Gordon Institute of Business Science
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Digital transformation and competitive performance in the mining industry: the role of dynamic capabilities

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A research project submitted to the Gordon Institute of Business Science, University of Pretoria, in partial fulfilment of the requirements for the degree of Master of Business Administration.

02 November 2025

ABSTRACT

The mining industry, which is usually slow to change and moderate in innovation, faces impending prospects of significant disruption due to a wave of Digital Transformation (big data analysis, internet of things (IoT), and artificial intelligence). When Digital Transformation (DT) is implemented correctly, the impact on Competitive Performance is significant. Despite this, empirical research on the impact of DT on Competitive Performance and other influencing factors has been limited.

The overall objective of this research was to study the role of Dynamic Capabilities on the relationship between DT and Competitive Performance in the mining industry. A quantitative study was designed, and survey data were collected from 212 employees in the mining industry.

Through Hierarchical Multiple Regression analysis, results showed that there is a positive relationship between DT and Competitive Performance. The research also showed a strong impact of DT on Dynamic Capabilities. While results could not support mediation effects of Dynamic Capabilities, the results show that Dynamic Capabilities (when compared to DT) have more impact on Competitive Performance.

The findings suggest that Dynamic Capabilities are important for mining organisations given the prospects of disruptions. Business leaders need to find a balance between pursuing DT while strengthening Dynamic Capabilities.

Keywords
Digital Transformation, Dynamic Capabilities, Competitive Performance, Mining Industry

Plagiarism 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 Business Administration at the Gordon Institute of Business Science, University of Pretoria. It has not been submitted before for any degree or examination in any other University. I further declare that I have obtained the necessary authorisation and consent to carry out this research.

Student number: 26236304
Date: 02 November 2025

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

TABLE OF ABBREVIATIONS

BDAC	Big Data Analytics Capabilities
CP	Competitive Performance
DT	Digital Transformation
IoT	Internet of Things
KMO	Kaiser-Meyer-Olkin
AI	Artificial Intelligence
ESG	Environmental, Social, and Governance
GenAI	Generative AI
GIBS	Gordon Institute of Business Science
IEEE	Institute of Electrical and Electronics Engineers
IT	Information Technology
MNE	Multinational Enterprise
PC	Personal Computer
QQ	Quantile-Quantile
QR	Quick Response
SME	small and medium enterprises

CHAPTER ONE: INTRODUCTION TO THE RESEARCH PROBLEM

1.1. Introduction

This research project's overall objectives are to understand the role of Dynamic Capabilities regarding Digital Transformation and Competitive Performance in the mining industry context. This chapter provides background to the research project and justifies the research problem and objectives. The rationale for the research project is articulated from both academic and business perspectives, ensuring academic and business relevance to the research.

1.2. Background and Research Problem

Organisations are facing significant disruptions due to the current wave of Digital Transformation (DT) led by big data analysis, Internet of Things, cloud computing, and artificial intelligence (Mele et al., 2024). Similarly, the mining industry, traditionally seen as slow to change and relatively moderate in innovation, faces the prospects of radical disruption due to DT (Fernandez, 2021; World Economic Forum, 2025). Porter (2008a) notes that technological change is important in competitive advantage and equally argues that the evolution of technology is not the same across all industries. While the early adopters of DT, such as retail and manufacturing, are realising economic benefits, the resource and energy sectors have lagged on the DT journey (Maroufkhani et al., 2022). The underperformance of resource and energy companies in DT stands in stark contrast to the significant opportunities for digitalisation within the mining sector. For example, Korbel & Grabbert (2024) suggests that the mining sector holds one of the highest potentials for automation and projects an adoption rate of approximately 33% by 2030.

As mineral resources become increasingly difficult to access due to the deepening of mines, the mining industry must innovate merely to sustain current production levels (Maroufkhani et al., 2022). In this context, the emphasis and urgency of DT within the mining industry are warranted, given (1) the sector's substantial potential and (2) the need to meet future mineral demand. Kanbach et al. (2024) caution that the rapid rise of generative AI will have significant implications for business models. The recent acceleration of artificial intelligence is expected to intensify pressure on DT initiatives within mining companies, and this will further challenge traditional models of value creation in the sector.

According to Chatterjee & Mariani (2024) enhancing competitiveness enables companies to lower operational costs, improve efficiency, and enables competitors to adopt emerging digital technologies as a strategic response to rivalry. The traditional schools of thought have predominantly aligned with the resource-based view, which claims that organisations achieve competitive advantage through the ownership of unique, inimitable resources (Zahra, 2021). The long-standing theory on resource-based view has been helpful for leaders of organisation to improve insights on how organisations can use their resources to have a competitive advantage (Zahra, 2021). To this end, what resources should leaders be attaining to have a competitive advantage? For example, in the mining industry, access to unique and rare mineral deposits—commonly referred to as long-life tier 1 resources—can be a source of competitive advantage for a mining company. However, this is not the only area of competitive advantage. Sellschop et al. (2025) notes that even though the mining industry is cyclical, few mining companies have been able to achieve exceptional results compared to their peers, and top performers are not separated by simply having higher quality assets.

With the advent of digital technologies, organisations that have shown success have not only adhered to a resource-based approach but have rather mastered their ability to respond timely and with strong abilities to innovate rapidly and to renew underlying competencies. In this case, merely having rare and unique mineral resources may be insufficient for mining organisations to achieve sustained competitive advantage. This underscores the growing importance of dynamic capabilities in the minerals industry, particularly given the transformative potential of digitisation and the disruptive nature of emerging technologies, such as artificial intelligence. This requirement is further amplified by the industry's reputation for being relatively slow in adopting new technologies (Sánchez & Hartlieb, 2020).

Moving beyond the resource-based view, Mele et al. (2024) argue that in the advent of DT, dynamic capabilities (DCs) are crucial to ensure alignment between business models and technology. DT requires organisation to elevate capabilities to sense, seize, and transform (so-called dynamic capabilities) when faced with a disruptive operating environment. Teece et al. (1997) argue that firms in the information technology sector have achieved a competitiveness advantage by being flexible and responding swiftly to emerging opportunities. Teece (2018) argues that while business models can be copied by competing organisations, the lack of DCs in rival companies may delay the adoption of the copied business model. From this perspective, a pertinent question emerges within the mining industry: why do mining firms with similar resource endowments and comparable resource profiles demonstrate differing levels of competitiveness?

Ancillai et al. (2023) notes that research has shown that the impact of digitalisation may differ across industries, given that some industries are more customer-facing and therefore need to focus on the value proposition. In this case, conducting industry specific research (such as the mining sector) on DT, DCs, and CP offers more perspective to the selected research areas. To the best of the researcher's knowledge, no mining-specific academic research has examined the relationship between DT and Competitive Advantage, nor the role of DCs within this relationship. DT and business model innovation have seen a rapid interest in the research communities over the last five years; however, a large proportion of research in digitalisation and business model innovation has focused on qualitative analysis instead of quantitative analysis (Ancillai et al., 2023). This indicates a growing interest in further research using quantitative methods.

1.3. Academic contribution of research project

On an emphatic call for research to revisit DC and DT research, Mele et al. (2024) argue that despite significant potential in DC and DT research, there is limited literature on DCs that relates to DT. This is puzzling given the potential of DT and the current threats and opportunities that exist for organisations with digital technologies. Ciampi et al. (2022) notes that researchers estimate an 80% increase in profit margins due to the adoption of digital technologies.

The research project was underpinned by DT, DCs, and the Competitive Performance (CP) theoretical framework. The research project aimed to contribute to the body of research by investigating the application of DT and DCs in the mining industry. This research aims to contribute to academic research in several ways. First, the focus in the mining industry allowed for nuanced views on the DT, DCs, and competitiveness within the mining industry. Based on the literature survey, research in this area has been largely generic and not industry specific. Research in the mining industry offers industry specific insights, more so, given the significant current reliance of having rare and so-called tier 1 mineral resources. Research in DCs and DT has primarily had a bias towards the early adopters of DT (retail, manufacturing, etc.). Soluk & Kammerlander (2021) argue that while there are significant studies on digital technologies, the bias towards technical research has left a gap in DT from a managerial view. This leaves a gap where the energy and resources organisations cannot easily relate to the research.

