVATIONS

As detailed at the start of this chapter, the research study had two main objectives, as expressed in the defined sub-questions and their six hypotheses (Appendix B). First, it hoped to validate the digitised indicators that were hypothesised to measure distinct sub-capabilities within the multi-dimensional construct of DDC. The results obtained from SPSS, and detailed in the previous sections, displayed statistical validation of these purported relationships. In addition, the analysis confirmed the construct validity and accuracy with which they measured their specific subdimensions within DDC, meeting the objective of the sub-questions defined for the research study.

The primary research question was addressed in the second set of hypotheses, which sought to validate the proposed moderation of DSC on each of the subdimensions, as they related to SDT. Unfortunately, the constructs and relationships defined within the conceptual model failed to statistically validate the relative impact of the moderators on each subdimension, despite achieving a good model fit. Disappointing as these results were within the context of the stated research problem, the study still produced some relevant contributions. The validation of the operationalised variables from the DDC process model, along with the statistically significant contributions of the dependant variables to SDT, produced considerations for both practical and academic applications. From these results, the concluding chapter summarises both the relevant contributions and limitations derived from the data.

CHAPTER 7 : CONCLUSION

7.1. INTRODUCTION

Hair et al. (2018) cautioned researchers that, even in instances where acceptable statistical parameters were met, inferences and conclusions were still bound to the proposed models, scales, and instruments contained within the research. Academic knowledge advanced only when the observed processes were subjected to repeated analyses and validation (Hair et al., 2018). Therefore, researchers should not be dissuaded if their models fail to predict (or improve upon) existing theories accurately, the authors suggested (Hair et al., 2018; Zikmund et al., 2010). Rather, they proposed, these experimental activities are built upon the principles of the “scientific method”, supported by a continuous search for truth around business phenomena (Hair et al., 2018; Zikmund et al., 2010). An objective review of the results (along with their contextual assumptions and implications) was needed to ensure sound analysis of the data, which would result in meaningful contributions to theory development (Hair et al., 2018).

With this perspective on mind, this concluding chapter of the research study humbly summarises the proposed contributions, as detailed in the discussions from the previous pages. The research study also acknowledges, pragmatically, the perceived limitations and flaws that became evident within the assessment of the various models and constructs. The results presented in these final sections are thus contextualised within the prevailing theory around DC and DDC, along with some suggested areas for application, replication, and improvement.

7.2 THEORETICAL IMPLICATIONS AND CONTRIBUTIONS

7.2.1 Digitised dynamic capabilities - Subdimension correlation and construct validity

Within the first three hypotheses (H1, H2, and H3), the research study hoped to translate the qualitative DDC process model developed by Warner and Wäger (2019) into a quantitative conceptual model. In operationalising the various higher-order constructs, their subdimensions, and associated discrete indicators, the study would build on existing theory in two ways. First, through a quantitative validation of the DDC constructs, their correlations and measurements, the research would contribute to the theory of DDC, along with its contextual contribution to DT (Warner & Wäger, 2019). Secondly, the data would contribute to the growing body of work exploring the various aspects, applications, and theoretical constructs of DC (Teece, 2007; 2014; 2018; Teece & Linden

2017; Teece et al., 1997; Teece et al., 2016), along with its association to DT as a strategic response to external, disruptive change (Helfat & Raubitschek, 2018; Schilke et al., 2018; Vial, 2019; Yeow et al., 2018). Accordingly, the research objective was structured around the statistical validation of those theoretical constructs that could move the scientific discussion forward in identifying digitally-focused DC that support DT, along with the observable routines that sustain them. The individual contributions, per hypothesis, are listed below.

This research study contributes to the academic literature by confirming that a statistically relevant correlation existed between the three subdimensions of DSN, as proposed by Warner and Wäger (2019). In addition, the specific routines, processes, and behaviours associated with each lower-order construct were found to achieve construct validity, accurately measuring the variables related to them. These findings contribute a contextual perspective on the body of work around the digitised sub-capabilities that support sensing competencies in firms (Day & Schoemaker, 2016; Nambisan et al., 2017; Teece, 2007; 2014; 2018; Teece & Linden 2017; Teece et al., 1997; Teece et al., 2016; Warner & Wäger, 2019). Finally, it contributes to the literature that seeks to gain a deeper understanding into the various, observable routines that support DSN in times of disruptive DT (Birkinshaw et al., 2016; Day & Schoemaker, 2016; Dong et al., 2016; Giudici et al., 2018; Helfat & Raubitschek, 2018; Loebbecke & Picot, 2015; Nambisan et al., 2017; Warner & Wäger, 2019).

Additionally, the research study contributes to the academic literature by confirming that a statistically relevant correlation existed between the three subdimensions of DSZ, as proposed by Warner and Wäger (2019). In addition, the specific routines, processes, and behaviours associated with each lower-order construct were found to achieve construct validity, accurately measuring the variables associated with them. These findings contribute a contextual perspective on the body of work around the digitised sub-capabilities that support seizing competencies in firms (Birkinshaw, 2018; Rigby et al., 2016; Teece, 2007; 2014; 2018; Teece & Linden 2017; Teece et al., 1997; Teece et al., 2016; Warner & Wäger, 2019). Finally, it contributes to the literature that seeks to gain a deeper understanding into the various, observable routines that support DSZ in times of disruptive DT (Birkinshaw, 2018; Rigby et al., 2016; Teece et al., 2016; Warner & Wäger, 2019).

Finally, the research study contributes to the academic literature by confirming that a statistically relevant correlation existed between the three subdimensions of DTF, as proposed by Warner and Wäger (2019). In addition, the specific routines, processes, and behaviours associated with each lower-order construct were found to achieve construct validity, accurately measuring the variables associated with them. These findings contribute a contextual perspective on the body of work around the digitised sub-capabilities that support transforming competencies in firms (Autio et al., 2018; Birkinshaw, 2018; Dattée et al., 2018; Nambisan et al., 2017; Teece, 2007; 2014; 2018; Teece & Linden 2017; Teece et al., 1997; Teece et al., 2016; Warner & Wäger, 2019). Additionally, it contributes to the literature that seeks to gain a deeper understanding into the various, observable routines that support DTF in times of disruptive DT (Schilke et al., 2018; Vial, 2019; Velu, 2017; Warner & Wäger, 2019; Yeow et al., 2018).

7.2.2 Contribution and moderated interaction per subdimension

The second set of hypotheses (H4, H5, and H6) – which supported the main research problem – attempted to build on the existing theory of DC (Teece, 2007; 2014; 2018; Teece & Linden 2017; Teece et al., 1997; Teece et al., 2016) and DDC (Autio et al., 2018; Birkinshaw et al., 2016; Dattée et al., 2018; Day & Schoemaker, 2016; Dong et al., 2016; Giudici et al., 2018; Helfat & Raubitschek, 2018; Loebbecke & Picot, 2015; Nambisan et al., 2017; Rigby et al., 2016; Warner & Wäger, 2019) with the introduction of DSC (De la Sablonnière, 2017) as a new substantive moderator. Through the introduction of this moderated interaction, the research study hoped to validate (and measure) the impact of the COVID-19 crisis on existing relationships and management routines (Battisti & Deakins, 2017; Nenonen et al., 2020; Ritter & Pedersen, 2020; Pedersen et al., 2020; Rapaccini et al., 2020) as seen within the context of DDC.

Ultimately, the null hypothesis would be accepted for each of the arguments, suggesting that the research study failed to statistically validate the proposed moderated interaction (Ritter & Pedersen, 2020; Pedersen et al., 2020; Rapaccini et al., 2020). However, as each of the variables achieved an excellent statistical fit (Hair et al., 2018) within the conceptual model (i.e., their contribution to the dependent variable), the findings were, nonetheless, relevant to the theory for DDC. The individual contributions, per hypothesis, are listed below.

The research study contributes to the academic literature by confirming the relative contribution of the three subdimensions of DSN to the dependent variable SDT. In doing so, the study has added to research on digitised, technology-centric sensing routines, processes, and behaviours (Birkinshaw et al., 2016; Day & Schoemaker, 2016; Dong et al., 2016; Giudici et al., 2018; Helfat & Raubitschek, 2018; Loebbecke & Picot, 2015; Warner & Wäger, 2019). Additionally, the results contribute to the research which sought to understand the contribution of sensing capabilities in the face of disruptive changes, unexpected shifts in consumer behaviour, or new technological trends (Birkinshaw et al., 2016; Day & Schoemaker, 2016; Dong et al., 2016; Giudici et al., 2018; Helfat & Raubitschek, 2018; Loebbecke & Picot, 2015; Teece, 2018; Teece & Linden, 2017; Vial, 2019; Yeow et al., 2018; Warner & Wäger, 2019).

Furthermore, the research study contributes to the academic literature by confirming the relative contributions of the three subdimensions of DSZ to the dependent variable SDT. In doing so, the study has added to research on digitised seizing routines, with specific validation on the contribution of strategic agility as a lower-order construct within DSZ (Birkinshaw, 2018; Rigby et al., 2016; Teece et al.; 2016; Warner & Wäger, 2019). Moreover, the data adds to the academic consensus around strategic agility as a significant enabler for effective responses to external, disruptive DT (Helfat & Raubitschek, 2018; Karimi & Walter, 2015; 2016; Rigby et al., 2016; Schilke et al., 2018; Teece, 2018; Teece & Linden, 2017; Vial, 2019; Velu, 2017; Yeow et al., 2018).

Finally, the research study contributes to the academic literature by confirming the three subdimensions of DTF's relative contributions to the dependent variable SDT. In doing so, the study has added to research on those digital processes that were deployed in firms to transform collaboration, interaction, and culture (Autio et al., 2018; Dattée et al., 2018; Nambisan et al., 2017; Warner & Wäger, 2019). Additionally, the single moderated interaction (against the subdimension: redesign internal structures) supported the assertions within the functional theory of DSC (De la Sablonnière, 2017), along with a contribution to the literature on the development of interconnected processes and innovative, cooperative solutions in response to crises (Autio et al., 2018; Dattée et al., 2018; Nambisan et al., 2017; Ritter & Pedersen, 2020; Pedersen et al., 2020; Rapaccini et al., 2020; Warner & Wäger, 2019).

Consequently, although the research study failed in its objective to validate the main research problem, it still achieved a moderate level of theory building (Colquitt & Zapata-Phelan, 2007) through the application of the DDC process model (Warner & Wäger, 2019) within a broader context. Through statistical validation of the model in a dynamic, localised, environment, the research study directly addressed a research gap identified in the Warner and Wäger (2019) paper, adding a minor contribution to the overall academic discourse around this relevant topic.

7.3 IMPLICATIONS FOR MANAGEMENT

The research study set out to answer Singh and Hess's (2017) call for a specific framework of activities that support dynamic competencies in organisations. These sets of inter-related actions should, the authors argued, facilitate the development (and deployment) of specific competencies in pursuit of opportunities that arose from digital disruption (Singh & Hess, 2017). From the data gathered through the various hypotheses, the research study statistically validated a set of 26 discrete and observable organisational routines. These digitised practices collectively and consistently measured not only the three aggregate dimensions of DC (Teece, 2007; 2014; 2018; Teece & Linden 2017; Teece et al., 1997; Teece et al., 2016) but also their contribution to SDT. In addition, the study was able to quantitatively define and verify the nine sub-capabilities that support these aggregate dimensions, measured through 26 digital processes, behaviours, and organisational routines (Autio et al., 2018; Birkinshaw et al., 2016; Dattée et al., 2018; Day & Schoemaker, 2016; Dong et al., 2016; Giudici et al., 2018; Helfat & Raubitschek, 2018; Loebbecke & Picot, 2015; Nambisan et al., 2017; Rigby et al., 2016; Warner & Wäger, 2019).

From these verified results, the research study humbly proposes that the latent constructs, defined within the context of this study, represent an academically-grounded contribution towards a practical, strategic, digitised framework of DC for SDT. While the DC construct was well-established and widely adopted within the business and academic literature, the COVID-19 crisis renewed the urgency for a deeper context to those capabilities specifically focused on DT and disruptive, technological change (Ritter & Pedersen, 2020; Pedersen et al., 2020; Rapaccini et al., 2020). The findings further validated the perspective that DT is fundamentally grounded in strategy, not technology (Rogers, 2016; Singh et al., 2020). Additionally, the study contributes to the literature that views disruptive, digitised, business model transformations as a strategic imperative for senior managers (Vial, 2019). Moreover, the results validated those (26) discrete strategic actions (along with their 9 sub-competencies) that support changes to an organisation’s structure, processes, and culture to generate new paths for digital value creation (Vial, 2019; Warner & Wäger, 2019).

Finally, the results supported the significant impact of a specific sub-capability, strategic agility, in its singular contribution to the transformative efforts of DT. As businesses struggled, in the aftermath of COVID-19, with new challenges around collaboration, digital readiness, supply chain shifts, and fluid consumer preferences (Ritter & Pedersen, 2020; Pedersen et al., 2020; Rapaccini et al., 2020), a clear strategic direction was required. Consequently, as suggested by the literature (Rigby et al., 2016; Teece et al., 2016), and validated in the research study, the deployment of agile methodologies was the single most influential and impactful action available to firms, as this would accelerate the successful redirection of their available resources to higher-yield, value-creating, activities.

7.4 LIMITATIONS

7.4.1 Methodological limitations

The first methodological limitation, inherent to the quantitative nature of the research project, was the survey questionnaire, with its subset of 35 standardised questions, which produced results without the additional insights, commentary, and detail to support the scope of responses. Specific nuances, perceptions, and complexities associated with the strategic impact of the COVID-19 crisis were, therefore, excluded from the quantitative study.

In addition, due to the time-constraints of the research project, the resulting cross-sectional study did not explore the various antecedents for SDT that preceded the COVID-19 crisis, nor did it confirm the continued (long-term) success of any DT initiatives launched during the lockdown.

The non-probability approach adopted for the research study resulted in a skewed sample, with potential bias in responses from three dominant represented industries. Consequently, the lack of a broader, randomised sample limited the comparative analytics that were available to the research study across various sectors, company sizes, and ownership structures. Specifically, the perspective of entrepreneurial businesses was under-represented in the resulting sample, excluding an important contextual contribution from these smaller firms within the COVID-19 crisis.

A significant consequence of the snowballing technique, adopted for the collection of responses outside the initial sample, was that a substantial percentage of invalid replies had to be excluded from the analysis. This reduced the overall sample size and eliminated selected parametric techniques (such as SEM) from the final report – due to the sample falling below the threshold of 200 responses.

A final consequence of the defined population and sampling technique is that it excluded replies from firms outside the borders of South Africa. The COVID-19 crisis is a global phenomenon, with widespread structural and strategic implications. Consequently, the hypotheses were restricted to a specific geographical context, with resulting methodological limitations on the resulting validation of the identified variables and relationships.

In conclusion, the researcher acknowledges their own limitations and fallibility within the emerging field of management science that focuses on navigating disruptive crises using DT. This constraint could have had an unintended impact on the resulting design, definition, and formation of selected constructs applied to the survey instrument, compounded by several theoretical limitations. These specific restrictions are briefly explored in the succeeding section.