Second, this research investigates why mining organisations with significant resource endowments may underperform relative to peers with similar resource profiles. By focusing on the mining industry, a more grounded perspective on the relationship between DT, DCs, and competitiveness is provided. This focus is relevant given the mining industry's muted progress in DT, as evidenced by the limited adoption of digital tools.

Third, the research projects aligned with the call from Mele et al. (2024) on the need to revisit DT and Dynamic Capabilities to provide more insights into the domain. The incorporation of multiple core theoretical perspectives (DT, DC) in this research project supports the need to provide more insights into DT and Dynamic Capabilities. A nuanced and wide-ranging understanding of CP within the mining industry is also explored. By employing the lens of DCs and DT, the study connects diverse theoretical frameworks to deepen insights into how competitiveness is shaped in this context. This multi-theoretical approach also aims to create a foundation for identifying additional avenues for further research.

1.4. Business rationale of research project

The business rationale for this research is motivated by the need to deepen understanding of how dynamic capabilities influence the success of DT initiatives aimed at enhancing CP in the mining sector. The mining industry is ripe for DT with a high potential for automation (Korbel & Grabbert, 2024). This study addressed that gap by offering practical insights on dynamic capabilities (specifically Sensing, Seizing, and Transforming) in the mining industry. The research argues for the need to strengthen Dynamic capabilities efforts to yield effective and sustainable results on CP in the mining industry.

Given the mining industry's traditionally slow approach to adopting new technologies (Fernandez, 2021) leaders must identify and address capability deficiencies that may hinder DT and the development of dynamic capabilities within their organisation. This research helps uncover specific weaknesses in dynamic capabilities that limit the impact of the mining company's CP. In doing so, the research provides a practical framework for capability development, enabling mining entities to respond more effectively to rapidly evolving technological and market environments.

1.5. Purpose statement and overarching research question

DCs are key in creating new business models (Teece, 2018). The speed and extent to which the company can align its resources and business models are determined by the strength of the organisation's DCs (Teece, 2018). To this end, strong DCs are a competitive advantage for an organisation. As described above, DCs are key enablers in DT. With the wave of DT projected to affect the mining industry as previously indicated, DCs and the ability to embed digital technologies will continue to be important for mining companies.

The purpose of the research project is to understand the role of Dynamic Capabilities (DCs) on the relationship between DT and CP in the mining industry. The research project has the following research questions:

> *Research Question 1: What is the role of Digital Transformation on Competitive Performance in the mining industry?*

Research Question 2: How do dynamic capabilities influence the relationship between Digital Transformation and Competitive Performance in the mining industry?

1.6. Document structure

The rest of the research paper has been organised as follows:

- **Chapter 2 – Literature Review**: Assesses the literature and the related theoretical frameworks relating to DT, CP, and Dynamic Capabilities. Analysis of the subconstructs of DCs (Sensing, Seizing, and Transforming) is also conducted. The literature review section focuses on the hypothesis developed for research based on the literature assessment.
- **Chapter 3 – Hypothesis**: A detailed hypothesis is provided in this chapter, and the applicable research model is also provided.
- **Chapter 4 – Methodology and Design**: A detailed account of the design choices is presented to provide a rationale for the method selection to respond to the research questions. The research methodology is also outlined with an account of the detailed research steps to ensure the reliability and validity of research results.
- **Chapter 5 – Results**: Detailed results of the study are presented in this chapter. The chapter presents results from validity and reliability assessments, followed by the descriptive statistics, and lastly, results from hypothesis testing are presented.
- **Chapter 6 – Discussion**: Results are discussed and grounded in the respective theoretical frameworks. A brief discussion is provided on descriptive statistics, followed by a detailed discussion on the hypotheses for the research project.
- **Chapter 7 – Conclusion and Recommendation**: The research project is concluded with a revisit of the research purpose and the research questions. Principal findings are outlined. Academic and business contributions of the project are provided. Lastly, the chapter concludes by outlining limitations and presenting potential future work.

CHAPTER TWO: LITERATURE REVIEW

2.1. Introduction

In a strong tribute to David Teece's work, Cavusgil & Deligonul (2024) argues that dynamic capabilities have had a significant relevance in the current generation, with several disciplines showing interest. Porter's five forces and resource-based theory have also contributed to various debates relating to the CP of organisation (Barney, 1991; Porter, 2008a). With the rapidly changing environment caused by DT, businesses' business models are being challenged, and businesses need to respond to remain competitive (Mele et al., 2024).

This research project aims to understand the role of Dynamic Capabilities (DCs) on the relationship between DT and CP in the mining industry. In this chapter, literature on Competitive Performance, DT, and Dynamic Capabilities is analysed. Additionally, the relationship between these constructs is also explored to enable the formulation of hypotheses. A literature map (shown in Figure 1 below) is provided to show linkages between the various theoretical frameworks.

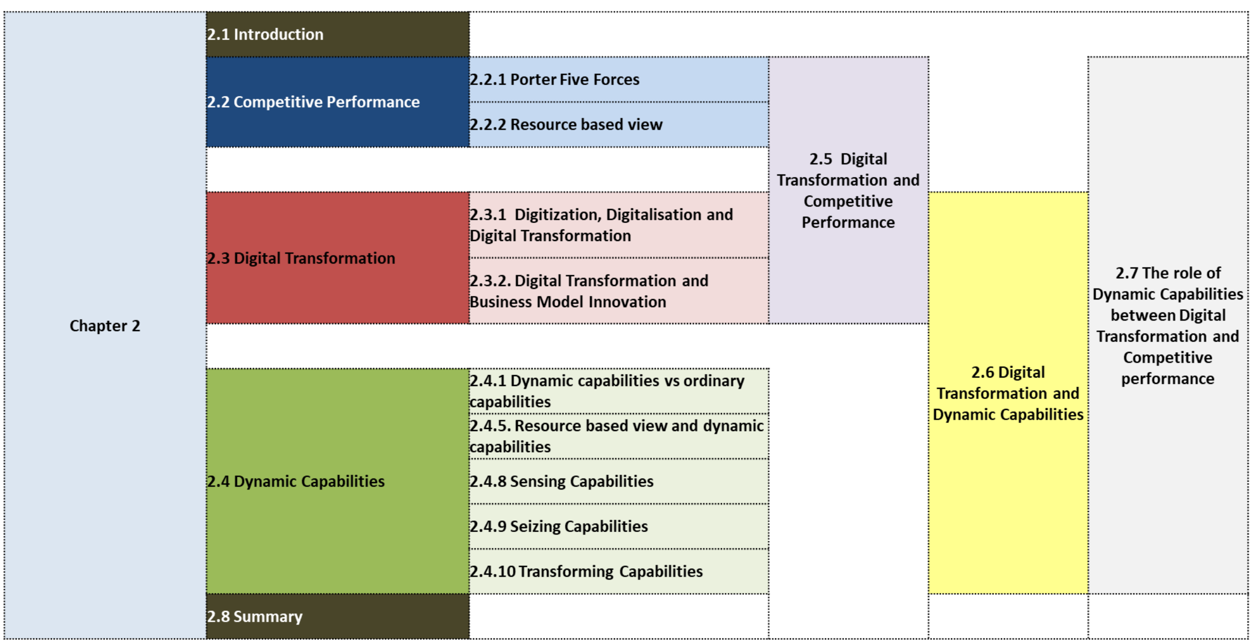

Figure 1: Literature review map

Source: Researchers' own compilation

2.2. Competitive Performance

This subsection covers key theory relating to CP, namely Porter's five forces and the resource-based view. A contrast of the two CP theoretical frameworks is provided in the subsection. While dynamic capabilities are also prominent in the CP research area, a separate section is used to discuss dynamic capabilities.

2.2.1. Porter's Five Forces

Porter (2008) argues that competition is fundamental to the success of organisation and furthermore competition is a cornerstone to the organisation's performance. In this case, given that competition is a key driver for performance, understanding how to obtain and maintain a competitive advantage becomes important. Fundamental aspects to consider in a competitive strategy are (1) how attractive the industry is and (2) what determines the company's competitive position relative to the industry in which the company is engaged (Porter, 2008a). In Porter (2008a) pivotal work, the five competitive forces were presented, contending that for an organisation to be successful, it needs to cope with the competition rules, namely: (1) rivalry, (2) power of suppliers, (3) power of buyers, (4) new competitors, and (5) substitutes. These forces were key determinants of how the industry performs. Porter (2008b)contends that the forces played a role in costs, and as an example, if there were strong suppliers, they would put pressure on the costs of raw materials. These forces have had a significant impact on the academic world and a significant impact on business practice for decades (Porter, 2008).