7.4.2 Theoretical limitations

Within the quantitative scale developed for the research study, no antecedent variables were included for consideration and measurement. Consequently, the results included no perspective on any preceding theoretical constructs (or variables) that could help to explain the relationship between the independent or dependant variables (Hair et al., 2018). Within the specific context of the research problem, an important antecedent that may need to be considered is that of DT. The responses reflected an unexpected bias towards successful execution of DT across all entities represented in the sample. This could be indicative of a significant theoretical limitation within the study, as different perceptions, interpretations, or definitions of DT may have resulted in biased responses. Quantitative measurement of the various environmental, structural, and conceptual precursors that contextualise DT would have added additional perspective to the results.

In a similar vein, the operationalisation of the DDC process model (Warner & Wäger, 2019) excluded several contextual factors detailed in their final, qualitative framework. These elements (labelled as internal constructs in Figure 2) could have been incorporated as mediating variables within the conceptual model, measured through items on the resulting scale. In excluding these from the model adopted for the research study, an additional perspective was lost on the predictive effect on the dependent variable (through those mediator mechanisms) from the independent variables.

As was evident from the data obtained from the DTF construct validity tests, the routines related to the appointment of a CDO (under the subdimension: redesign internal structures) were judged not to adequately measure the associated concept. The indicator was thus excluded from the item total for this higher-order construct. As a result, the data is limited in its analysis and exploration of the various structures, roles, and mechanisms associated to this specific DDC indicator (Singh et al., 2020; Warner & Wäger, 2019). Re-framing the questions that measure this item within the survey instrument may have produced more insightful data.

In adopting a unidimensional dependant variable, the research study imposed a limitation on the analytics and statistical validations that could be carried out against the associated construct. The single question included in the survey instrument omitted the multi-dimensional aspects of SDT specified in the DDC process model. As a result, contextual, statistical assessment was not available in the data against the three attributes specified by Warner and Wäger (2019) – 1) business model renewal, 2) collaborative approach renewal, and 3) culture renewal.

The acceptance of the null hypotheses against hypotheses 4, 5, and 6 represent the most significant limitation of the research study. More specifically, the subset of arguments that sought to measure the moderation interaction of DSC against the defined constructs failed to be statistically verified. By implication, the exploration of the moderating effect, brought about by COVID-19, on the execution of DT could not be substantiated within the results. Consequently, the main research question sought in the research project could not be answered.

7.5 SUGGESTIONS FOR FUTURE RESEARCH

Based on the observations and limitations detailed in the preceding sections, the researcher recommends the following opportunities for future research that could expand, or improve upon, the results presented for this research study.

Future research could adopt a qualitative approach to replicate the DDC process model within a comparable, highly dynamic environment. By applying the DDC process model, along with its qualitative framework, to a South African context, the application and analysis of one-on-one interviews could produce further validation of the DDC context, along with additional perspectives and insights into the various mechanisms that develop, deploy, and support DDC in times of disruptive change.

Should researchers prefer to adhere to a quantitative methodology, some opportunities exist to enhance the study even further within this context. First, randomised probability sampling would assist in obtaining additional perspectives and responses from a broader base of firms and industries. In doing so, the results from the current study would act as a compelling basis for comparative analytics and validation. It would also allow future research to explore additional analytics, with comparative statistical data, to investigate the variance in DT efforts between different industries, firm sizes, etc. Furthermore, extending the population to include firms outside the borders of South Africa could introduce broader insights and data that would contribute, significantly, to the theoretical constructs of DDC and DT. Additionally, should the research not be bound to a limited timeframe, a longitudinal study – which explores the various DDC antecedents as well as the long-term effects of DT – could statistically validate important constructs and introduce relevant contributions to the field of DC.

Finally, future research could address some of the limitations inherent to the constructs (and relationships) defined within the conceptual model for the research project. The substantive moderator adopted for the research should be substituted with an academic construct supported by a more extensive set of qualified measurements, subdimensions, and indicators. In doing so, the moderated interaction theorised within the context of the main research problem could be explored, and validated, in more detail than was the case in the reported results. Future researchers should explore the more contemporary literature that followed the events of the COVID-19 crisis to establish if more quantitative constructs could be applied in this context. In addition, the dependent variable of SDT could be expanded into a multi-dimensional construct which reflects the various, complex attributes and relationships within this concept. In conclusion, future research could consider the inclusion of mediators within the operationalised model. These mediators could, by example, introduce internal contextual factors within the DDC process model, and assess the impact of these on the relationships between the independent and dependent variables.

7.6 CONCLUDING REMARKS

When the research project was first conceptualised in May of 2020, the impact of the COVID-19 crisis – on both academic and management perspectives – was still largely unknown. While some theoretical precedents had explored the strategic influence of disasters within the context of the 2008 financial crisis or, alternatively, from the perspective of localised natural disasters, it became increasingly evident that the business world had never experienced events quite like those in 2020.

While contemporary authors have recently attempted to define some academic context, along with proposed frameworks and models to understand the dynamics associated with the (ongoing) epidemiological crisis (Nenonen et al., 2020; Ritter & Pedersen, 2020; Pedersen et al., 2020; Rapaccini et al., 2020), a lot of work remains to be done. As the new theories grow in influence and replicability, numerous opportunities remain to expand upon the various academic perspectives and constructs within this unprecedented, disruptive, environment. Moreover, as highlighted in the results of this study, the digitised aspects of DC remain a relevant, impactful, and important area of study, particularly in its contribution as a strategic response to external, technological change. Flawed as though aspects of the research instrument may have been, the data still hints at some compelling, academically relevant contributions which deserve continued replication, improvement, and validation.

As Rapaccini et al. (2020) soberly reflected, the post-COVID world will never be the same for businesses. Consequently, as suggested by both the literature and the data presented in this study, firms need to evolve and adapt, create new practices, reconfigure established models, and establish radical new networks if they have any hope to develop the flexibility required for survival in this “new normal” (Ritter & Pedersen, 2020; Pedersen et al., 2020; Rapaccini et al., 2020).

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APPENDICES

Appendix A - Survey Questionnaire

QUESTION NO.	CATEGORY	HYPOTHESIS	DESCRIPTOR SUB-CAPABILITY	QUESTION
INFORMED CONSENT STATEMENT – Click on button with label: I AGREE TO THE ABOVE [Alternative will exit survey]				
1	COV1	C1	CONTROL_VAR1	I am conducting research into the various capabilities that contribute to successful digital transformation in South African firms. In addition, the research aims to understand the impact on these efforts by the COVID-19 epidemiological crisis. To that end, you are requested to complete a survey that seeks to explore the various digitised capabilities, and the influence of COVID-19 on each of these. This will contribute to the body of knowledge aiming to understand the impact of localised dramatic social change on digital projects and should take no more than 10 minutes of your time. Your participation is voluntary, and you can withdraw at any time without penalty. Your participation is completely 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, using the contact details supplied below.
DEMOGRAPHIC ORDINAL QUESTIONS – Selection from pre-populated drop-down boxes				
2	COV2	C2	CONTROL_VAR2	What Industry does your company operate in?
3	DEM1	D1	DEMOGRAPH_1	Which of the following best describes your current role in your company?
4	DEM2	D2	DEMOGRAPH_2	Have you personally been involved with, or overseen, one or more digital transformation projects over the last 6 months?
INTERVAL QUESTIONS – 6-point Likert scale, ranging from "strongly disagree" [1] to "strongly agree" [6]				
5	SDT1	S1	SUCCESS_DT	Most of the digital transformation initiatives within my company are a success
6	DSN1	H1	DIG_SCOUTING	My company continuously scans for new or emerging technological trends
7	DSN2	H1	DIG_SCOUTING	My company continuously screens for potential digital competitors
8	DSN3	H1	DIG_SCOUTING	My company regularly, and correctly, senses customer-centric trends
9	DSN4	H1	DIG_SCEN_PLN	My company is good at analysing and interpreting digital scouting signals
10	DSN5	H1	DIG_SCEN_PLN	My company is good at developing and interpreting digital future scenarios
11	DSN6	H1	DIG_SCEN_PLN	My company is good at formulating digital strategies
12	DSN7	H1	DIG_MND_CRAF	My company has established a long-term digital vision
13	DSN8	H1	DIG_MND_CRAF	My company is supportive of an entrepreneurial mindset
14	DSN9	H1	DIG_MND_CRAF	My company actively promotes a digital mindset
15	MOD1	H4	MOD_SENSING	The dramatic social change brought about by COVID-19 has had an impact on the digital trends and consumer behaviour in my industry

Appendix A - Survey Questionnaire (continued)

16	DSZ1	H2	RAPID_PROTOT	As a company, we create minimum-viable-products for digital prototyping
17	DSZ2	H2	RAPID_PROTOT	As a company, we actively support a lean “start-up” mindset or approach
18	DSZ3	H2	RAPID_PROTOT	As a company, we make use of a digital innovation laboratory
19	DSZ4	H2	BAL_DIG_PORT	My company is good at balancing internal & external digital options
20	DSZ5	H2	BAL_DIG_PORT	My company is good at quickly scaling up innovative business models
21	DSZ6	H2	BAL_DIG_PORT	My company always sets up appropriate speed of execution within our various digital portfolios
22	DSZ7	H2	STRA_AGILITY	My company is agile in its capability to rapidly reallocate resources
23	DSZ8	H2	STRA_AGILITY	My company is agile in its capability to accept redirection and change
24	DSZ9	H2	STRA_AGILITY	My company is agile in its capability to adequality pace strategic responses
25	MOD2	H5	MOD_SIEZING	The dramatic social change brought about by COVID-19 has had an impact on strategic planning and speed of execution within my company
26	DTF1	H3	NAV_INNO_ECO	My company has joined, or actively participates in, an external digital ecosystem
27	DTF2	H3	NAV_INNO_ECO	My company regularly interacts with multiple external partners around innovation
28	DTF3	H3	NAV_INNO_ECO	My company has successfully exploited new digital eco-system capabilities
29	DTF4	H3	RED_INT_STRC	My company currently has, or will soon appoint, a Chief Digital Officer
30	DTF5	H3	RED_INT_STRC	My company actively pursues the digitisation of existing business models
31	DTF6	H3	RED_INT_STRC	My company actively designs internal structures around cross-functional teams
32	DTF7	H3	IMPR_DIG_MAT	My company actively assesses and evaluates our digital workforce maturity
33	DTF8	H3	IMPR_DIG_MAT	My company often recruits external digital natives to improve our digital maturity
34	DTF9	H3	IMPR_DIG_MAT	My company actively leverages off, and develops, in-house knowledge and capabilities to improve our digital maturity
35	MOD3	H6	MOD_TRANSFO	The dramatic social change brought about by COVID-19 has changed the way our teams communicate, manage, and support new ideas

Appendix B - Operationalisation of Variables: Operational Dictionary

Construct	Variable	Measurement Instrument Descriptor	Measurement Instrument Category	Conceptual Definition	Operational Definition Please indicate much you agree or disagree with each of the following statements:
Digital Sensing	Digital Scouting	DIG_SCOUTING	DSN1 – DSN3	In the digital age, firms face an increased urgency to develop digitised sensing capabilities (Nambisan, Lyytinen, Majchrzak, & Song, 2017; Warner & Wäger, 2019). Developing capabilities in both digital scouting and digital scenario planning will facilitate rapid sense-making of unexpected technological developments in dynamic environments (Dong, Garbuio, & Lovallo, 2016; Monteiro & Birkinshaw, 2017; Warner & Wäger, 2019). Digital mindset crafting incorporates the classic principles of strategic thinking from Mintzberg (1994), and highlights the necessity of new, digitised, types of strategic thinking that are required to counter disruptive, external, threats (Kane et al., 2017). In addition to these strategic functions, posit Warner and Wäger (2019), digital sensing capabilities require digital mindset crafting. This capability is enhanced by the presence of digitally capable, cross-functional, teams but may be constrained by hierarchical, inflexible, strategic planning processes (Warner & Wäger, 2019).	1. My company continuously scans for new or emerging technological trends 2. My company continuously screens for potential digital competitors 3. My company regularly, and correctly, senses customer-centric trends 4. My company is good at analysing and interpreting digital scouting signals 5. My company is good at developing and interpreting digital future scenarios 6. My company is good at formulating digital strategies 7. My company has established a long-term digital vision 8. My company is supportive of an entrepreneurial mindset 9. My company actively promotes a digital mindset
	Digital Scenario Planning	DIG_SCEN_PLN	DSN4 – DSN6		
	Digital Mindset Crafting	DIG_MND_CRAF	DSN7 – DSN9		

Appendix B (continued) – Operationalisation of Variables: Operational Dictionary

<table>
<tr><th rowspan="2">Construct</th><th rowspan="2">Variable</th><th rowspan="2">Measurement Instrument Descriptor</th><th rowspan="2">Measurement Instrument Category</th><th rowspan="2">Conceptual Definition</th><th>Operational Definition</th></tr>
<tr><th>Please indicate much you agree or disagree with each of the following statements:</th></tr>
<tr><td rowspan="3">Digital Seizing</td><td>Rapid Prototyping</td><td>RAPID_PROTOT</td><td>DSZ1 – DSZ3</td><td rowspan="3">The development of digital seizing capabilities is “contingent on pacing strategic actions” state Warner and Wäger (2019, p. 345), a view which is supported by research on dynamic capabilities within hyper-competitive environments (Eisenhardt & Martin, 2000; Peteraf, Stefano, & Verona, 2013). Furthermore, time-pacing skills should facilitate the creation of profitable product development cycles for firms, with a focus on rapid prototyping, constant redirection, and the ability to balance multiple digital portfolios (Eisenhardt & Martin, 2000; Peteraf, Stefano, & Verona, 2013; Warner & Wäger, 2019).

Finally, strategic agility is seen as a critical dynamic capability for seizing new digital trends (Warner & Wäger, 2019). Fast decision making enables firms to seize technological opportunities, which further supports the contribution of strategic agility to successful transformative efforts in conditions of deep uncertainty (Rigby, Sutherland, & Takeuchi, 2016; Teece, Peteraf, & Leih, 2016). Strategic agility, posits Teece et al. (2016), is the primary catalyst for continued business model innovation.</td><td rowspan="3">1. As a company, we create minimum-viable-products for digital prototyping
2. As a company, we have considered a lean start-up methodology or approach
3. As a company, we make use of a digital innovation laboratory
4. My company is good at balancing internal & external digital options
5. My company is good at quickly scaling up innovative business models
6. My company always sets up appropriate speed of execution within our various digital portfolios
7. My company is agile in its capability to rapidly reallocate resources
8. My company is agile in its capability to accept redirection and change
9. My company is agile in its capability to adequality pace strategic responses</td></tr>
<tr><td>Balancing digital portfolios</td><td>BAL_DIG_PORT</td><td>DSZ4 – DSZ6</td></tr>
<tr><td>Strategic Agility</td><td>STRA_AGILITY</td><td>DSZ7 – DSZ9</td></tr>
</table>

Appendix B (continued) – Operationalisation of Variables: Operational Dictionary

Construct	Variable	Measurement Instrument Descriptor	Measurement Instrument Category	Conceptual Definition	Operational Definition Please indicate much you agree or disagree with each of the following statements:
Digital Transforming	Navigating innovation ecosystems	NAV_INNO_ECO	DTF1 – DTF3	"Digital transformation involves the ongoing strategic renewal of a firms' business model, collaborative approach, and eventually, the culture" (Warner & Wäger, 2019, p. 345). Moreover, Warner and Wäger (2019) specifically highlight the importance of navigating and participating in collaborative innovation ecosystems, an emerging capability within the DT context which supports and facilitates radical business model innovation (Autio, Nambisan, Thomas, & Wright, 2018; Dattée, Alexy, & Autio, 2018; Nambisan et al., 2017). Finally, improving the digital maturity of the workforce is a fundamental dynamic capability for ongoing DT (Warner & Wäger, 2019). This is supported by research on management innovation, which identifies the building of new digital governance capabilities as a key enabler for the DT of internal collaborative approaches and culture shifts (Birkinshaw, 2018; Warner & Wäger, 2019).	1. My company has joined, or actively participated in, a digital ecosystem 2. My company regularly interacts with multiple external partners around innovation 3. My company has successfully exploited new digital ecosystem capabilities 4. My company currently has, or will soon appoint, a Chief Digital Officer 5. My company actively pursues the digitisation of existing business models 6. My company actively designs team-based structures 7. My company actively assesses and evaluates digital workforce maturity 8. My company often recruits external digital natives to improve our digital maturity 9. My company actively leverages off, or develops, in-house knowledge and capabilities to improve our digital maturity
	Redesigning internal structures	RED_INT_STRC	DTF4 – DTF6		
	Improving digital maturity	IMPR_DIG_MAT	DTF7 – DTF9		

Appendix B (continued) – Operationalisation of Variables: Operational Dictionary

Construct	Variable	Measurement Instrument Descriptor	Measurement Instrument Category	Conceptual Definition	Operational Definition Please indicate much you agree or disagree with each of the following statements:
Dramatic Social Change	Moderator	MED_SENSING	MOD1	DSC: A situation where a rapid event leads to profound societal transformation, producing a rupture in the equilibrium of social and normative structures (De la Sablonnière, 2017). Functionalist theory: Society is in a constant state of equilibrium. When a change occurs in one part of society, adjustments are made – social change occurs when the equilibrium is compromised due to the rapidity with which events occur (Parsons, 2010).	Using the nine contextual factors identified by Warner and Wäger (2019) – which represent the various triggers, enablers, and barriers of building DC for DT, as illustrated in Figure 2 – the following questions were derived for each of the three, primary, aggregate dimensions associated with DDC. This was done so that the survey could assess the impact of DSC on each construct, using the various theories and concepts of DSC as part of the consideration:
		MED_SEIZING	MOD2	Adjustment to change theory: Considers how individuals adjust to DSC and argues that factors (such as the nature of the event) predict the way individuals and groups evaluate and respond to social change (Goodwin, 2006).	1. The dramatic social change brought about by COVID-19 has had an impact on the digital trends and consumer behaviour in my industry 2. The dramatic social change brought about by COVID-19 has had an impact on strategic planning and speed of execution within my company
		MED_TRANSFO	MOD3	DC may be regarded as a multi-dimensional construct, reflected in the interrelated capacities of sensing, seizing, and transforming (Kump et al., 2018; Teece, 2007; Teece et al., 1997). Furthermore, DC may be viewed as a set of latent capacities, manifested in observable routines and their associated outcomes (Kump et al., 2018; Teece, 2007; Teece et al., 1997).	3. The dramatic social change brought about by COVID-19 has changed the way our teams communicate, manage, and support new ideas

Appendix C - Consistency Matrix

Sub-Question/s	References	Hypothesis (and sub-hypotheses)	Source of Data	Type of Data	Statistical Analysis: IBM SPSS
Population Demographics & Control Variable	Beavers et al. (2013) Becker (2005) Creswell (2014) Creswell and Creswell (2018) Field (2018) Hair et al. (2018) Schwab (2004) Sousa (2010) Zikmund et al. (2010)	Informed consent statement, along with relevant demographic details of respondents – used for validation of suitability for research study, as well as control variable to exclude selected industries identified in research design	Questionnaire Survey: **COV1 –> COV2** *Q1 / Q2* **DEM1 –> DEM2** *Q3 / Q4*	Ordinal (Q1-Q4) Selection from pre-populated list (Q2 and Q3) or radio buttons with pre-defined answers (Q1 and Q4)	Ordinal: Frequency, %, x^2
What are the various routines and processes that may be used to predict or measure the subdimensions of **digital sensing**?	**Literate Review:** Autio et al. (2018) Birkinshaw (2018) Dattée et al. (2018) Dong et al. (2016) Eisenhardt and Martin (2000) Kane et al. (2017) Monteiro and Birkinshaw (2017) Nambisan et al. (2017) Peteraf et al. (2013) Rigby et al. (2016) Teece (2007, 2018) Teece and Linden (2017) Teece et al. (2016) Teece et al. (1997) Velu (2017) Vial (2019) Warner and Wäger (2019)	**H1:** The contribution of the higher-order construct: **digital sensing** towards the dependent variable: **successful digital transformation,** can be measured through three distinct subdimensions: **H1.1:** *The lower-order construct (subdimension) of* ***digital scouting*** *can be measured through three discrete operationalised indicators: 1) scanning for technological trends, 2) screening of digital competitors, and 3) sensing customer-centric trends* **H1.2:** *The lower-order construct (subdimension) of* ***digital scenario planning*** *can be measured through three discrete operationalised indicators: 1) analysing scouted signals, 2) interpreting digital future scenarios, and 3) formulating digital strategies*	Questionnaire Survey: **DSN1 –> DSN9** *Q6 / Q7 / Q8* *Q9 / Q10 / Q11* *Q12 / Q13 / Q14*	Scale (2 decimal points) Interval Likert-scale rating *Strongly Agree* ***7*** *Agree* ***6*** *Somewhat Agree* ***5*** *Neither Agree nor Disagree* ***4*** *Somewhat Disagree* ***3*** *Disagree* ***2*** *Strongly Disagree* ***1***	Run the following analytics per **lower order construct (subdimension)**: **Descriptive Statistics:** Minimum, Maximum, Mean, Standard Deviation **Construct Validity:** Bivariate Analysis; Pearson's Correlation using item totals for each subdimension with significance at the 0.01 level **Reliability & Internal Consistency of Scales:** Standardised version of Cronbach's alpha **Exploratory Factor Analysis & Dimension Reduction:** – Kaisen-Meyer-Olkin [KMO], Bartlett's test of sphericity, Eigenvalues % of variance, Number of components extracted **Normality:** Shapiro-Wilk test, Histogram, Normal Q-Q plot

Sub-Question/s	References	Hypothesis (and sub-hypotheses)	Source of Data	Type of Data	Statistical Analysis: IBM SPSS
	Statistical Analysis: Beavers et al. (2013) Creswell (2014) Creswell and Creswell (2018) Field (2018) Hair et al. (2018) Zikmund et al. (2010)	**H1.3:** *The lower-order construct (subdimension) of **digital mindset crafting** can be measured through three discrete operationalised indicators: 1) establishing a long-term digital vision, 2) enabling an entrepreneurial mindset, and 3) promoting a digital mindset*			**Multicollinearity:** Mean-centering per subdimension **Multiple Linear Regression:** Adjusted R square (correlation coefficient) relative contribution, multi-level interpretation, ANOVA for model fit
What are the various routines and processes that may be used to predict or measure the subdimensions of **digital seizing**?	**Literate Review:** Autio et al. (2018) Birkinshaw (2018) Dattée et al. (2018) Dong et al. (2016) Eisenhardt and Martin (2000) Kane et al. (2017) Monteiro and Birkinshaw (2017) Nambisan et al. (2017) Peteraf et al. (2013) Rigby et al. (2016) Teece (2007, 2018) Teece and Linden (2017) Teece et al. (2016) Teece et al. (1997) Velu (2017) Vial (2019) Warner and Wäger (2019) **Statistical Analysis:** Beavers et al. (2013) Creswell (2014) Creswell and Creswell (2018) Field (2018)	**H2:** The contribution of the higher-order construct **digital seizing** towards the dependent variable: **successful digital transformation,** can be measured through three distinct subdimensions: **H2.1:** *The lower-order construct (subdimension) of **rapid prototyping** can be measured through three discrete operationalised indicators: 1) create minimum viable products, 2) a lean start-up methodology, and 3) using a digital innovation lab* **H2.2:** *The lower-order construct (subdimension) of **balance digital portfolios** can be measured through three discrete operationalised indicators: 1) balance internal and external options, 2) scaling up innovative business models, and 3) set up appropriate speed of execution* **H2.3:** *The lower-order construct (subdimension) of **strategic agility** can be measured through three discrete operationalised indicators: 1) rapidly reallocating resources, 2)*	Questionnaire Survey: **DSZ1 –> DSZ9** *Q16 / Q17 / Q18* *Q19 / Q20 / Q21* *Q22 / Q23 / Q24*	Scale (2 decimal points) Interval Likert-scale rating *Strongly Agree **7*** *Agree **6*** *Somewhat Agree **5*** *Neither Agree nor Disagree **4*** *Somewhat Disagree **3*** *Disagree **2*** *Strongly Disagree **1***	Run the following analytics per **lower order construct (subdimension)**: **Descriptive Statistics:** Minimum, Maximum, Mean, Standard Deviation **Construct Validity:** Bivariate Analysis; Pearson's Correlation using item totals for each subdimension with significance at the 0.01 level **Reliability & Internal Consistency of Scales:** Standardised version of Cronbach's alpha **Exploratory Factor Analysis & Dimension Reduction:** – Kaisen-Meyer-Olkin [KMO], Bartlett's test of sphericity, Eigenvalues % of variance, Number of components extracted **Normality:** Shapiro-Wilk test, Histogram, Normal Q-Q plot **Multicollinearity:** Mean-centering per subdimension **Multiple Linear Regression:** Adjusted R square (correlation coefficient) relative contribution, multi-level interpretation, ANOVA for model fit

Sub-Question/s	References	Hypothesis (and sub-hypotheses)	Source of Data	Type of Data	Statistical Analysis: IBM SPSS
	Hair et al. (2018) Zikmund et al. (2010)	*accept redirection and change, and 3) pacing strategic responses*			
What are the various routines and processes that may be used to predict or measure the subdimensions of **digital transforming**?	**Literate Review:** Autio et al. (2018) Birkinshaw (2018) Dattée et al. (2018) Dong et al. (2016) Eisenhardt and Martin (2000) Kane et al. (2017) Monteiro and Birkinshaw (2017) Nambisan et al. (2017) Peteraf et al. (2013) Rigby et al. (2016) Teece (2007, 2018) Teece and Linden (2017) Teece et al. (2016) Teece et al. (1997) Velu (2017) Vial (2019) Warner and Wäger (2019) **Statistical Analysis:** Beavers et al. (2013) Creswell (2014) Creswell and Creswell (2018) Field (2018) Hair et al. (2018) Zikmund et al. (2010)	**H3:** The contribution of the higher-order construct **digital transforming** towards the dependent variable: **successful digital transformation,** can be measured through three distinct subdimensions: **H3.1:** *The lower-order construct (subdimension) of* ***innovation ecosystems*** *can be measured through three discrete operationalised indicators: 1) joining digital ecosystem, 2) interact with multiple external partners, and 3) exploit new ecosystem capabilities* **H3.2:** *The lower-order construct (subdimension) of* ***redesign internal structures*** *can be measured through three discrete operationalised indicators: 1) hiring a Chief Digital Officer, 2) digitise business models, and 3) design team-based structures* **H3.3:** *The lower-order construct (subdimension) of* ***improve digital maturity*** *can be measured through three discrete operationalised indicators: 1) identify digital workforce maturity, 2) external recruiting of digital natives, and 3) leverage digital knowledge inside firm*	Questionnaire Survey: **DTF1 –> DTF9** *Q26 / Q27 / Q28* *Q29 / Q30 / Q31* *Q32 / Q33 / Q34*	Scale (2 decimal points) Interval Likert-scale rating *Strongly Agree* ***7*** *Agree* ***6*** *Somewhat Agree* ***5*** *Neither Agree nor Disagree* ***4*** *Somewhat Disagree* ***3*** *Disagree* ***2*** *Strongly Disagree* ***1***	Run the following analytics per **lower order construct (subdimension)**: **Descriptive Statistics:** Minimum, Maximum, Mean, Standard Deviation **Construct Validity:** Bivariate Analysis; Pearson's Correlation using item totals for each subdimension with significance at the 0.01 level **Reliability & Internal Consistency of Scales:** Standardised version of Cronbach's alpha **Exploratory Factor Analysis & Dimension Reduction:** – Kaisen-Meyer-Olkin [KMO], Bartlett's test of sphericity, Eigenvalues % of variance, Number of components extracted **Normality:** Shapiro-Wilk test, Histogram, Normal Q-Q plot **Multicollinearity:** Mean-centering per subdimension **Multiple Linear Regression:** Adjusted R square (correlation coefficient) relative contribution, multi-level interpretation, ANOVA for model fit

Sub-Question/s	References	Hypothesis (and sub-hypotheses)	Source of Data	Type of Data	Statistical Analysis: IBM SPSS
What is the moderating effect of dramatic social change on the contribution of the subdimensions of **digital sensing** to successful digital transformation?	**Literate Review:** De la Sablonnière (2017) Goodwin (2006) Kump et al. (2018) Parsons (2010) Teece (2007) Teece et al. (1997) Warner and Wäger (2019) **Statistical Analysis:** Beavers et al. (2013) Creswell (2014) Creswell and Creswell (2018) Field (2018) Hair et al. (2018) Zikmund et al. (2010)	**H4:** The strength of the relationship between the higher order construct: **digital sensing** and the dependent variable: **successful digital transformation**, is moderated by **dramatic social change** **H4.1:** *The strength of the contribution that the subdimension:* ***digital scouting*** *has to the dependent variable:* **successful digital transformation** *is moderated by* ***dramatic social change*** **H4.2:** *The strength of the contribution that the subdimension:* ***digital scenario planning*** *has to the dependent variable:* **successful digital transformation** *is moderated by* ***dramatic social change*** **H4.3:** *The strength of the contribution that the subdimension:* ***digital mindset crafting*** *has to the dependent variable:* **successful digital transformation** *is moderated by* ***dramatic social change***	Questionnaire Survey: **MOD1** *Q15*	Scale (2 decimal points) Interval Likert-scale rating *Strongly Agree **7*** *Agree **6*** *Somewhat Agree **5*** *Neither Agree nor Disagree **4*** *Somewhat Disagree **3*** *Disagree **2*** *Strongly Disagree **1***	Run the following analytics per **moderator (for each subdimension)**: **Descriptive Statistics:** Minimum, Maximum, Mean, Standard Deviation **Multicollinearity:** Mean-centering per (subdimension) moderator **Multiple Linear Regression:** Adjusted R square (correlation coefficient) relative contribution, multi-level interpretation, ANOVA for model fit – using calculated interaction variable