2.2.2. Resource-based view

Another lens to look at CP is the resource-based view theory, wherein Barney (1991) challenges Porter (2008a) underlying assumptions that organisations in the same industry have similar resources and, in part, are following similar strategic goals. This challenge is based on the Porter (2008) view that the first element of an organisation being profitable, is how attractive the industry is.

The second assumption that Barney (1991) challenges in Porter's model is that, if a new entrant or competitor introduces diversity of resources in the industry, the diversity of resources is not sustained for long periods of time. This is because existing organisations in the industry would simply acquire the same resources that introduces diversity in the industry. In this case, Barney (1991) was arguing against the assumptions that these new resources introduced in the industry are highly mobile, and so competitors in the industry can easily acquire or purchase these differentiating resources.

The resource-based view takes a more internal view of the CP of an organisation. Barney (1991) claims that organisation in the same industry may have differences in resources under their control and that these strategic resources cannot easily be bought or acquired by competitors. In this case, the resource-based view posits that organisations that control unique resources that are difficult to imitate have a source of competitive advantage (Zahra, 2021).

To provide clarity on resources, Barney (1991) classify these resources not only as physical resources (i.e., raw materials, equipment, etc.) but also as human capital resources (experience, relationships, etc.) and lastly, as organisational resources (planning processes, organisational structure setup, etc.). In this case, Zahra (2021) also notes that these strategic resources can be classified as tangible and intangible.

As argued by Zahra (2021), resource-based theory has provided long-standing insights on how organisations use resources to attain and maintain competitive advantage. To this end, the theory has been helpful for leaders of organisation for better insights on how organisations can use their resources to have a competitive advantage. In part, resource-based theory assists leaders in thinking of what resources to select in attaining a competitive advantage.

2.3. Digital Transformation

DT has had a significant impact on business models and has resulted in disruption to several traditional firms. Verhoef et al. (2021) note that academic research has largely paid limited attention to anything other than the focus on operationalisation of digital business models and the adoption of digital technologies. However, Verhoef et al. (2021) assert that there is limited academic research on the multidisciplinary scope of DT. In this case, the argument is clear that DT research is relatively narrow. Similarly, Kraus et al. (2022) contend that while there is an increase in the number of publications, the research in DT is still specialised to a specific domain and with minimal focus on business and managerial aspects.

The narrow research scope is puzzling, given that Ciampi et al. (2022) note that researchers estimate 80% increases in profit margins due to the adoption of digital technologies, wherein big data analytics, Internet of Things (IoT), and blockchain fundamentally improve company performance. In this case, DT is not just simply concerned with technology, as Kraus et al. (2022) argues that DT changes are vast, impacting business processes and operations, and can also adjust how the organisations generate revenue in terms of business models.

2.3.1. Digitisation, Digitalisation and Digital Transformation

To contextualise DT, a distinction is made between (1) Digitisation (converting from analogue into digital data), (2) Digitalisation (how technology can be used to alter or enhance existing business processes), and (3) DT, which is broader and even more multidisciplinary when compared to digitalisation (Verhoef et al., 2021). I addition, Kraus et al. (2022) state that DT focuses on integrating digital technologies across the organisation, including how the company is operated. In this regard, the broader definition of DT fundamentally touches all aspects of an organisations.

2.3.2. DT and Business Model Innovation

Mele et al. (2024) defines DT as organisation seeking to create value by deploying digital technologies to develop new business models. In part, DT can generate value for an organisation through operational efficiencies and increased innovation (Chatterjee & Mariani, 2024). Maroufkhani et al. (2022) highlight that digital technologies, such as big data analytics and artificial intelligence, can have a significant impact on operational excellence and CP for the resource and energy industry.

Recent research on DT has mainly focused on how DT can drive business model innovation, and in part, how digital technologies can target specific business model elements, such as the product itself (Ancillai et al., 2023). To offer a more comprehensive and multidisciplinary view of the DT definition, Verhoef et al., p. (2021, p. 889) defines DT as “a change in how a firm employs digital technologies, to develop a new digital business model that helps to create and appropriate more value.” With this definition, the argument is that DT is a broader concept that impacts the entire organisation.

2.4. Dynamic Capabilities

In strategic management, the overarching question is centred around how organisations maintain competitive advantage, and DC's theory is a key theory in unpacking other sources of competitive advantage beyond the resource-based perspective (Teece et al., 1997). To this end, dynamic capabilities offer another lens on CP over and above the resource-based view and Porter's five forces. The original definition of DCs focused on “the firm's ability to integrate, build and reconfigure internal and external competence to address rapidly changing environments” (Teece et al., 1997, p. 156). In this regard, being dynamic or adaptable to changes in the environment is central to Dynamic Capabilities.

In defining DCs, Teece et al. (1997) states that DCs are centred around the organisation’s ability to “achieve new forms of competitive advantage.” D. J. Teece et al., p. (1997, p. 515) further highlights that the word ‘dynamic’ denotes the company’s ability to respond (or adjust competencies) to align with the changes to the operating landscape or environment, and capabilities underscores the contributions of strategic management in directing the firm’s ability to adapt. DC’s focus on detecting potential future opportunities (Sensing), developing business models for future opportunities (Seizing), and selecting the best configuration of the business for the future (Transforming) (Teece, 2018). In this regard, DCs are key in ensuring that organisations respond promptly and effectively to rapid changes in the operating environment. In part, the DCs are key in maintaining the companies' competitive performances as they allow organisations to change in response to market adjustments.

A business model is defined as the architecture in which a business creates and delivers value and is concerned with revenue, costs, and ultimately profits (Teece, 2018). In this case, the relationship between DCs and business model innovation is apparent in that organisations with strong DCs will be able to review and adjust their business model quickly when the market or operating landscape is changing. In this regard, Teece (2018) argues that having strong dynamic capabilities leads to the development and implementation of business models to transform organisations.

2.4.1. Dynamic capabilities vs ordinary capabilities

For organisation, DCs direct organisation efforts towards high-payoff activities (Teece, 2018). Additionally, Teece (2014) makes a distinction of DCs from ordinary capabilities by highlighting that ordinary capabilities involve administrative activities, daily routines, and governance activities to deliver on production requirements. In this case, DCs are higher-order compared to ordinary capabilities.

Further tiering of dynamic capabilities can also be observed in academic literature. Teece (2018) argues that even in the above ordinary dynamic capabilities, there are two categories: micro foundations and highest order dynamic capabilities, focusing on Sensing, Seizing, and Transforming. In this case, micro foundations focus mainly on adjusting firms' ordinary capabilities, such as product extension and exploring new regions.

2.4.2. Need to internally develop dynamic capabilities

A further difference can be observed between ordinary capabilities and dynamic capabilities, given that Teece (2023) notes that Dynamic capabilities cannot simply be acquired and should be developed within an organisation as they rely on management learning and are partly ingrained into organisation culture and legacy. In this case, ordinary capabilities were seen as capabilities that could be acquired and fine-tuned for the organisation. In other words, Dynamic capabilities are idiosyncratic.

2.4.3. Role of top management in dynamic capabilities

Teece (2014) argues that top management teams' capabilities in Sensing, Seizing, and Transforming are particularly crucial in a dynamic and changing environment, and while these capabilities can be institutionalised over time, the instability of top management teams can have adverse impacts on these capabilities in the organisation. In this case, the importance of management taking a lead in developing dynamic capabilities within their organisation is essential.

2.4.4. Strategy and dynamic capabilities

When it comes to strategy, Teece (2014) connects the underpinnings of good strategy by stating that strategy focuses on diagnosis, policy, and action, which are synonymous with the dynamic capabilities (Sensing, Seizing, and Transforming). In this regard, the adaptability of organisation with strong dynamic capabilities supports the delivery of the strategy. Teece (2023) cautions that for organisations to enhance dynamic capabilities, management teams should have an entrepreneurial mindset and should be involved in developing and testing solutions that could be brought about by emerging trends in the market and technology.