Sub-Question/s	References	Hypothesis (and sub-hypotheses)	Source of Data	Type of Data	Statistical Analysis: IBM SPSS
What is the moderating effect of dramatic social change on the contribution of the subdimensions of **digital seizing** to successful digital transformation?	**Literate Review:** De la Sablonnière (2017) Goodwin (2006) Kump et al. (2018) Parsons (2010) Teece (2007) Teece et al. (1997) Warner and Wäger (2019) **Statistical Analysis:** Beavers et al. (2013) Creswell (2014) Creswell and Creswell (2018) Field (2018) Hair et al. (2018) Zikmund et al. (2010)	**H5:** The strength of the relationship between the higher order construct: **digital seizing** and the dependent variable: **successful digital transformation,** is moderated by **dramatic social change** **H5.1:** *The strength of the contribution that the subdimension:* ***rapid prototyping*** *has to the dependent variable:* **successful digital transformation** *is moderated by* ***dramatic social change*** **H5.2:** *The strength of the contribution that the subdimension:* ***balance digital portfolios*** *has to the dependent variable:* **successful digital transformation** *is moderated by* ***dramatic social change*** **H5.3:** *The strength of the contribution that the subdimension:* ***strategic agility*** *has to the dependent variable:* **successful digital transformation** *is moderated by* ***dramatic social change***	Questionnaire Survey: **MOD2** *Q25*	Scale (2 decimal points) Interval Likert-scale rating *Strongly Agree **7*** *Agree **6*** *Somewhat Agree **5*** *Neither Agree nor Disagree **4*** *Somewhat Disagree **3*** *Disagree **2*** *Strongly Disagree **1***	Run the following analytics per **moderator (for each subdimension)**: **Descriptive Statistics:** Minimum, Maximum, Mean, Standard Deviation **Multicollinearity:** Mean-centering per (subdimension) moderator **Multiple Linear Regression:** Adjusted R square (correlation coefficient) relative contribution, multi-level interpretation, ANOVA for model fit – using calculated interaction variable
What is the moderating effect of dramatic social change on the contribution of the subdimensions of **digital transforming** to successful digital transformation?	**Literate Review:** De la Sablonnière (2017) Goodwin (2006) Kump et al. (2018) Parsons (2010) Teece (2007) Teece et al. (1997) Warner and Wäger (2019) **Statistical Analysis:** Beavers et al. (2013)	**H6:** The strength of the relationship between the higher order construct: **digital transforming** and the dependent variable: **successful digital transformation**, is moderated by **dramatic social change** **H6.1:** *The strength of the contribution that the subdimension:* ***innovation ecosystems*** *has to the dependent variable:* **successful digital transformation** *is moderated by* ***dramatic social change***	Questionnaire Survey: **MOD3** *Q35*	Scale (2 decimal points) Interval Likert-scale rating *Strongly Agree **7*** *Agree **6*** *Somewhat Agree **5*** *Neither Agree nor Disagree **4*** *Somewhat Disagree **3*** *Disagree **2*** *Strongly Disagree **1***	Run the following analytics per **moderator (for each subdimension)**: **Descriptive Statistics:** Minimum, Maximum, Mean, Standard Deviation **Multicollinearity:** Mean-centering per (subdimension) moderator **Multiple Linear Regression:** Adjusted R square (correlation coefficient) relative contribution, multi-level interpretation,

Sub-Question/s	References	Hypothesis (and sub-hypotheses)	Source of Data	Type of Data	Statistical Analysis: IBM SPSS
	Creswell (2014) Creswell and Creswell (2018) Field (2018) Hair et al. (2018) Zikmund et al. (2010)	**H6.2:** *The strength of the contribution that the subdimension:* ***redesign internal structures*** *has to the dependent variable:* **successful digital transformation** *is moderated by* ***dramatic social change*** **H6.3:** *The strength of the contribution that the subdimension:* ***improve digital maturity*** *has to the dependent variable:* **successful digital transformation** *is moderated by* ***dramatic social change***			ANOVA for model fit – using calculated interaction variable

Appendix D - Quantitative Reports (sourced from IBM SPSS v26, Author's own Research)

Table 20: Quantitative report – Validity correlations: Digital sensing subdimensions

Digital Scouting Subdimension		ITEM_TOTAL SCOUTING	SENSE_1 SCOUTING	SENSE_2 SCOUTING	SENSE_3 SCOUTING
ITEM_TOTAL_SCT	Pearson Correlation	**1**	**.813****	**.866****	**.863****
	Sig. (2-tailed)		**0,000**	**0,000**	**0,000**
	N	**142**	**142**	**142**	**142**
SENSE_1 SCOUTING	Pearson Correlation	.813**	1	.551**	.579**
	Sig. (2-tailed)	0,000		0,000	0,000
SENSE_2 SCOUTING	Pearson Correlation	.866**	.551**	1	.607**
	Sig. (2-tailed)	0,000	0,000		0,000
SENSE_3 SCOUTING	Pearson Correlation	.863**	.579**	.607**	1
	Sig. (2-tailed)	0,000	0,000	0,000	
Scenario Planning Subdimension		ITEM_TOTAL SCENARIO PLANNNING	SENSE_4 SCENARIO PLANNING	SENSE_5 SCENARIO PLANNING	SENSE_6 SCENARIO PLANNING
ITEM_TOTAL_SPL	Pearson Correlation	**1**	**.885****	**.922****	**.910****
	Sig. (2-tailed)		**0,000**	**0,000**	**0,000**
	N	142	142	142	142
SENSE_4 SCENARIO PLANNING	Pearson Correlation	.885**	1	.713**	.672**
	Sig. (2-tailed)	0,000		0,000	0,000
SENSE_5 SCENARIO PLANNING	Pearson Correlation	.922**	.713**	1	.807**
	Sig. (2-tailed)	0,000	0,000		0,000
SENSE_6 SCENARIO PLANNING	Pearson Correlation	.910**	.672**	.807**	1
	Sig. (2-tailed)	0,000	0,000	0,000	
Digital Mindset Crafting Subdimension		ITEM_TOTAL DIGITAL MINDSET CRAFTING	SENSE_7 DIGITAL MINDSET CRAFTING	SENSE_8 DIGITAL MINDSET CRAFTING	SENSE_9 DIGITAL MINDSET CRAFTING
ITEM_TOTAL_DMC	Pearson Correlation	**1**	**.753****	**.840****	**.817****
	Sig. (2-tailed)		**0,000**	**0,000**	**0,000**
	N	142	142	142	142
SENSE_7 DIGITAL MINDSET CRAFTING	Pearson Correlation	.753**	1	.385**	.417**
	Sig. (2-tailed)	0,000		0,000	0,000
SENSE_8 DIGITAL MINDSET CRAFTING	Pearson Correlation	.840**	.385**	1	.607**
	Sig. (2-tailed)	0,000	0,000		0,000
SENSE_9 DIGITAL MINDSET CRAFTING	Pearson Correlation	.817**	.417**	.607**	1
	Sig. (2-tailed)	0,000	0,000	0,000	

Table 21: Quantitative report – Validity correlations: Digital seizing subdimensions

Rapid Prototyping Subdimension		ITEM_TOTAL RAPID PROTOTYPING	SEIZE_1 RAPID PROTOTYPING	SEIZE_2 RAPID PROTOTYPING	SEIZE_3 RAPID PROTOTYPING
ITEM_TOTAL_RPR	Pearson Correlation	**1**	**.780****	**.740****	**.821****
	Sig. (2-tailed)		**0,000**	**0,000**	**0,000**
	N	**142**	**142**	**142**	**142**
SEIZE_1 RAPID PROTOTYPING	Pearson Correlation	.780**	1	.397**	.430**
	Sig. (2-tailed)	0,000		0,000	0,000
SEIZE_2 RAPID PROTOTYPING	Pearson Correlation	.740**	.397**	1	.425**
	Sig. (2-tailed)	0,000	0,000		0,000
SEIZE_3 RAPID PROTOTYPING	Pearson Correlation	.821**	.430**	.425**	1
	Sig. (2-tailed)	0,000	0,000	0,000	
Balance Digital Portfolios Subdimension		ITEM_TOTAL BALANCE DIGITAL PORTFOLIO	SEIZE_4 BALANCE DIGITAL PORTFOLIO	SEIZE_5 BALANCE DIGITAL PORTFOLIO	SEIZE_6 BALANCE DIGITAL PORTFOLIO
ITEM_TOTAL_BDP	Pearson Correlation	**1**	**.830****	**.885****	**.867****
	Sig. (2-tailed)		**0,000**	**0,000**	**0,000**
	N	**142**	**142**	**142**	**142**
SEIZE_4 BALANCE DIG PORTFOLIO	Pearson Correlation	.830**	1	.612**	.567**
	Sig. (2-tailed)	0,000		0,000	0,000
SEIZE_5 BALANCE DIG PORTFOLIO	Pearson Correlation	.885**	.612**	1	.656**
	Sig. (2-tailed)	0,000	0,000		0,000
SEIZE_6 BALANCE DIG PORTFOLIO	Pearson Correlation	.867**	.567**	.656**	1
	Sig. (2-tailed)	0,000	0,000	0,000	
Strategic Agility Subdimension		ITEM_TOTAL STRATEGIC AGILITY	SEIZE_7 STRATEGIC AGILITY	SEIZE_8 STRATEGIC AGILITY	SEIZE_9 STRATEGIC AGILITY
ITEM_TOTAL_STA	Pearson Correlation	**1**	**.847****	**.871****	**.854****
	Sig. (2-tailed)		**0,000**	**0,000**	**0,000**
	N	**142**	**142**	**142**	**142**
SEIZE_7 STRATEGIC AGILITY	Pearson Correlation	.847**	1	.571**	.587**
	Sig. (2-tailed)	0,000		0,000	0,000
SEIZE_8 STRATEGIC AGILITY	Pearson Correlation	.871**	.571**	1	.651**
	Sig. (2-tailed)	0,000	0,000		0,000
SEIZE_9 STRATEGIC AGILITY	Pearson Correlation	.854**	.587**	.651**	1
	Sig. (2-tailed)	0,000	0,000	0,000	

Table 22: Quantitative report – Validity correlations: Digital transforming subdimensions

Innovation Ecosystem Subdimension		ITEM_TOTAL INNOVATION ECOSYSTEM	TRANSF_1 INNOVATION ECOSYSTEM	TRANSF_2 INNOVATION ECOSYSTEM	TRANSF_3 INNOVATION ECOSYSTEM
ITEM_TOTAL_ECO	Pearson Correlation	**1**	**.889****	**.827****	**.862****
	Sig. (2-tailed)		**0,000**	**0,000**	**0,000**
	N	**142**	**142**	**142**	**142**
TRANSF_1 INNOVATION ECOSYSTEM	Pearson Correlation	.889**	1	.588**	.650**
	Sig. (2-tailed)	0,000		0,000	0,000
TRANSF_2 INNOVATION ECOSYSTEM	Pearson Correlation	.827**	.588**	1	.591**
	Sig. (2-tailed)	0,000	0,000		0,000
TRANSF_3 INNOVATION ECOSYSTEM	Pearson Correlation	.862**	.650**	.591**	1
	Sig. (2-tailed)	0,000	0,000	0,000	

Redesign Internal Structures Subdimension		ITEM_TOTAL REDESIGN INT STRUCTURES	TRANSF_4 REDESIGN INT STRUCTURES	TRANSF_5 REDESIGN INT STRUCTURES	TRANSF_6 REDESIGN INT STRUCTURES
ITEM_TOTAL_RIS	Pearson Correlation	**1**	**.809****	**.763****	**.755****
	Sig. (2-tailed)		**0,000**	**0,000**	**0,000**
	N	**142**	**142**	**142**	**142**
TRANSF_4 REDESIGN INT STRUCTURES	Pearson Correlation	.809**	1	.380**	.317**
	Sig. (2-tailed)	0,000		0,000	0,000
TRANSF_5 REDESIGN INT STRUCTURES	Pearson Correlation	.763**	.380**	1	.564**
	Sig. (2-tailed)	0,000	0,000		0,000
TRANSF_6 REDESIGN INT STRUCTURES	Pearson Correlation	.755**	.317**	.564**	1
	Sig. (2-tailed)	0,000	0,000	0,000	

Improve Digital Maturity Subdimension		ITEM_TOTAL IMPROVE DIGITAL MATURITY	TRANSF_7 IMPROVE DIGITAL MATURITY	TRANSF_8 IMPROVE DIGITAL MATURITY	TRANSF_9 IMPROVE DIGITAL MATURITY
ITEM_TOTAL_IDM	Pearson Correlation	**1**	**.854****	**.818****	**.803****
	Sig. (2-tailed)		**0,000**	**0,000**	**0,000**
	N	**142**	**142**	**142**	**142**
TRANSF_7 IMPROVE DIGITAL MATURITY	Pearson Correlation	.854**	1	.517**	.592**
	Sig. (2-tailed)	0,000		0,000	0,000
TRANSF_8 IMPROVE DIGITAL MATURITY	Pearson Correlation	.818**	.517**	1	.463**
	Sig. (2-tailed)	0,000	0,000		0,000
TRANSF_9 IMPROVE DIGITAL MATURITY	Pearson Correlation	.803**	.592**	.463**	1
	Sig. (2-tailed)	0,000	0,000	0,000	

Table 23: Quantitative report – Reliability item total statistics

Digital Sensing Higher-Order Construct	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's alpha if Item Deleted
SENSE_1 SCOUTING	11,2042	4,958	0,630	0,754
SENSE_2 SCOUTING	11,6690	3,854	0,654	0,727
SENSE_3 SCOUTING	11,4789	4,109	0,674	0,697
SENSE_4 SCENARIO PLANNING	11,1479	4,510	0,728	0,892
SENSE_5 SCENARIO PLANNING	11,0493	4,728	0,829	0,803
SENSE_6 SCENARIO PLANNING	10,9155	4,574	0,794	0,828
SENSE_7 DIGITAL MINDSET CRAFTING	11,3592	5,423	0,445	0,744
SENSE_8 DIGITAL MINDSET CRAFTING	11,5704	4,460	0,578	0,584
SENSE_9 DIGITAL MINDSET CRAFTING	11,1690	5,418	0,619	0,555
Digital Seizing Higher-Order Construct	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's alpha if Item Deleted
SEIZE_1 RAPID PROTOTYPING	9,8873	5,845	0,491	0,581
SEIZE_2 RAPID PROTOTYPING	9,3732	6,718	0,487	0,598
SEIZE_3 RAPID PROTOTYPING	10,2465	4,996	0,511	0,563
SEIZE_4 BALANCE DIGITAL PORTFOLIO	9,7535	6,371	0,648	0,792
SEIZE_5 BALANCE DIGITAL PORTFOLIO	9,8944	5,301	0,717	0,720
SEIZE_6 BALANCE DIGITAL PORTFOLIO	10,3099	5,535	0,684	0,755
SEIZE_7 STRATEGIC AGILITY	10,3803	5,869	0,636	0,781
SEIZE_8 STRATEGIC AGILITY	10,2887	5,569	0,682	0,733
SEIZE_9 STRATEGIC AGILITY	10,1479	6,538	0,699	0,727
Digital Transform Higher-Order Construct	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's alpha if Item Deleted
TRANSF_1 INNOVATION ECOSYSTEM	10,5070	5,628	0,695	0,742
TRANSF_2 INNOVATION ECOSYSTEM	10,0070	7,553	0,648	0,779
TRANSF_3 INNOVATION ECOSYSTEM	10,3169	6,998	0,699	0,727
TRANSF_4 REDESIGN INT STRUCTURES	11,0423	5,431	0,390	0,714
TRANSF_5 REDESIGN INT STRUCTURES	9,8521	8,070	0,557	0,459
TRANSF_6 REDESIGN INT STRUCTURES	10,3028	7,461	0,484	0,498
TRANSF_7 IMPROVE DIGITAL MATURITY	10,1761	6,487	0,642	0,623
TRANSF_8 IMPROVE DIGITAL MATURITY	10,3380	6,708	0,551	0,736
TRANSF_9 IMPROVE DIGITAL MATURITY	9,7958	7,894	0,604	0,681

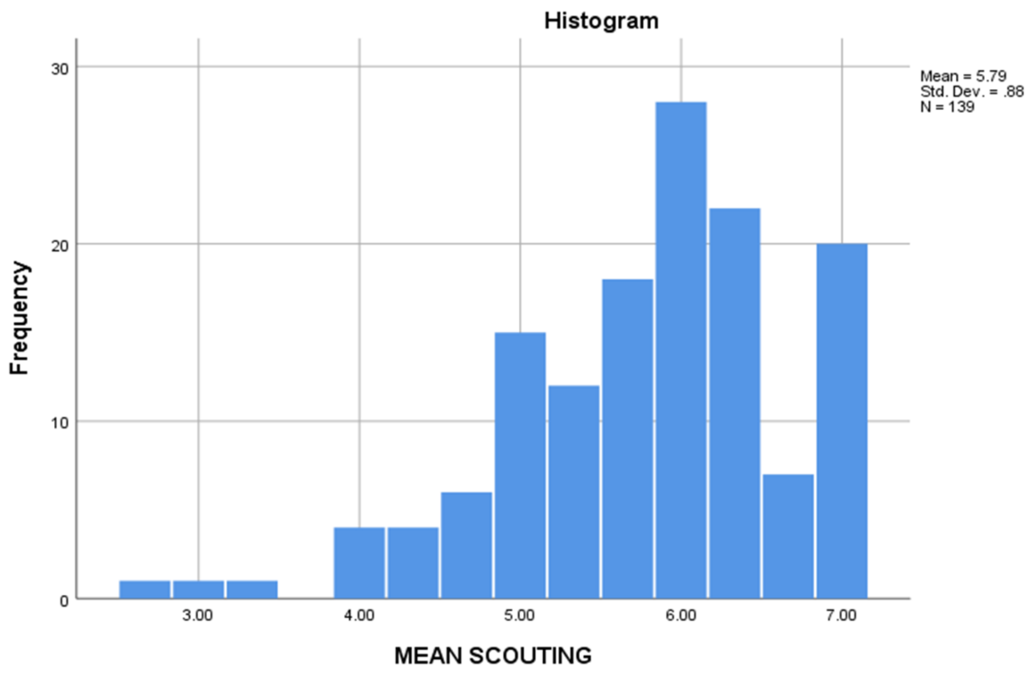

Figure 7: Quantitative report – Histogram: Digital scouting composite index

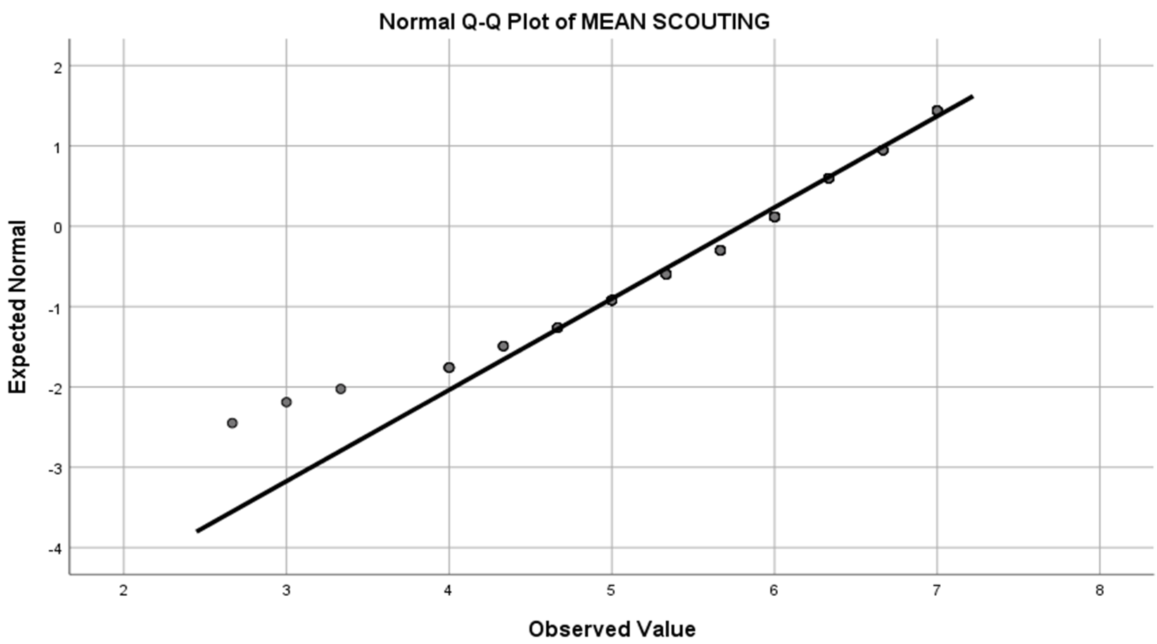

Figure 8: Quantitative report – Normal Q-Q plot: Digital scouting composite index

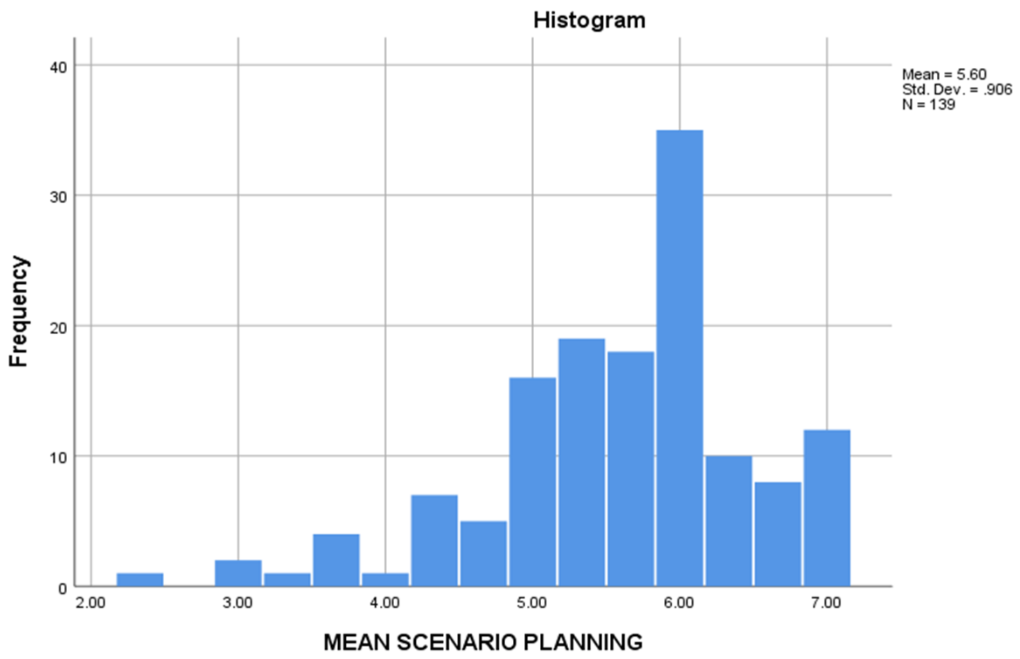

Figure 9: Quantitative report – Histogram: Scenario planning composite index

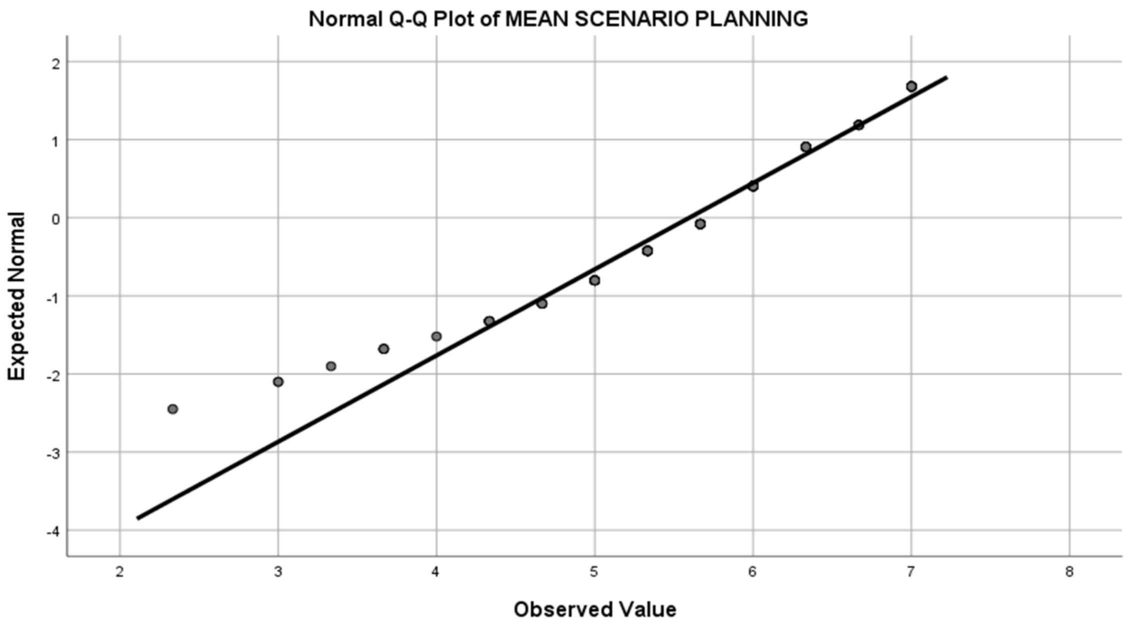

Figure 10: Quantitative report – Normal Q-Q plot: Scenario planning composite index

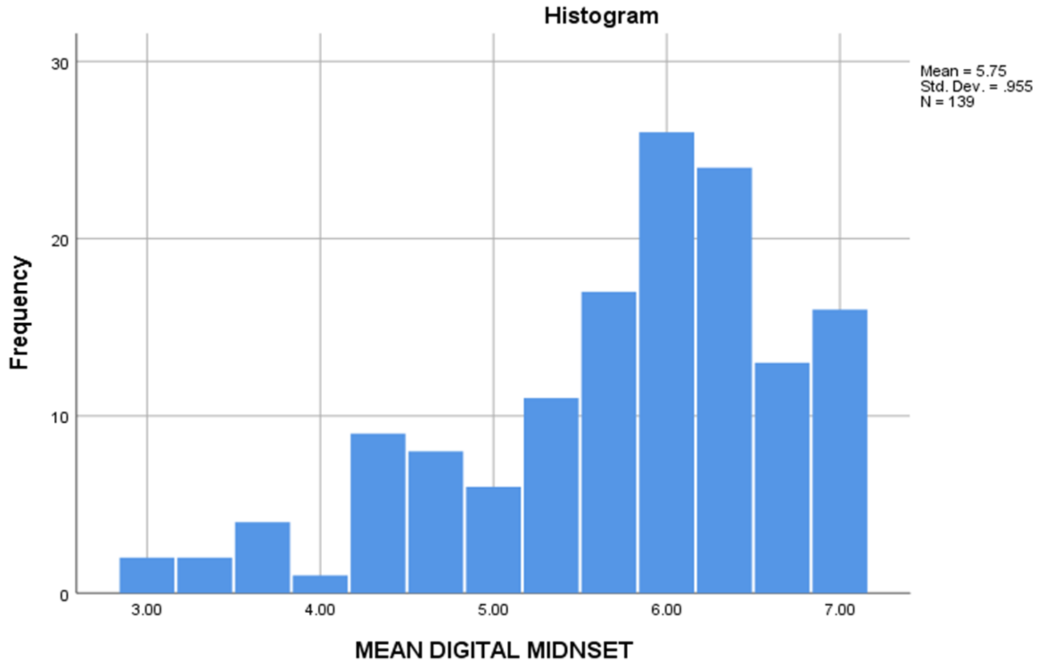

Figure 11: Quantitative report – Histogram: Crafting digital mindset composite index

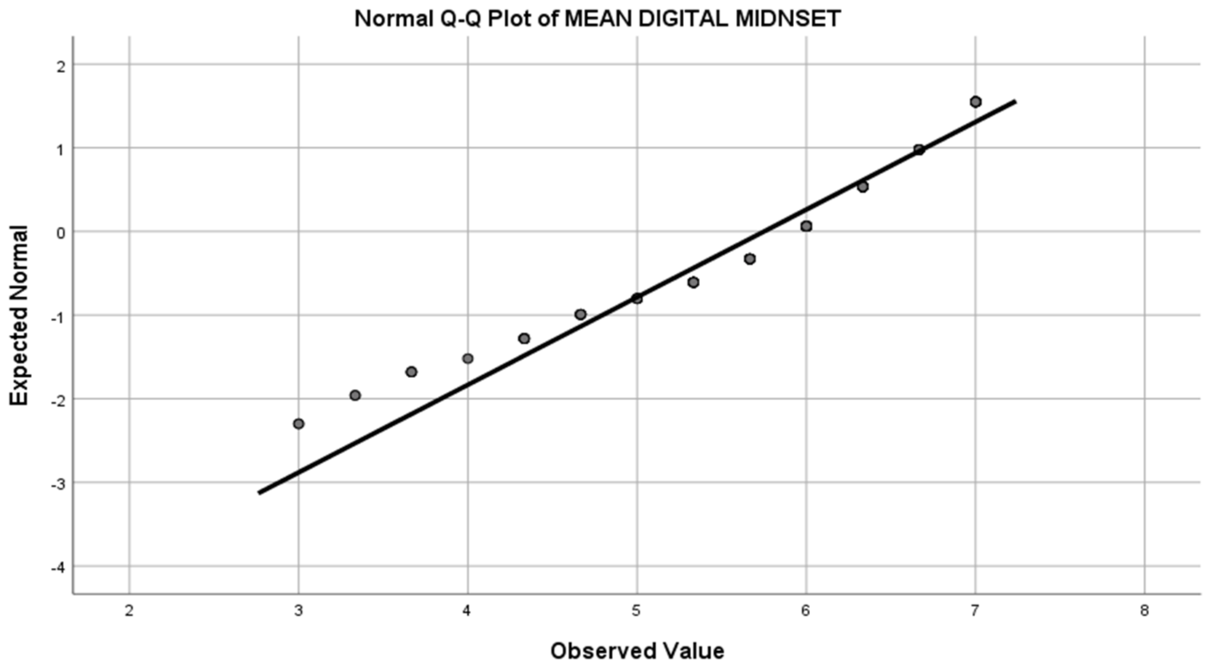

Figure 12: Quantitative report – Normal Q-Q plot: Crafting digital mindset composite index