2.4.5. Resource based view and dynamic capabilities

DC's research challenged the traditional strategic management theory of resource-based view. The resource-based view theory emphasises that organisations achieve and maintain competitiveness through the rare or unique resources that are hard to imitate (Zahra, 2021). In a highly dynamic environment, knowing what unique resources are hard to imitate in the future is thus a challenge. D. J. Teece et al. (1997) further notes that the resource-based view puts emphasis on diversification and vertical integration as means of improving competitiveness.

D. J. Teece et al. (1997) highlight the limitations of the resource-based theory, indicating that significant growth and competitiveness in the IT industry require researchers to expand the understanding of competitive advantage beyond the resource-based view. This argument is grounded in the view that firms in the technology sector have achieved competitive advantage not only by accumulating valuable technological assets, but also through their ability to respond rapidly and flexibly to emerging opportunities, and to redeploy core competencies effectively.

2.4.6. Dynamic capabilities – multinationals

Debates on the Dynamic Capabilities approach to international and multinational enterprises have continued into academic research. Given the diverse markets in which multinationals operate, Zahra et al. (2022a) challenge the inherent need to constantly adapt and reinvent that is inherent in Dynamic Capabilities theory, noting that multinationals need to preserve signature processes or endowments to maintain competitive advantage. Another lens to look at dynamic capabilities and multinationals is from a strategy development perspective. Pitelis et al. (2024) argue that dynamic capabilities are even more important for multinationals, given the need to cope with a dynamic political landscape and shape the broader external environment.

2.4.7. Debate on Dynamic Capabilities and Routines

Researchers have debated whether dynamic capabilities can be classified as routines in the organisation or not. Wilhelm et al. (2022) argue that rigid routines may be simplistic and find that firms in a changing environment apply the routines and a non-routine approach when it comes to developing dynamic capabilities in the organisation.

2.4.8. Sensing Capabilities

Sensing capabilities involve the company’s ability to identify emerging threats and opportunities, and in simple terms, Sensing is about “identifying where markets and technology are heading” (Teece, 2023, p. 116). In the application of dynamic capabilities, Teece (2014) notes that Sensing can be thought of as the capabilities of the organisations that involve identifying and developing technology opportunities to service the needs of the customer. In strategy development, ability to conduct diagnosis is important in market scanning. In a similar view, Teece (2014) argues that Sensing is important for strategy development, as broad scanning or Sensing is important is required to elicit opportunities and threats due to market or technology changes.

Teece (2023) argues that Sensing is a key first step in identifying opportunities brought about by new technologies, and the importance of relating the technology to customer needs that are not met. With the increase in technology, Teece (2023) suggests that it is easier to study customer needs and the impact of new technology in a rapid manner. In a similar finding, Jenkinson et al. (2024) found that big data analytics capabilities can support Sensing capabilities, which in turn lead to organisation transformation.

2.4.9. Seizing Capabilities

Teece (2014) states that Seizing is the capability of an organisation to direct resources to identified opportunities for value creation. In simple terms, Seizing is about grasping the opportunities and neutralising identified threats (Zahra et al., 2022b). Teece (2023) further states that Seizing is concerned with how the business generates revenue (i.e., developing a business model). Furthermore, Teece (2018) notes that management competencies in the development and refining of business models are crucial in the firm's ability to seize opportunities. Zahra et al. (2022a) suggest that while Sensing opportunities and threats is helpful, most of the research and focus is shifting towards Seizing, given the importance of moving beyond Sensing to Seizing, whereby organisations can focus on adjusting business models to harness the opportunities from Sensing.

2.4.10. Transforming Capabilities

Dynamic capabilities are an organisation's capability to study and understand market and technology trends (Sensing) and capabilities on how organisations can generate revenue through emerging trends (Seizing). The third element of Dynamic Capabilities is Transformation. The focus of continuous Sensing, Seizing, and Transformation underpins the dynamic capabilities as Teece (2014) argues that Transformation always focuses on renewal amidst changes in technology and competitor landscape. Furthermore, Teece (2023) notes that Transformation capabilities are about how the company reorganises itself to deliver on the promise of the new vision.

2.4.11. Summary – Dynamic Capabilities

Despite the impact of Dynamic Capabilities theory in academic research and the ongoing interest, some criticism and debates have been carried out in academic research. Cavusgil & Deligonul (2024) provide an analysis of some of the criticism, citing that operationalising dynamic capabilities is rather limited. Criticism has been labelled on the vague definition of dynamic capabilities, and debates continue whether Dynamic Capability is a theory or framework (Cavusgil & Deligonul, 2024). Despite the criticism, the ongoing academic reference on dynamic capabilities has caught the attention of researchers for decades. Cavusgil & Deligonul (2024) contends that the Dynamic Capabilities theory has challenged the view around competitive advantage, markets, and even strategy.

2.5. Digital Transformation and Competitive Performance

To achieve success in DT, Chatterjee & Mariani (2024) further highlight that for organisation to achieve success in DT, it needs to focus on explorative and exploitative DT. In this case, leadership become important in balancing explorative and exploitative activities. Jia et al. (2022) emphasise the importance of ambidextrous leadership, highlighting the need for organisations to concurrently pursue exploration and exploitation activities to foster innovation, while effectively managing the innate tension between these approaches, particularly in the context of limited organisational resources.

The balancing act between exploration and exploitation activities is therefore necessary for maintaining CP, given that it would allow companies to innovate while leveraging existing capabilities. Ancillai et al. (2023) argues that DT can drive incremental changes to business models, and in a similar vein, digital technologies can lead to radical disruption. Bhatti et al. (2021) highlights that digital technologies can support the development of new business models, enabling firms to adapt to a new operating landscape and thereby enhance their CP.

2.5.1. Quantitative studies on Digital Transformation and Competitive Performance

In a quantitative study focusing on the relationship between DT and sustainable performance; Li (2022) surveys similar studies looking at DT and CP, and argues that in most cases, the studies assumed results of a linear pattern between the two variables. These results provide insights to quantitative studies highlighting that there are several factors at play on the relationship between DT and CP. Therefore, the relationship between DT and CP can also be impacted by other variables.

Li (2022) further adds that 70% of DT programmes fail largely due to organisational inertia, whereby the organisations maintain existing routines despite the change. However, Li (2022) notes that dynamic capabilities have an opposite effect (when compared to organisational inertia) on DT and performance. The impact of DT on performance may be complicated, given the mixed effects of dynamic capabilities and organisational inertia that may come to play.

While conducting quantitative analysis of servitisation (shifting from selling products to services), Abou-Foul et al. (2021) found that DT had a positive influence on firm performance as well as a direct influence on servitisation in the manufacturing industry. To explain the results, Abou-Foul et al. (2021) noted that DT affected servitisation due to the ability of DT to create a digital ecosystem to support servitisation.

2.5.2. Hypothesis: Digital Transformation and Competitive Performance

Based on the preceding literature review on DT and competitiveness, the following hypothesis is proposed:

H1: There is a positive relationship between Digital Transformation (DT) and Competitive Performance (CP) in the context of the mining industry.

2.6. Digital Transformation and Dynamic Capabilities

Growth and evolution of research in Dynamic Capabilities has continued from the original formulation, and Teece (2023) notes that recent studies have used the Dynamic Capabilities theory to study DT for a wide number of industries. Teece (2018) argues that DCs are key to enabling companies to adapt in a constantly changing operating environment. In this regard, an organisation’s ability to sense, seize, and reconfigure enables it to effectively integrate digital technologies into its business activities.

Digitalisation and DCs would be key to enabling organisations to not only achieve but also sustain CP. DT can generate value for an organisation through operational efficiencies and increased innovation, and sustainable development (Kraus et al., 2022). In part, digitalisation allows organisations to adapt and be more flexible, and therefore, in response to changes in the dynamic operating environment (Chatterjee & Mariani, 2024).

2.6.1. Alignment of Digital Transformation and Dynamic Capabilities

Research in DT and Dynamic Capabilities has also focused on knowledge creation, mirroring dynamic capabilities and tailoring them to DT. For instance, Mele et al. (2024) highlight alignments such as (1) digital Sensing (identification of technology opportunities or threats), (2) digital Seizing (developing capability for managers to seize opportunities), and (3) DT (adaptation of resources and knowledge). Cannas (2023) notes that big data analytics is essential for digital Sensing to understand customer and technology trends. Similarly, digital Seizing is related to strategic agility, which requires rapid prototyping. Lastly, DT is related to the maturing digital capability of the workforce, which is important for organisational Transformation.