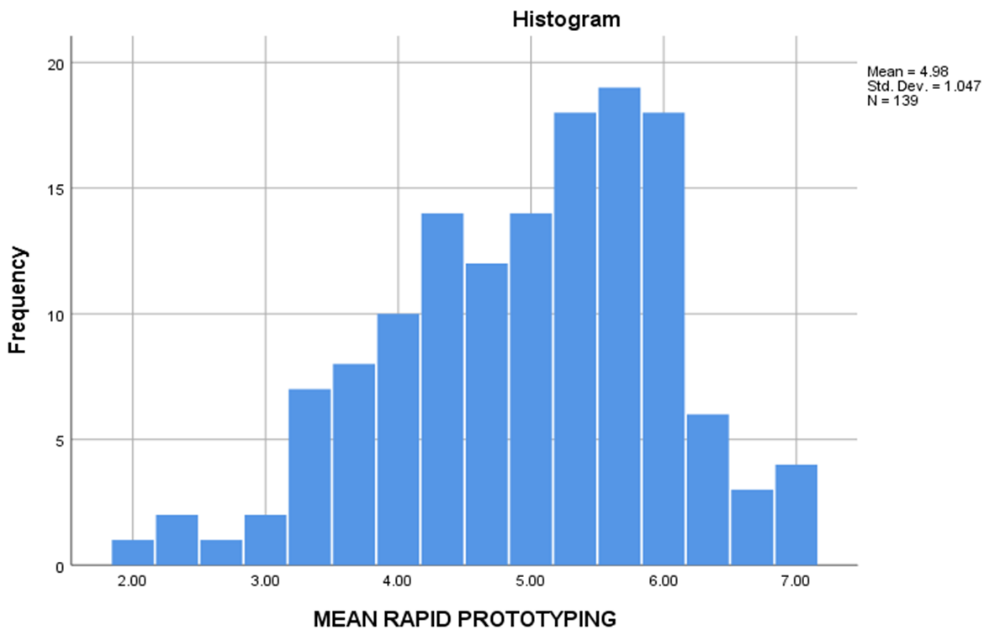

Figure 13: Quantitative report – Histogram: Rapid prototyping composite index

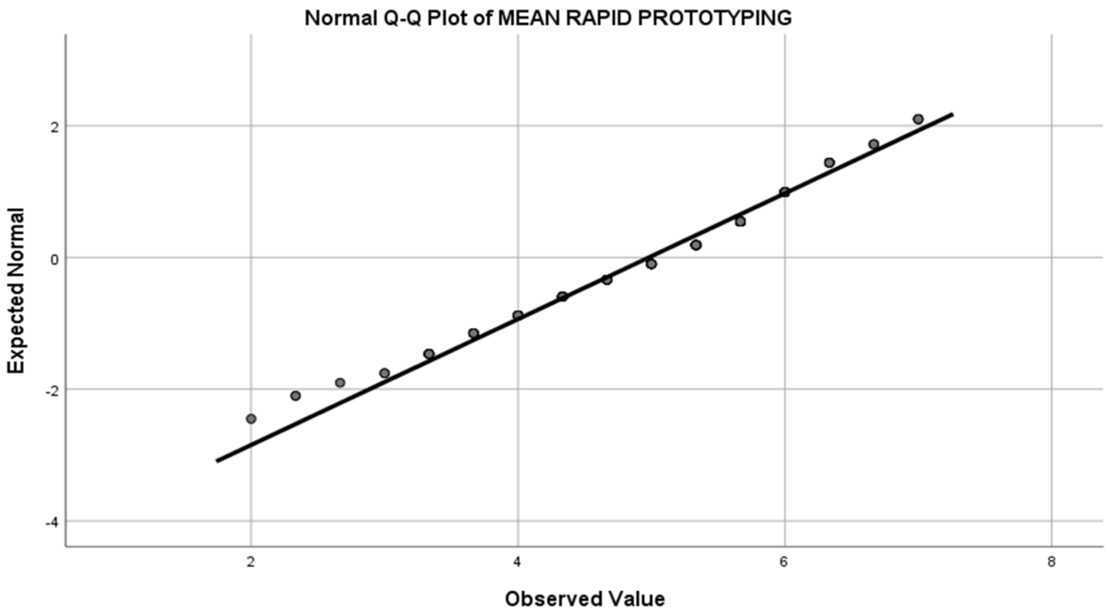

Figure 14: Quantitative report – Normal Q-Q plot: Rapid prototyping composite index

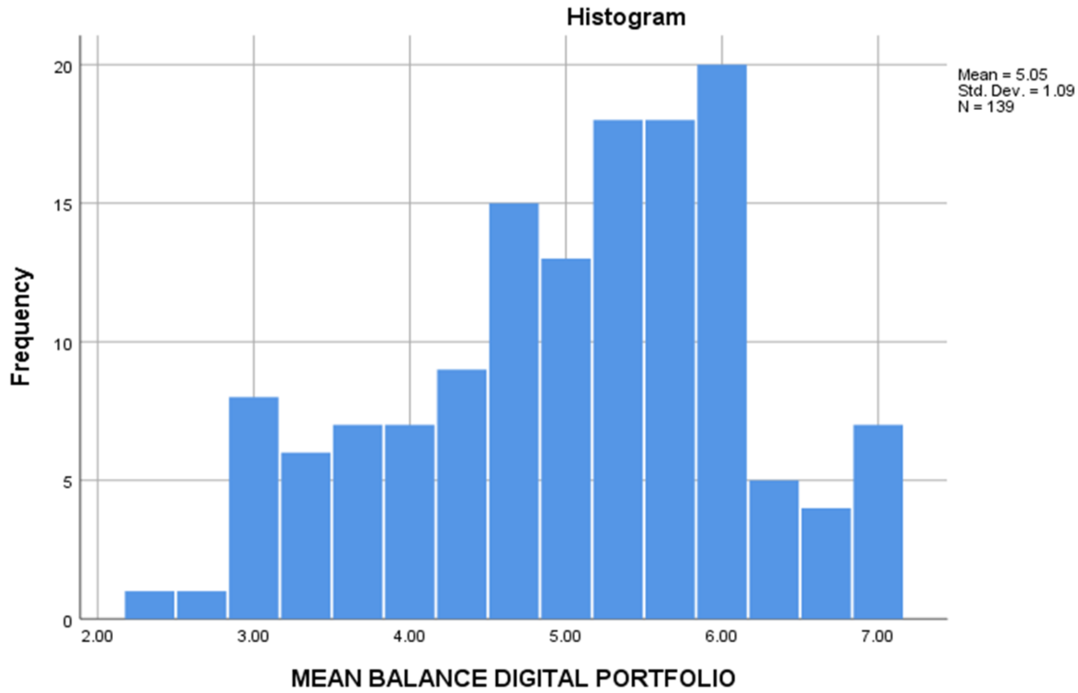

Figure 15: Quantitative report – Histogram: Balance digital portfolio composite index

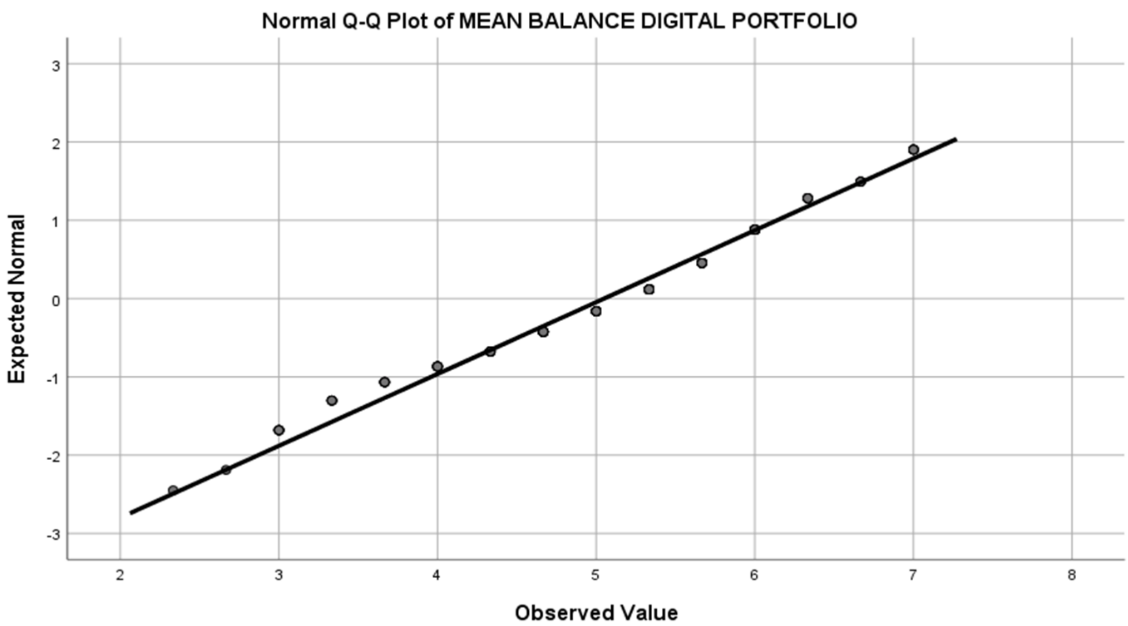

Figure 16: Quantitative report – Normal Q-Q plot: Balance digital portfolio composite index

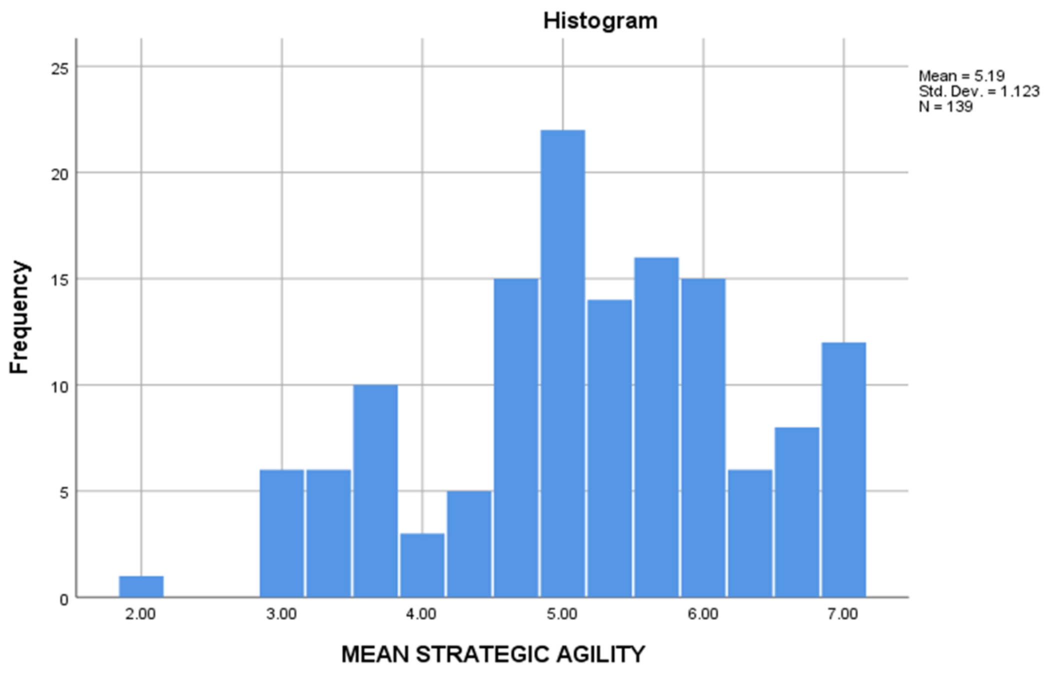

Figure 17: Quantitative report – Histogram: Strategic agility composite index

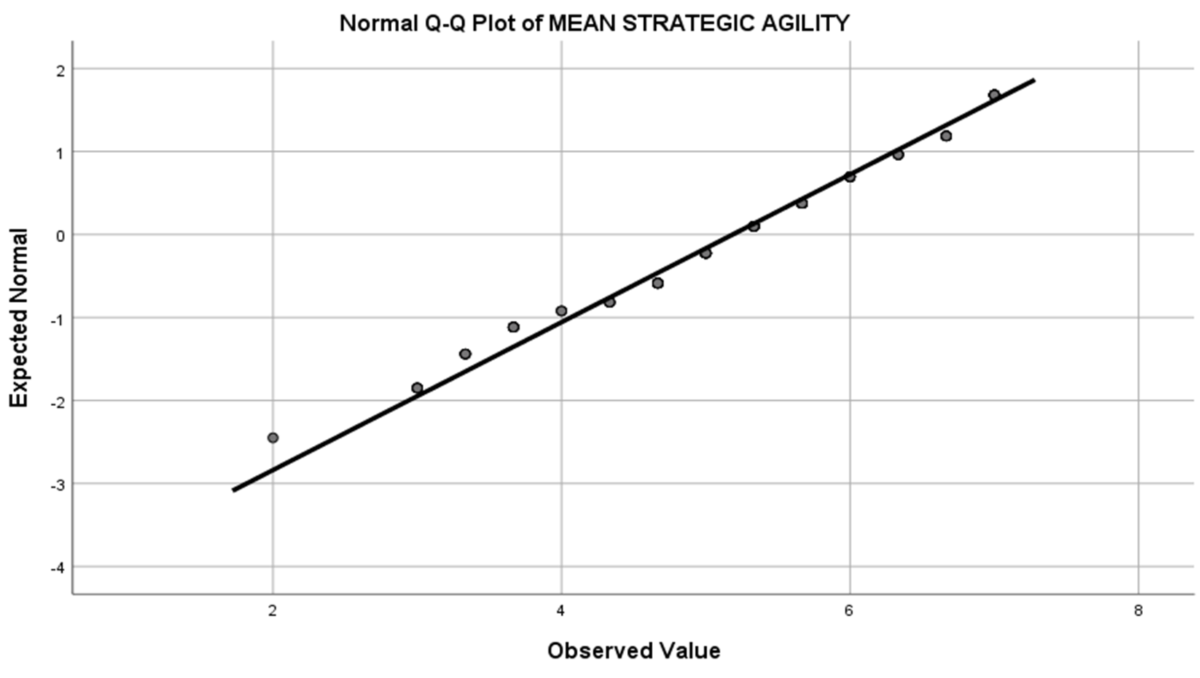

Figure 18: Quantitative report – Normal Q-Q plot: Strategic agility composite index

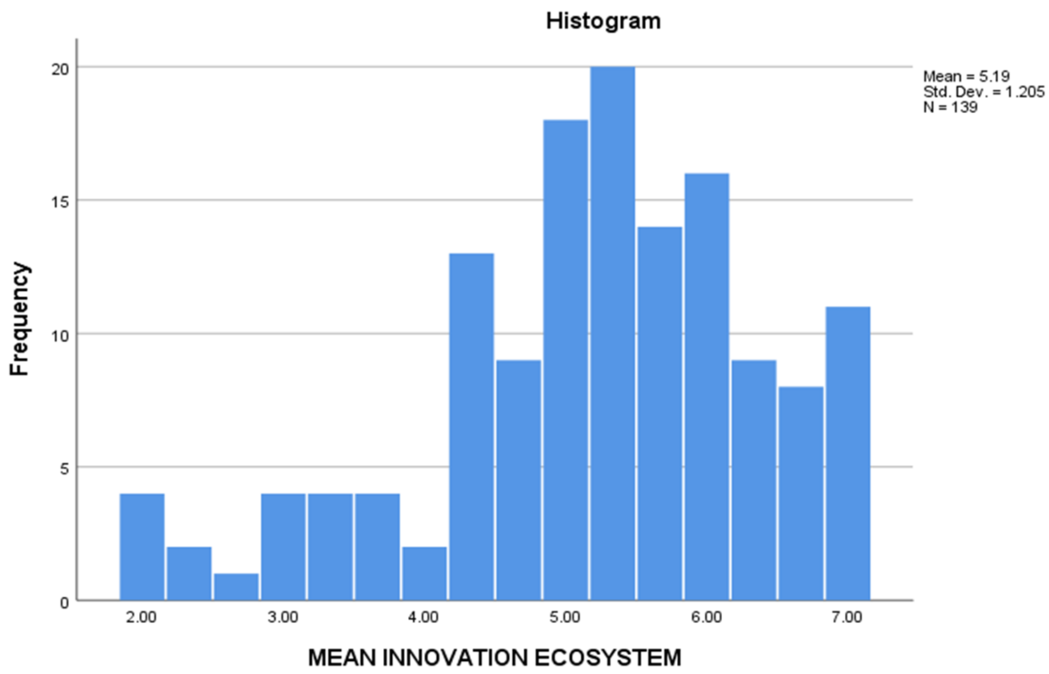

Figure 19: Quantitative report – Histogram: Innovation ecosystem composite index

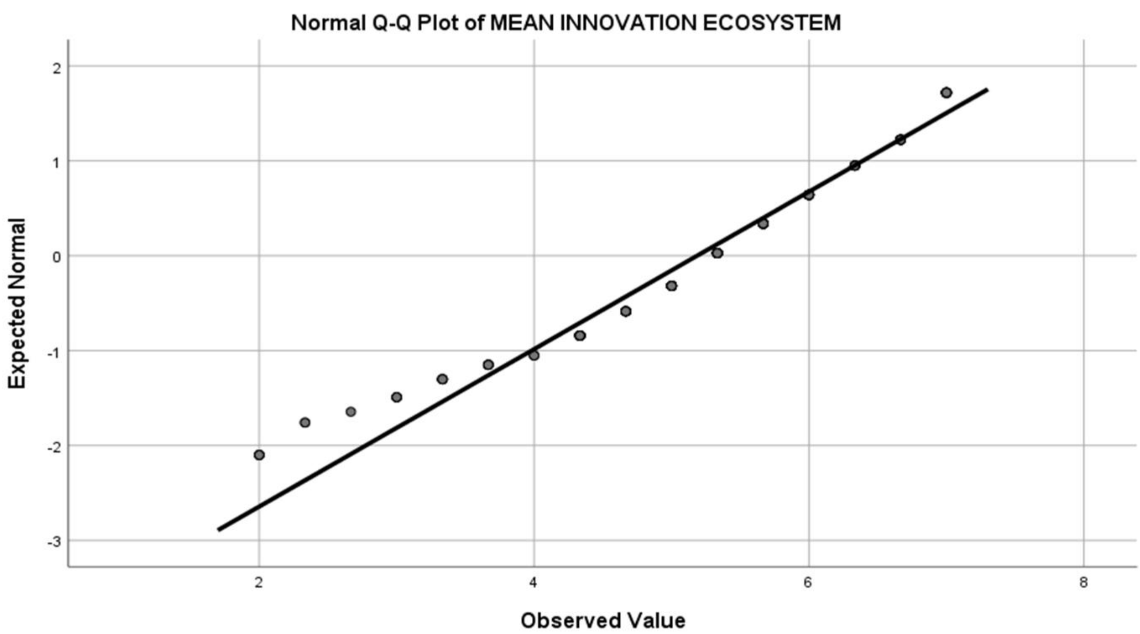

Figure 20: Quantitative report – Normal Q-Q plot: Innovation ecosystem composite index

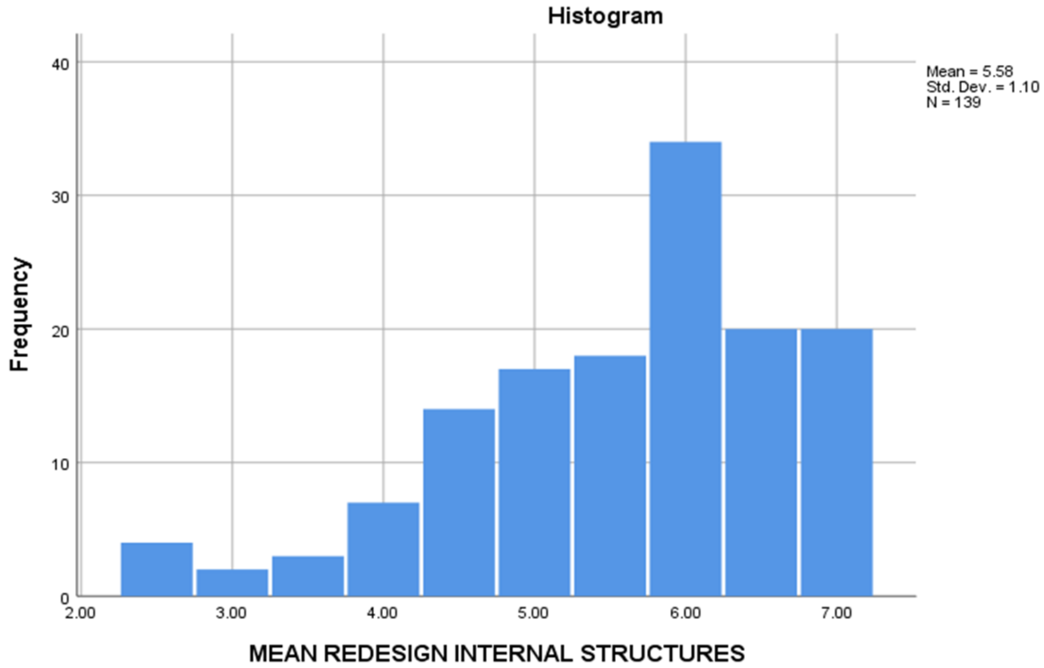

Figure 21: Quantitative report – Histogram: Redesign internal structures composite index

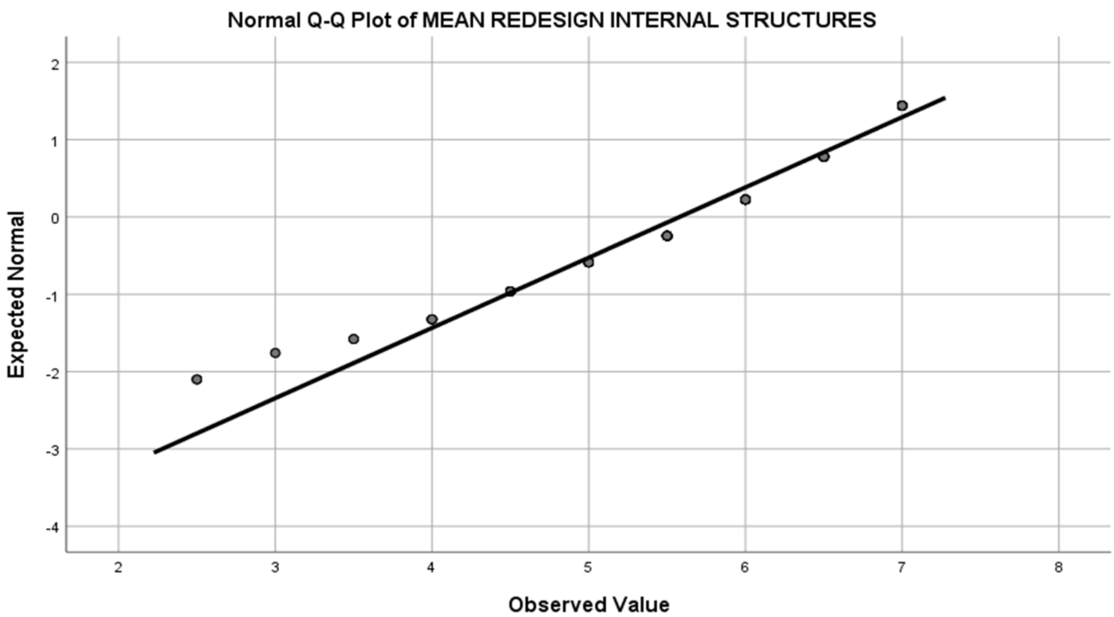

Figure 22: Quantitative report – Normal Q-Q plot: Redesign internal structures composite index

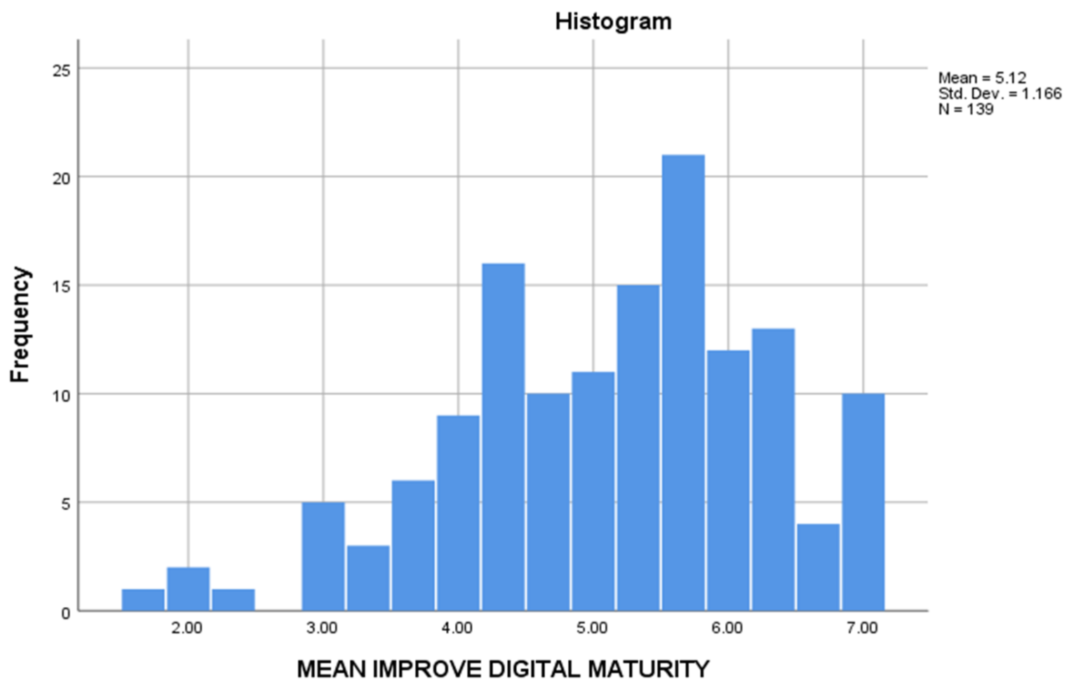

Figure 23: Quantitative report – Histogram: Improve digital maturity composite index

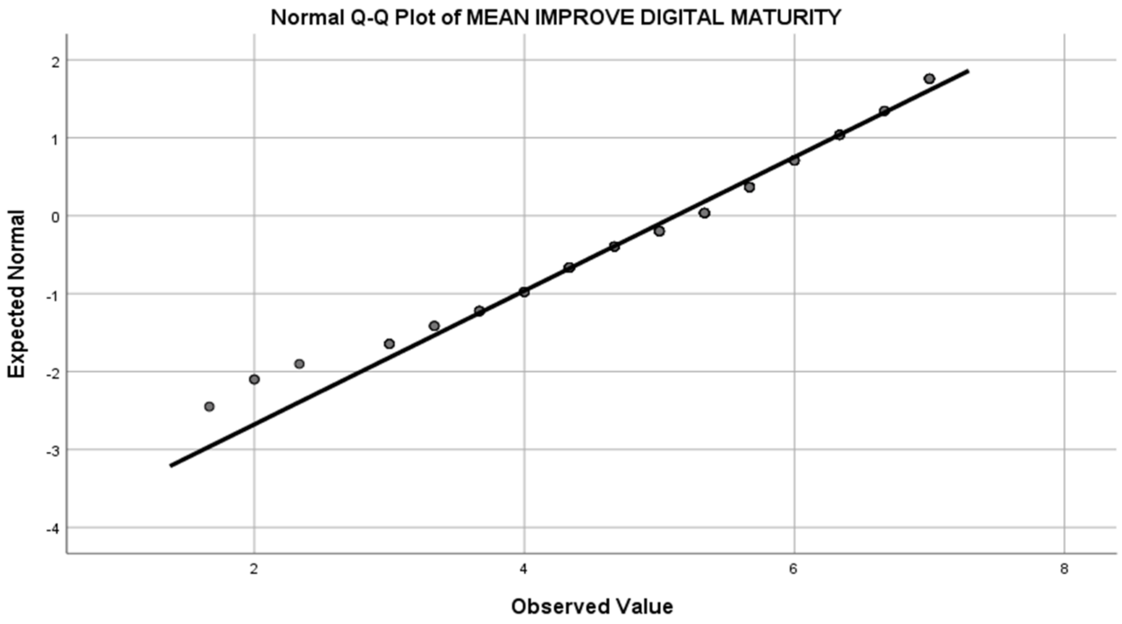

Figure 24: Quantitative report – Normal Q-Q plot: Improve digital maturity composite index

Table 24: Quantitative report – Linear regression: Model summary for digital scouting

Model Summary

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	.347[a]	0,120	0,114	1,08331	0,120	18,747	1	137	0,000
2	.347[b]	0,120	0,107	1,08727	0,000	0,003	1	136	0,955

a. Predictors: (Constant), CENTRED MEAN SCOUTING

b. Predictors: (Constant), CENTRED MEAN SCOUTING, INTERACTION VARIABLE SCOUTING

Table 25: Quantitative report – Linear regression: ANOVA scores for digital scouting

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	22,000	1	22,000	18,747	.000[b]
	Residual	160,777	137	1,174		
	Total	182,777	138			
2	Regression	22,004	2	11,002	9,307	.000[c]
	Residual	160,773	136	1,182		
	Total	182,777	138			

a. Dependent Variable: SUCCESS_DT
b. Predictors: (Constant), CENTRED MEAN SCOUTING

c. Predictors: (Constant), CENTRED MEAN SCOUTING, INTERACTION VARIABLE SCOUTING

Table 26: Quantitative report – Linear regression: Coefficients for digital scouting

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95,0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	5,667	0,092		61,678	0,000	5,486	5,849
	CENTRED MEAN SCOUTING	0,453	0,105	0,347	4,330	0,000	0,246	0,661
2	(Constant)	5,666	0,095		59,924	0,000	5,479	5,853
	CENTRED MEAN SCOUTING	0,455	0,110	0,348	4,130	0,000	0,237	0,673
	INTERACTION VARIABLE SCOUTING	0,005	0,082	0,005	0,056	0,955	-0,158	0,167

a. Dependent Variable: SUCCESS_DT

Table 27: Quantitative report – Linear regression: Model summary for scenario planning

Model Summary

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	0,141	1,06684	0,147	23,590	1	137	0,000
2	.396[b]	0,156	0,144	1,06474	0,010	1,543	1	136	0,216

a. Predictors: (Constant), CENTRED MEAN SCENARIO PLANNING

b. Predictors: (Constant), CENTRED MEAN SCENARIO PLANNING, INTERACTION VARIABLE SCENARIO PLANNING

Table 28: Quantitative report – Linear regression: ANOVA scores for scenario planning

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	26,849	1	26,849	23,590	.000[b]
	Residual	155,928	137	1,138		
	Total	182,777	138			
2	Regression	28,599	2	14,300	12,614	.000[c]
	Residual	154,178	136	1,134		
	Total	182,777	138			

a. Dependent Variable: SUCCESS_DT

b. Predictors: (Constant), CENTRED MEAN SCENARIO PLANNING

c. Predictors: (Constant), CENTRED MEAN SCENARIO PLANNING, INTERACTION VARIABLE SCENARIO PLANNING

Table 29: Quantitative report – Linear regression: Coefficients for scenario planning