Extending on the Dynamic Capabilities theory, Day & Schoemaker (2016) extends dynamic capabilities by proposing sub-capabilities. For Sensing, peripheral vision (the ability to detect weak signals) and vigilant learning (the ability to have the correct meaning of weak signals) were proposed. For Seizing, probe and lean (trial and error through rapid prototyping), and flexible investing were proposed. For Transforming, organisation redesign (internal organisation Transformation) and external shaping (reshaping external ecosystems) were proposed.

Lastly, it is important to think about where DT is applied to ensure there are returns from DT. Li (2022) argues that there is a limitation on DT if it is not aligned with appropriate business processes. Li (2022) argues that DT is related to dynamic capabilities.

2.6.2. Digital Transformation with Sensing, Seizing and Transforming

Soluk & Kammerlander (2021) conceptualises DT into three overarching steps: (1) process digitalisation, (2) product and service digitalisation, and (3) business model, and further makes a correlation between DT and DCs. Soluk & Kammerlander (2021) argue that during the process digitalisation, the Sensing capabilities are key to identifying and understanding digital capabilities. Similarly, Teece (2023) adds that digital tools allow organisation to rapidly test potential solutions to upcoming threats or opportunities to support with Seizing.

Soluk & Kammerlander (2021) note that Seizing capabilities is crucial during the product or service digitalisation stage, as firms begin to capitalise on opportunities identified in earlier phases, and finally, during the business model digitalisation stage; organisations can transform their structures and focus on organisational renewal. Lastly, Li (2022) argues that DT also enables Transforming capabilities by ensuring the business has diverse options to enable organisations to transform rapidly to changes.

2.6.3. Quantitative studies on Digital Transformation and Dynamic Capabilities

Chatterjee & Mariani (2024), in an empirical study found that DT assists companies in being more innovative and competitive. This is in part due to the use of digital technologies in improving user experience and using data to offer better products. Additionally, Chatterjee & Mariani (2024) note that DT facilitates dynamic capabilities. DT can assist in Sensing, Seizing, and ultimately Transforming activities.

Similarly, studies have shown that big data analytics capabilities (which are accepted as a dynamic capability) have an impact on firm performance (Bahrami & Shokouhyar, 2022; Jenkinson et al., 2024). This is achieved by creating rapid and rich insights into changes to technology and market environments, and in this case, creates an advantage for the firm when it comes to competition.

2.6.4. Hypothesis: Digital Transformation and Competitive Performance

Based on the preceding literature review on DT and DCs (Sensing, Seizing, Transforming), the following hypotheses are proposed:

> *H2(a): Digital Transformation has a positive impact on Sensing (Dynamic Capabilities) within the mining industry.*
> *H2(b): Digital Transformation has a positive impact on Seizing (Dynamic Capabilities) within the mining industry.*
> *H2(c): Digital Transformation has a positive impact on Transforming (Dynamic Capabilities) within the mining industry.*

2.7. The role of Dynamic Capabilities between Digital Transformation and Competitive Performance

Chatterjee & Mariani, p. (2024, p. 13617) underscore that DT is "an effective facilitator of dynamic capabilities." In this case, DT plays a role in Sensing, Seizing, and Transforming activities by exploring new technologies, building new capabilities, and implementing new technologies. While digitalisation Transformation has many advantages for the firms' competitiveness and adaptability, Chatterjee & Mariani (2024) argue that DT can also be disruptive and may require companies to review their business models, and require organisations to develop new skillsets (Chatterjee & Mariani, 2024). This indicates that other factors influence the relationship between DT and CP.

2.7.1. Contributing factors to the relationship between Digital Transformation and Competitive Performance

The benefits of DT are widely acknowledged; however, the need to develop new capabilities within organisations pursuing DT presents significant challenges, particularly as these capabilities often do not yet exist within the organisation (Soluk & Kammerlander, 2021). Although the benefits of reducing costs and developing new business models are apparent, these benefits can be countered by the consumption of resources and the cost of the DT project, and the levels of uncertainty in the delivery of value (Soluk & Kammerlander, 2021). This argument denotes that there are a number of factors that influence the relationship between DT and CP.

In pursuit of offering a balance between DT and CP, Li et al. (2022) proceeds to argue that some studies do show digitalisation capabilities can assist companies to mature dynamic capabilities and, in turn, deliver uplifts in firm performance. However, on the same token Li et al. (2022) notes that digitalisation capabilities may also pose risks, and it is not always guaranteed that digitalisation leads to upliftment of dynamic capabilities, which in turn deliver CP.

Teece (2018) contends that organisations strength in underlying elements of DCs may differ; some organisation may be good at Sensing opportunities but struggle to translate these into new business models. In a similar vein, some organisations may be strong at developing a conceptual view of the business model but struggle to implement the designed business model. In this regard, quantitative analysis on the relationship between DCs and CP can offer better insights into the underlying relationship between variables.

2.7.2. Hypothesis: Mediating effects on Digital Transformation and Competitive Performance

Based on the preceding literature review on DCs and competitiveness, the following hypotheses are proposed:

H3(a): Sensing mediates the relationship between Digital Transformation and Competitive Performance.

H3(b): Seizing mediates the relationship between Digital Transformation and Competitive Performance.

H3(c): Transforming mediates the relationship between Digital Transformation and Competitive Performance.

In this relationship, a mediator is introduced. The aim is to understand the extent to which the mediating variable accounts for the relationship or impact between the independent variable and the dependent variable (Baron & Kenny, 1986). In this case, the research focuses on the extent to which DCs (Sensing, Seizing, Transforming) account for the relationship between DT and CP. Here, there is an interest in understanding how DT influences CP by understanding the relationship of dynamic capabilities.

2.8. Summary

This chapter surveyed literature relating to relevant constructs for the research project, namely: CP, DT, and dynamic capabilities. The comparison of Porter’s five forces with resource-based view was conducted. This analysis highlighted the shortcomings of Porter's model, given the underlying assumption that organisations' similar resources could be acquired. When discussing Dynamic Capabilities, the limitations of resource-based views are discussed since Dynamic Capabilities argues against the resource-based view as the environment is so dynamic that it would be hard to know what rare resources are hard to imitate.

The chapter proceeds to review literature on DT, highlighting research gaps that further support the research study. The growing importance of DT was highlighted in academia and in business this is more so given the current rapidly changing environment. The definition of DT was covered, and the need to have a multidisciplinary definition was presented. Lastly, dynamic Capabilities are discussed extensively and include the DCs elements of Sensing, Seizing, and Transforming.

The chapter then profiles literature that relates to the relationship between the three constructs. This assists research in formulating hypotheses to support the research objectives.

CHAPTER THREE: HYPOTHESIS

3.1. Introduction

This research project's overall aim was to study the relationship between DT and CP in the mining industry context. The research project's aim was also to test the mediating role of Dynamic capabilities between DT and the CP variable.

Chapter 1 focused on the background, rationale, and purpose of the research. Chapter 2 conducted a literature survey relating to the three key constructs, namely: DT, CP, and Dynamic Capabilities. Chapter 2 also profiled debates in academia related to the three constructs to position the overall research project. This chapter focuses on presenting the research questions and the related hypotheses. A research model is presented with the variables and related hypotheses.

3.2. Research questions and hypotheses

The research project aims to study DT and CP, and the role that Dynamic Capabilities play in the mining sector. The research questions are presented below.

3.2.1. Research question 1: Digital Transformation and Competitive Performance

Research question 1 focuses on understanding the role of DT on CP in the mining industry.

To respond to this question, the following hypothesis was proposed (step 1):

> *H1: There is a positive relationship between Digital Transformation (DT) and Competitive Performance (CP) in the context of the mining industry.*

3.2.2. Research question 2: Mediation of Dynamic Capabilities

Research question 2 focuses on the role of DCs in the relationship between DT and CP in the mining industry. Do dynamic capabilities mediate the relationship between DT and CP in the mining industry?

To respond to this question, the following sets of hypotheses are proposed in two steps:

Step 2: Digital Transformation and Dynamic Capabilities

H2(a): Digital Transformation (DT) has a positive impact on Sensing (Dynamic Capabilities).

H2(b): Digital Transformation (DT) has a positive impact on Seizing (Dynamic Capabilities).

H2(c): Digital Transformation (DT) has a positive impact on Transforming (Dynamic Capabilities).

Step 3: Mediating Effects of Dynamic Capabilities

H3(a): Sensing mediates the relationship between Digital Transformation and Competitive Performance in the mining industry.

H3(b): Seizing mediates the relationship between Digital Transformation and Competitive Performance in the mining industry.

H3(c): Transforming mediates the relationship between Digital Transformation and Competitive Performance in the mining industry.

3.3. Research Model

To provide full clarity of the research questions and relevant hypotheses, a research model was developed showing the three constructs: DT, DCs, and CP. The subconstructs of dynamic capabilities (Sensing, Seizing, and Transforming) are also presented in the model. The independent variables, dependent variables, and mediators are identified. Figure 2 below shows the developed research model for testing the preceding hypotheses and the research questions in this project.

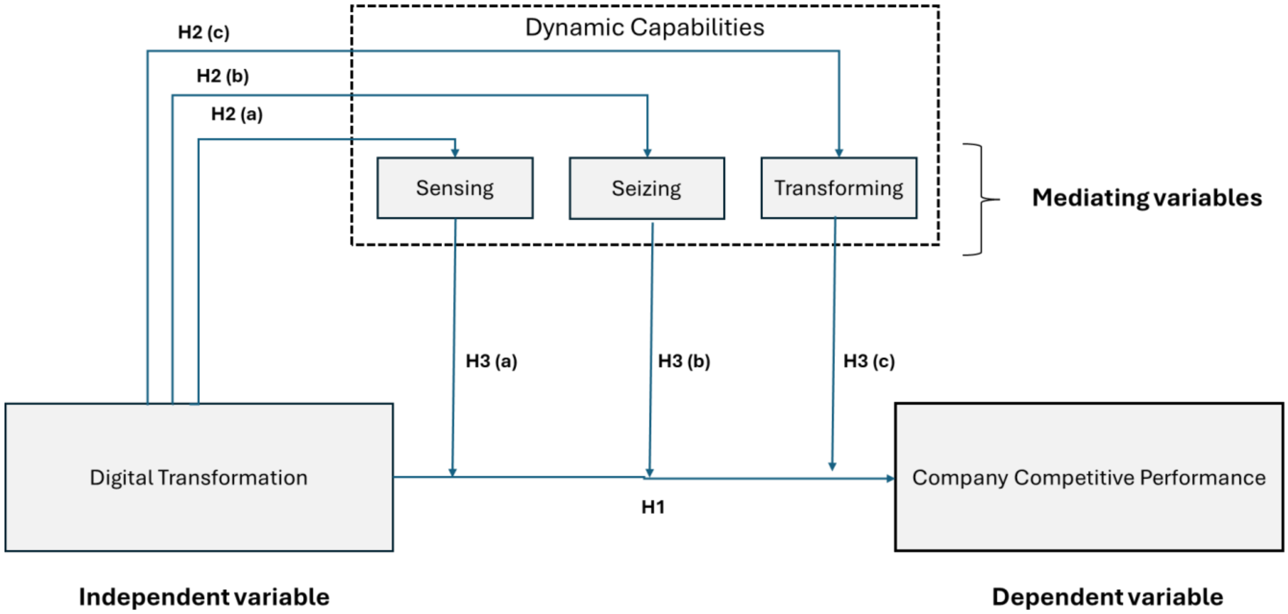

Figure 2: Project Research Model

Source: Researchers' own compilation

3.4. Conclusion

The chapter focused on the research question and the relevant hypothesis generated. To simplify the research project, a clear model was developed to outline variables, hypotheses, and relationships between variables tested.

CHAPTER FOUR: RESEARCH METHODOLOGY AND DESIGN

4.1. Introduction

It is important to make the right choices in research methodology and design so that the results from the research project can be considered credible (Saunders & Lewis, 2018). This research project studied the role of Dynamic Capabilities (DCs) on the relationship between DT and CP for mining entities. To this end, the overarching research question is as follows:

> *How do dynamic capabilities influence the relationship between Digital Transformation and Competitive Performance in the mining industry?*

This chapter focuses primarily on the research design choices made to respond to the overall research question. The chapter also details the research methodology used to conduct the research.

4.2. Choice of research design

4.2.1. Purpose of research design

The design and research methodology should follow on from the research questions and the intended objectives of the project (Saunders & Lewis, 2018). In this project, the researchers studied the relationships between DT and CP in the mining industry. In part, the research sought to understand the role of DCs in the relationship between DT and CP in the mining industry. Saunders & Lewis (2018) notes that descriptive research aims to explain a specific phenomenon by understanding causal relationships between variables. As relationships are being tested, the research design is explanatory in nature.

4.2.2. Philosophy

Saunders & Lewis (2018) state that positivism philosophy focuses on actual observations and measurements in developing meaning to a research phenomenon. The constructs of DT, DCs, and CP are well researched (Ancillai et al., 2023; Mele et al., 2024). The research followed a positivism philosophy as the study aimed to quantitatively analyse the relationship between multiple constructs that have been researched extensively. However, Ancillai et al. (2023) note that a large body of earlier research in DT and business model innovation is largely qualitative. So, while the constructs are well explored qualitatively, there are significant opportunities to contribute to the research through quantitative analysis.

4.2.3. Approach selected

The deductive research approach is suited for testing a theory, and additionally, the deductive approach is appropriate when there is substantive literature on the research area (Saunders & Lewis, 2018). The research project adopted a deductive approach where the theory of interest (DT, DCs, and CP) was identified. Hypotheses were drafted for the relationships that were tested, and data were collected to quantitatively test the hypotheses.

4.2.4. Methodological choices

In quantitative research, the mono method uses a single method to collect the data (Saunders & Lewis, 2018). Given the limited time available for the research project (as the research was for a partial contribution to a master's degree), a mono method was selected (i.e., a single technique of collecting data was selected). Using multiple methods of collecting data would have simply put the research project at risk, given the limited time to complete the research. A questionnaire (adapted from existing literature) was developed and used as the tool for data gathering.

In quantitative research design, Bettany-Saltikov & Whittaker (2014) argue that there are two types of approaches: one is descriptive (i.e., one-off relationship) analysis or experimental, where the measures are taken before a treatment and after a treatment. This research project used descriptive analysis, where a regression analysis between variables was conducted. The research did not include pre- or post-treatment measurements.

4.2.5. Strategy

A survey strategy was adopted to collect data using standardised set of questionnaires. Saunders & Lewis (2018) state that the questionnaire approach allows for data collection wherein the respondents answer the same set of questions, and questionnaires are suitable for descriptive or explanatory research. The research project is a quantitative study focusing on the relationship between DT, DCs, and CP; a survey method with standardised set of questions was selected in the research project. A questionnaire was developed using an existing quality questionnaire (instrument) from top-tier journals by other academic researchers in the following areas: DCs, DT, and CP. Please refer to Appendix 1 for the questionnaire adopted for the respective constructs.

As the research focuses on the mining industry, a slight adjustment was made to the following question under the competitive advantage instrument:
"CP4: Compared with our competitors, we have better product and service quality".

Omitting the term 'service' underscores the research's focus on the mining industry, wherein organisations primarily engage in the extraction, processing, and delivery of minerals to clients, rather than the provision of services.

4.2.6. Time horizon

Cross-sectional projects take a snapshot of data while longitudinal studies track events over time (Saunders & Lewis, 2018). The research project had a limited time footprint, and there would have been a significant risk if a longitudinal study had been undertaken. For practical purposes, this research project followed a cross-sectional approach as the project was conducted as a partial fulfilment of a Master of Business Administration qualification, and the constraint in time did not allow for a longitudinal study.

4.3. Proposed research methodology

4.3.1. Population

Substantial research on DT has largely focused on industries where leaders constantly utilise technologies to develop new products or services, such as the IT industry (Bhatti et al., 2021). However, the mining industry faces prospects of radical innovation due to DT (World Economic Forum, 2025). Ancillai et al. (2023) argue that studying the relationship between digital technologies in a specific domain might be more helpful to understand industry specific nuances. The research project focused on the mining industry. The target population for the research project was employees working in the mining industry. To ensure that only individuals working in the mining industry were included, a qualifying question was posed to the respondents before beginning the survey to ensure that only those individuals responded to the survey. After the consent statement in the research questionnaire, the question “Do you work in the mining industry?” was posed to the respondents. If the respondent selected “No”, the respondent was guided to the closing page where they were thanked, and their effort was acknowledged. The respondent would then submit and close the form.