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	95,0% Confidence Interval for B Lower Bound	95,0% Confidence Interval for B Upper Bound
1	(Constant)	5,670	0,090		62,665	0,000	5,492	5,849
	CENTRED MEAN SCENARIO PLANNING	0,487	0,100	0,383	4,857	0,000	0,289	0,685
2	(Constant)	5,683	0,091		62,538	0,000	5,503	5,863
	CENTRED MEAN SCENARIO PLANNING	0,453	0,104	0,357	4,373	0,000	0,248	0,658
	INTERACTION VARIABLE SCENARIO PLANNING	-0,092	0,074	-0,101	-1,242	0,216	-0,237	0,054

a. Dependent Variable: SUCCESS_DT

Table 30: Quantitative report – Linear regression: Model summary for crafting digital mindset

Model Summary

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	.351[a]	0,123	0,117	1,08164	0,123	19,226	1	137	0,000
2	.369[b]	0,136	0,123	1,07750	0,013	2,056	1	136	0,154

a. Predictors: (Constant), CENTRED MEAN DIGITAL MINDSET

b. Predictors: (Constant), CENTRED MEAN DIGITAL MINDSET, INTERACTION VARIABLE DIGITAL MINDSET

Table 31: Quantitative report – Linear regression: ANOVA scores for crafting digital mindset

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	22,493	1	22,493	19,226	.000[b]
	Residual	160,284	137	1,170		
	Total	182,777	138			
2	Regression	24,881	2	12,440	10,715	.000[c]
	Residual	157,896	136	1,161		
	Total	182,777	138			

a. Dependent Variable: SUCCESS_DT

b. Predictors: (Constant), CENTRED MEAN DIGITAL MINDSET

c. Predictors: (Constant), CENTRED MEAN DIGITAL MINDSET, INTERACTION VARIABLE DIGITAL MINDSET

Table 32: Quantitative report – Linear regression: Coefficients for crafting digital mindset

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95,0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	5,669	0,092		61,790	0,000	5,487	5,850
	CENTRED MEAN DIGITAL MINDSET	0,423	0,096	0,351	4,385	0,000	0,232	0,614
2	(Constant)	5,700	0,094		60,639	0,000	5,514	5,886
	CENTRED MEAN DIGITAL MINDSET	0,380	0,101	0,315	3,780	0,000	0,181	0,579
	INTERACTION VARIABLE DIGITAL MINDSET	-0,089	0,062	-0,120	-1,434	0,154	-0,212	0,034

a. Dependent Variable: SUCCESS_DT

Table 33: Quantitative report – Linear regression: Model summary for rapid prototyping

Model Summary

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	.239[a]	0,057	0,050	1,12150	0,057	8,318	1	137	0,005
2	.254[b]	0,064	0,051	1,12137	0,007	1,033	1	136	0,311

a. Predictors: (Constant), CENTRED MEAN RAPID PROTOTYPING

b. Predictors: (Constant), CENTRED MEAN RAPID PROTOTYPING, INTERACTION VARIABLE RAPID PROTOTYPING

Table 34: Quantitative report – Linear regression: ANOVA scores for rapid prototyping

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	10,462	1	10,462	8,318	.005[b]
	Residual	172,315	137	1,258		
	Total	182,777	138			
2	Regression	11,762	2	5,881	4,677	.011[c]
	Residual	171,015	136	1,257		
	Total	182,777	138			

a. Dependent Variable: SUCCESS_DT

b. Predictors: (Constant), CENTRED MEAN RAPID PROTOTYPING

c. Predictors: (Constant), CENTRED MEAN RAPID PROTOTYPING, INTERACTION VARIABLE RAPID PROTOTYPING

Table 35: Quantitative report – Linear regression: Coefficients for rapid prototyping

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95,0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	5,669	0,095		59,594	0,000	5,481	5,857
	CENTRED MEAN RAPID PROTOTYPING	0,263	0,091	0,239	2,884	0,005	0,083	0,443
2	(Constant)	5,657	0,096		59,003	0,000	5,467	5,846
	CENTRED MEAN RAPID PROTOTYPING	0,269	0,091	0,245	2,944	0,004	0,088	0,450
	INTERACTION VARIABLE RAPID PROTOTYPING	0,061	0,060	0,084	1,017	0,311	-0,057	0,179

a. Dependent Variable: SUCCESS_DT

Table 36: Quantitative report – Linear regression: Model summary for balance digital portfolio

Model Summary

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	.366[a]	0,134	0,127	1,07503	0,134	21,154	1	137	0,000
2	.374[b]	0,140	0,128	1,07493	0,006	1,024	1	136	0,313

a. Predictors: (Constant), CENTRED MEAN BALANCE DIGITAL PORTFOLIO

b. Predictors: (Constant), CENTRED MEAN BALANCE DIGITAL PORTFOLIO, INTERACTION VARIABLE BALANCE DIGITAL PORT

Table 37: Quantitative report – Linear regression: ANOVA scores for balance digital portfolio

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	24,448	1	24,448	21,154	.000[b]
	Residual	158,329	137	1,156		
	Total	182,777	138			
2	Regression	25,631	2	12,816	11,091	.000[c]
	Residual	157,146	136	1,155		
	Total	182,777	138			

a. Dependent Variable: SUCCESS_DT
b. Predictors: (Constant), CENTRED MEAN BALANCE DIGITAL PORTFOLIO
c. Predictors: (Constant), CENTRED MEAN BALANCE DIGITAL PORTFOLIO, INTERACTION VARIABLE BALANCE DIGITAL PORT

Table 38: Quantitative report – Linear regression: Coefficients for balance digital portfolio

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95,0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	5,669	0,091		62,171	0,000	5,489	5,849
	CENTRED MEAN BALANCE DIGITAL PORTFOLIO	0,386	0,084	0,366	4,599	0,000	0,220	0,552
2	(Constant)	5,642	0,095		59,415	0,000	5,454	5,830
	CENTRED MEAN BALANCE DIGITAL PORTFOLIO	0,386	0,084	0,365	4,594	0,000	0,220	0,552
	INTERACTION VARIABLE BALANCE DIGITAL PORT	0,071	0,070	0,080	1,012	0,313	-0,067	0,208

a. Dependent Variable: SUCCESS_DT

Table 39: Quantitative report – Linear regression: Model summary for strategic agility

Model Summary

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	.454[a]	0,206	0,200	1,02926	0,206	35,534	1	137	0,000
2	.455[b]	0,207	0,195	1,03227	0,001	0,200	1	136	0,655

a. Predictors: (Constant), CENTRED MEAN STRATEGIC AGILITY

b. Predictors: (Constant), CENTRED MEAN STRATEGIC AGILITY, INTERACTION VARIABLE STRATEGIC AGILITY

Table 40: Quantitative report – Linear regression: ANOVA scores for strategic agility

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	37,643	1	37,643	35,534	.000[b]
	Residual	145,134	137	1,059		
	Total	182,777	138			
2	Regression	37,857	2	18,928	17,763	.000[c]
	Residual	144,920	136	1,066		
	Total	182,777	138			

a. Dependent Variable: SUCCESS_DT

b. Predictors: (Constant), CENTRED MEAN STRATEGIC AGILITY

c. Predictors: (Constant), CENTRED MEAN STRATEGIC AGILITY, INTERACTION VARIABLE STRATEGIC AGILITY

Table 41: Quantitative report – Linear regression: Coefficients for strategic agility

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95,0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	5,670	0,087		64,953	0,000	5,498	5,843
	CENTRED MEAN STRATEGIC AGILITY	0,465	0,078	0,454	5,961	0,000	0,311	0,619
2	(Constant)	5,662	0,090		63,179	0,000	5,485	5,839
	CENTRED MEAN STRATEGIC AGILITY	0,474	0,081	0,462	5,874	0,000	0,314	0,633
	INTERACTION VARIABLE STRATEGIC AGILITY	0,024	0,054	0,035	0,448	0,655	-0,082	0,130

a. Dependent Variable: SUCCESS_DT

Table 42: Quantitative report – Linear regression: Model summary for innovation ecosystem

Model Summary

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	.212[a]	0,045	0,038	1,12876	0,045	6,455	1	137	0,012
2	.261[b]	0,068	0,055	1,11903	0,023	3,393	1	136	0,068

a. Predictors: (Constant), CENTRED MEAN INNOVATION ECOSYSTEM

b. Predictors: (Constant), CENTRED MEAN INNOVATION ECOSYSTEM, INTERACTION VARIABLE INNOVATION ECOSYSTEM

Table 43: Quantitative report – Linear regression: ANOVA scores for innovation ecosystem

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	8,224	1	8,224	6,455	.012[b]
	Residual	174,553	137	1,274		
	Total	182,777	138			
2	Regression	12,473	2	6,237	4,980	.008[c]
	Residual	170,304	136	1,252		
	Total	182,777	138			

a. Dependent Variable: SUCCESS_DT

b. Predictors: (Constant), CENTRED MEAN INNOVATION ECOSYSTEM

c. Predictors: (Constant), CENTRED MEAN INNOVATION ECOSYSTEM, INTERACTION VARIABLE INNOVATION ECOSYSTEM

Table 44: Quantitative report – Linear regression: Coefficients for innovation ecosystem

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95,0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	5,670	0,096		59,219	0,000	5,480	5,859
	CENTRED MEAN INNOVATION ECOSYSTEM	0,203	0,080	0,212	2,541	0,012	0,045	0,360
2	(Constant)	5,682	0,095		59,711	0,000	5,494	5,870
	CENTRED MEAN INNOVATION ECOSYSTEM	0,220	0,080	0,230	2,762	0,007	0,062	0,377
	INTERACTION VARIABLE INNOVATION ECOSYSTEM	-0,134	0,073	-0,154	-1,842	0,068	-0,279	0,010

a. Dependent Variable: SUCCESS_DT

Table 45: Quantitative report – Linear regression: Model summary for redesign internal structures

Model Summary

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	.290[a]	0,084	0,077	1,10550	0,084	12,555	1	137	0,001
2	.343[b]	0,118	0,105	1,08903	0,034	5,176	1	136	0,024

a. Predictors: (Constant), CENTRED MEAN REDESIGN INT STRUCTURES

b. Predictors: (Constant), CENTRED MEAN REDESIGN INT STRUCTURES, INTERACTION VARIABLE REDESIGN INT STRUCTURES

Table 46: Quantitative report – Linear regression: ANOVA scores for redesign internal structures

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	15,344	1	15,344	12,555	.001[b]
	Residual	167,433	137	1,222		
	Total	182,777	138			
2	Regression	21,482	2	10,741	9,057	.000[c]
	Residual	161,295	136	1,186		
	Total	182,777	138			

a. Dependent Variable: SUCCESS_DT

b. Predictors: (Constant), CENTRED MEAN REDESIGN INT STRUCTURES

c. Predictors: (Constant), CENTRED MEAN REDESIGN INT STRUCTURES, INTERACTION VARIABLE REDESIGN INT STRUCTURES

Table 47: Quantitative report – Linear regression: Coefficients for redesign internal structures

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	95,0% Confidence Interval for B Lower Bound	95,0% Confidence Interval for B Upper Bound
1	(Constant)	5,669	0,094		60,461	0,000	5,484	5,855
	CENTRED MEAN REDESIGN INT STRUCTURES	0,303	0,086	0,290	3,543	0,001	0,134	0,472
2	(Constant)	5,703	0,094		60,980	0,000	5,518	5,887
	CENTRED MEAN REDESIGN INT STRUCTURES	0,268	0,086	0,257	3,134	0,002	0,099	0,438
	INTERACTION VARIABLE REDESIGN INT STRUCTURES	-0,142	0,063	-0,186	-2,275	0,024	-0,266	-0,019

a. Dependent Variable: SUCCESS_DT

Table 48: Quantitative report – Linear regression: Model summary for improve digital maturity

Model Summary

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	.255[a]	0,065	0,058	1,11674	0,065	9,560	1	137	0,002
2	.303[b]	0,092	0,078	1,10491	0,026	3,951	1	136	0,049

a. Predictors: (Constant), CENTRED MEAN IMPROVE DIGITAL MATURITY

b. Predictors: (Constant), CENTRED MEAN IMPROVE DIGITAL MATURITY, INTERACTION VARIABLE IMPROVE DIGITAL MATURITY

Table 49: Quantitative report – Linear regression: ANOVA scores for digital maturity

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	11,923	1	11,923	9,560	.002[b]
	Residual	170,854	137	1,247		
	Total	182,777	138			
2	Regression	16,746	2	8,373	6,858	.001[c]
	Residual	166,031	136	1,221		
	Total	182,777	138			

a. Dependent Variable: SUCCESS_DT

b. Predictors: (Constant), CENTRED MEAN IMPROVE DIGITAL MATURITY

c. Predictors: (Constant), CENTRED MEAN IMPROVE DIGITAL MATURITY, INTERACTION VARIABLE IMPROVE DIGITAL MATURITY

Table 50: Quantitative report – Linear regression: Coefficients for digital maturity

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95,0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	5,668	0,095		59,844	0,000	5,481	5,856
	CENTRED MEAN IMPROVE DIGITAL MATURITY	0,252	0,082	0,255	3,092	0,002	0,091	0,413
2	(Constant)	5,690	0,094		60,311	0,000	5,504	5,877
	CENTRED MEAN IMPROVE DIGITAL MATURITY	0,257	0,081	0,260	3,182	0,002	0,097	0,416
	INTERACTION VARIABLE IMPROVE DIGITAL MATURITY	-0,140	0,071	-0,163	-1,988	0,049	-0,280	-0,001

a. Dependent Variable: SUCCESS_DT

Appendix E - Ethical Clearance

From: **MastersResearch2020** <MastersResearch2020@gibs.co.za>
Date: Wed, 30 Sept 2020 at 12:38
Subject: Ethical Clearance Approved
To: 19405813@mygibs.co.za <19405813@mygibs.co.za>

Gordon Institute of Business Science
University of Pretoria

Ethical Clearance Approved

Dear Morné van Heerden,

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.

Appendix F - Certification of Additional Support

I hereby certify that I RECEIVED additional/outside assistance on my research report in the form of technical and language editorial services, as detailed below.

Summary of language editorial services:

1. General language usage and style
2. Coherence and cohesion
3. Sentence structure
4. Tenses and concord
5. Punctuation
6. Unnecessary capital letters
7. British instead of American spelling
8. Consistency of all usage throughout
9. Ensure all usage is in keeping with the requirements and standards of GIBS (University of Pretoria)

Summary of technical editorial services:

1. Correct format, margins, typing font, pitch, spacing, etc.
2. Insert styles in headings where necessary
3. Cross-check abbreviations
4. Include electronic table of contents, list of tables/figures etc.
5. Ensure the thesis is technically ready for submission, meeting all the requirements of GIBS (University of Pretoria)
6. Correct references in text
7. Correct referencing in reference list (according to GIBS's recommended APA referencing style)
8. Cross-check references

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Appendix F (continued) - Certification of Additional Support

In support of the above, the following electronic documents will be made available upon submission of this research report:

- Confidentiality Agreement: Language Editor
- Confidentiality Agreement: Technical Editor
- Proof of Editing Certificate

I hereby declare that all interpretations (statistical and/or thematic) arising from the analysis; and write-up of the results for my study was completed by myself without outside assistance.

____

Morné van Heerden

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Date: 31 January 2021