4.3.2. Unit of analysis

The research project focused on the relationship between DT, DCs, and CP. DT focuses on how organisations create value by deploying digital technologies to develop new business models (Mele et al., 2024). Teece (2018), in defining DCs, notes that these are organisation activities involving Sensing, Seizing, and Transforming in the pursuit of creating new business models. The unit of analysis was at the organisation level as the study looks at DCs, DT, and CP for mining organisations. This was conducted by gathering perceptions and views from employees in the mining industry, hence the unit of analysis.

4.3.3. Sampling method and size

Saunders & Lewis (2018) profile several probabilistic and non-probabilistic sampling techniques and suggest that where the researcher can obtain a full list of the population, probability sampling can be applied. Since the target population is employees in the mining industry, the researcher was not able to obtain a full list of employees in the mining industry. Non-probability sampling techniques were selected.

Saunders & Lewis (2018) further highlights that there are several non-probability sampling methods, namely: (1) quota sampling with a set quota on the segment of a population, (2) purposive sampling where the researcher uses judgement to select participants, (3) volunteer sampling where the participants volunteer or are volunteered, and (4) convenience sampling in which easy to access individuals are selected. Apart from the quota sampling, the researcher adopted a mixture of purposive, volunteer, and convenience sampling to ensure reach to the targeted employees in the mining industry. The researcher's approach of using a mixture of purposive, volunteer approaches was due to the generally lower response rates to questionnaires. The average response rate from academic surveys is about 53% (36% from organisations) (Saunders & Lewis, 2018). Chidlow et al. (2015) note that a disadvantage of surveys is the response rates. The limited footprint to complete the research meant that a significant effort was required to gather responses to questionnaires.

The researcher started with purposive, then volunteer, and lastly, convenience sampling. Purposive sampling was helpful since the target population was individuals in the mining industry, and the researcher intentionally selected individuals based on whether they worked in the mining industry. The researcher simply used the mining industry networks; forums to share the research questionnaire. Volunteering sampling was further used through online posts of the research questionnaire and asking individuals to repost or reshare the questionnaire. Convenience sampling was also used, where peers were also contacted for the research questionnaire, including posting on personal WhatsApp status.

Saunders & Lewis (2018) argues that for non-probability sampling (other than quota sampling), the sampling techniques require a smaller sample and often depend on the research question. This research focused on the relationship between DT, DCs, and CP in the mining sector. Hill (1998) notes that without a clear view of the total population size, a decision on the sample size is a balance between available time and energy to complete the research, and further recommends a minimum of 10 x (number of variables) for multiple regression analysis. This research had five variables in total and therefore a minimum sample of 50. Hill (1998) notes that while there is judgement that needs to be made on the sample size, larger datasets have higher statistical power. For this research project, the aim was to achieve a sample size of at least 150 using a mixture of purposive, volunteer, and convenience sampling. A total sample of 224 was achieved (212 qualified for the research project). Achieving a sample size of over 200 supports the original research design of ensuring higher statistical power on the statistical tests.

4.3.4. Measurement Instrument

The objective of the research was to study the role of DCs in the relationship between DT and CP. As indicated, a survey questionnaire was adopted for this research. Please refer to Appendix 1 for the detailed survey instrument with the constructs that were measured, including the relative measurement items. The survey questionnaire was developed from the questionnaires that exist in academic literature covering the following constructs: (1) DT (Rahman et al., 2025), (2) DCs (Kump et al., 2019), and (3) CP (Behl et al., 2022). The rationale for reusing existing questionnaires was that these questionnaires have been tested and validated by well-established journals. The survey instruments have been adapted from previous research in a verbatim manner, and others with a slight adjustment on CP to reflect that mining companies produce products instead of services.

A Likert five-point scale was used to gather responses from respondents. The Likert scale was set up to allow participants to select Strongly Agree (5); Agree (4); Neutral (3); Disagree (2); and Strongly Disagree (1).

The questionnaire also included brief demographic information of the respondent, such as age, gender, education level, years in the organisation, discipline of respondent, mining company size, level in the organisation, continent where the respondents primarily work, and mining company size. The questionnaire also included the consent statement above the questionnaire.

As the research project focuses on employees in the mining industry, a respondent had to confirm that he or she is an employee in the mining industry. The questionnaire was designed to limit incorrect inputs. This was achieved by ensuring that questions are completed before submitting the results (i.e., questions were made mandatory, and the submission could only be made once the responses had been captured). Where a single response was expected, the questionnaire restricted inputs appropriately by using radio buttons.

Pilot testing and validation of the questionnaire were conducted to prevent errors when the Google Form is released to the participants. The workflow to assist in excluding individuals not in the mining industry was tested to ensure that the tool can filter individuals not from the mining industry. More checks were conducted to ensure mandatory questions were completed before submitting the survey. The research instrument was tested with nine individuals to ensure that the tool is accurate and the workflow works. Feedback was elicited on the usability of the tool, and generally positive responses were received; however, a few recommendations were made. Feedback showed that the text needed to be formatted to cater for mobile and PC access. Unnecessary line spaces were adjusted on the research instrument for formats of mobile and PC access. Also, export to Excel was conducted to test how the data would be extracted and that the correct values are showing. Feedback on timing was elicited from the testers to validate the length of the survey to complete. Respondents were comfortable with the response time of between 5 to 10 minutes. Pilot testing of the online questionnaires ensured that the instructions and technical issues were ironed out before launching the tool.

4.3.5. Data gathering process

The survey questionnaire was developed on Google Forms, ensuring a simple interface for the respondents to access the survey (link and QR code). Data was gathered following a mixture of purposive, volunteer, and convenience sampling. The first phase focused on using purposive sampling, reaching out to contacts in the mining industry via various social media platforms (LinkedIn, WhatsApp, Facebook, etc.). In the second phase of data gathering, convenience and volunteering approaches were used to gather data. The researcher used current contacts to assist in extending the research to other contacts they might have to ensure a broader reach.

Questionnaires were distributed via social media platforms, primarily LinkedIn, WhatsApp, and mining groups on Facebook, where the link to the questionnaire was shared. Saunders & Lewis (2018) recommend several ‘netiquettes’ when using internet-based questionnaires, such as avoiding spam emails, multiple emails to the same individual, and emails that could be perceived as a security risk. The researcher placed several controls to minimise technical issues that may constrain responses. The distribution channels (various social media platforms, LinkedIn, WhatsApp, etc.) and cover notes were developed to ensure appropriate reach to the targeted employees in the mining industry. Chidlow et al. (2015) recommends a four staged mail correspondence with the targeted individuals: (1) initial mail of the questionnaire, (2) ‘thank you’ note and reminder for those who had not submitted, (3) a second copy of questionnaire for those who has not submitted, and (4) a third copy of questionnaire with more emphasis on the importance of the questionnaire.

To meet the minimum 10-year period where research information needs to be stored, a Google Drive folder was used to store survey results. To ensure anonymity, the survey instrument did not request names or identifiers, such as organisations information. Lastly, only aggregated information was included in the research report.

To ensure an adequate timeframe for gathering responses, the research study focused on individuals in the mining industry. The data gathering began on the 21st of July 2025 to the 2nd of September 2025. This meant the research questionnaire had a resident time of 43 days (c. 1.5 months) to enable individuals to respond.

4.3.6. Analysis approach

Data gathered via the online survey (Google Forms) was downloaded and converted into a Microsoft Excel file. The dataset was checked for completeness. Once the data had been converted into an Excel file, IBM SPSS statistical software was used for analysis. The data was then coded appropriately to ensure the correct interpretation of the data obtained from the survey results. Please refer to Appendix 3 for the codebook.

Wegner (2020) notes that descriptive statistics are useful for basic statistics such as location, spread, and shape of data being analysed. Once data is available on SPSS, descriptive statistics were generated on the variables being measured to confirm that the data is decoded and loaded appropriately. The descriptive statistics also allowed the researcher to validate the size of the populations and gather basic statistics such as the mean and spread. The use of basic statistics assisted in describing the data that was gathered.

For quantitative analysis, Bettany-Saltikov & Whittaker (2014) note that it is important to have clear variables and understand whether the variable is dependent or independent, as quantitative research mostly focuses on the relation between the independent variable and the dependent variable. The research project focuses on testing the relationship between several variables within the DT, DCs, and CP. Figure 2 the research design model and the variables being tested. When testing the relationship between Digital Transformation and CP, CP is the dependent variable and DT is the independent variable. Sensing, Seizing, and Transforming were mediating variables. Bettany-Saltikov & Whittaker (2014) argue that there is no single precise answer regarding the choice of statistical test; however, the emphasis should be on selecting the most appropriate analytical method that effectively addresses the research question.

Regression analysis can help researchers understand the variability observed in the dependent variable, which independent variables or predictors may explain. Zhang et al. (2009) highlight that the Hierarchical Multiple Regression model assists in mediator investigation and in understanding the mediation process. In part, the Hierarchical Multiple Regression can be used in analysing the results of the independent variable (predictor) on the dependent variables by controlling other variables. The research aims to focus on mediating effects of Sensing (Dynamic Capabilities), Seizing (Dynamic Capabilities), and Transforming (Dynamic Capabilities) on the relationship between DT and CP. In this case, the researcher can analyse the effects of DT while controlling other variables (Sensing, Seizing, and Transforming). Through an examples for Hierarchical Regression, Zhang et al. (2009) suggests the following steps: (1) analyse or show the relationship between independent variable (IV), or predictor and the dependent variable (DV); (2) the second step is to analyse or show the relationship between independent variable (IV) and the mediator variable; (3) analyse or show that once the mediator variable is added to the model, the impact of independent variable on dependent variable is reduced. Applying these steps to this research project, the following steps will be followed:

1. Analyse the relationship between DT and CP in the mining industry. The Hierarchical Multiple Regression method will be used for this case.
2. For each mediator: analyse the relationship between DT and the mediator (i.e., Sensing, Seizing, Transforming). The method used here will be simple linear regression.
3. For each mediator (Sensing, Seizing, Transforming), show that the impact of DT on CP is reduced. The Hierarchical Multiple Regression method will be used for this case.

Lewis (2007) notes that by calculating the change in adjusted R^2 at every step of Hierarchical Regression analysis, the incremental variance of each variable added is thus observed. Therefore, the researcher can also understand the impact of each mediating variable by introducing each mediator to understand the incremental variance change. Lastly, Pallant (2020) outlines a number of assumptions for Hierarchical Multiple Regression namely: sample size, testing for outliers, and normality test. The subsequent results chapter will present the outcomes of these.

4.3.7. Quality controls

The online questionnaire was tested and validated to prevent any survey development errors. Heale & Twycross (2015) state that measuring Cronbach's alpha is a common tool that is used to measure internal consistency. Cronbach's alpha assists in understanding the reliability of the scale. A Cronbach's alpha of more than 0.7 is recommended in terms of the quality of the instrument (Heale & Twycross, 2015). The scales used to measure DT, DCs, and CP have a Cronbach's alpha ranging from 0.82 to 0.89, as reported by Rahman et al. (2025), Kump et al. (2019), and Behl et al. (2022). Please see Appendix 1 with the instrument and respective Cronbach Alpha values. In this case, the measurement scale shows reliability, from prior research, as they have a value above 0.7. Once the survey results were gathered, Cronbach's alpha values were calculated based on collected data. These reliability results are presented in the Results Chapter.

4.3.8. Ethical Consideration

The research project had to adhere to requisite ethical requirements, and the following considerations were made for the research.

- Consent was sought from the participant by ensuring a consent statement was shared ahead of beginning the survey.
- Participation in the research was voluntary, and participants could withdraw at any time without penalty.
- Participation was also anonymous, and the research project needed to report only on aggregate data.

Please refer to Appendix 2 for the ethical clearance approval.

4.3.9. Limitations

The research project was a quantitative research study, and as a limitation, there was no opportunity to probe further into the submitted questionnaires to gather further insights. As the population of mining employees was not fully known, a mixture of purposive, volunteer, and convenience sampling was followed. The rationale for this approach was to de-risk the project to ensure adequate responses. Not using random sampling may have introduced selection bias, which may subsequently limit the findings of the research.

While the research is aimed at survey participants to provide inputs and insights from different mining regions across the globe, there was a limitation that the respondents concentrated on a specific region and did not achieve equal representation from different regions.

4.4. Summary

This chapter provided an account of the number of decisions made to respond to the overall research question. The selected research design for this research supports the aim of the project to study the relationship between DT and CP, and the role of dynamic capabilities in this relationship. The research followed a positivism philosophy to quantitatively analyse the relationship between constructs that have been researched.

The study focuses on the mining industry, and the target respondents of the research were the employees working in the mining industry. A measurement instrument was developed using previous survey questions from high-quality journals. The adopted research instrument achieved an appropriate level of internal consistency with a reported Cronbach's alpha above 0.8. Pilot testing of the survey was conducted, and the research project achieved over 200 responses, well above the target of 150 respondents.

Given the need to test for mediation, Hierarchical Multiple Regression was adopted in the research project. Hierarchical Multiple Regression allows for studying the relationship between the independent variable (Digital Transformation) and the dependent variable (Competitive Performance) while controlling for other variables such as Sensing, Seizing, and Transforming.

CHAPTER FIVE: RESULTS

5.1. Introduction

This chapter focuses on presenting the results from the research study. The chapter starts by presenting the response to the research survey. Thereafter, validity and reliability results to demonstrate due care and quality of the data obtained. Factor Analysis is presented to confirm the factors in the research instrument. Descriptive statistics are presented, focusing on demographics and the constructs in the research. To simplify results on constructs, stacked bar charts are used to ensure easier interpretation of large datasets relating to results from the Likert scale. Lastly, results of the hypothesis testing are presented as a segway to the discussion chapter. Careful attention is placed on presenting decisions made on what is appropriate data to include to maintain the quality of the research. A summary of the decisions is also presented before providing the results of hypothesis testing.

5.2. Response to Survey

The overall number of survey links sent to target individuals was 440, primarily through direct LinkedIn (412) and WhatsApp (28) messages. The survey was also forwarded by several colleagues to various social media groups, mining groups on social media. Distributions were also conducted via own personal status (LinkedIn and WhatsApp), and the number of individuals who requested to complete a survey is unknown to the researcher. The precise response rate is impossible to determine. The overall number of surveys that were completed was 224.

The survey instrument was designed for one qualification question to ensure that respondents worked in the mining industry. The rationale was to confine the research respondents to individuals working in the mining industry, as the research aimed to elicit views from these individuals relating to DT, dynamic capabilities, and CP in the mining industry. Of the 224 surveys completed, 12 answered “No” to the question, “Do you work in the mining industry?” The 12 respondents who answered “No” to the qualifying criteria were removed from the total number of respondents. This meant that 212 were the correct respondents (or 95% of the respondents worked in the mining industry, and therefore an appropriate sample for this research, as it is based in the mining industry). The first question of checking if the individual works in the mining industry allowed the research instrument to be 'closed' if the individual does not work in the mining industry and ensures that only appropriate users are selected and without wasting the time of the individual.

Of the 212 valid respondents, analysis was conducted across all the questions, and all responses were valid. I.e., there were no missing values across all the questions. The minimum and maximum values also aligned with the expected value as per the codebook.

5.3. Validity of research instrument

To assess the validity of the research instrument and related questions, a total score for each construct was calculated. This was achieved by summing items (or questions) for each respondent. Once the total score was calculated for each construct per respondent, a Pearson Bi-variate correlation was conducted. Results of Pearson Bi-variate correlation were then analysed to assess a statistical significance level when each item/question is compared with the total score. All questions across the five constructs had a sig. values or p-values less than 0.05, suggesting that all questions proved valid. Please see Appendix 8 containing detailed correlation results per construct as evidence for the validity of the research instrument.

5.4. Reliability of research instrument.

To analyse internal consistency of the constructs, reliability assessments (using the Cronbach Alpha) were conducted on all the constructs, namely: (1) Digital Transformation (independent variable), (2) Sensing (mediating variable), (3) Siezing (mediating variable), (4) Transforming (mediating variable) and (5) Competitive Performance (dependent variable). The Cronbach's alpha of all the constructs is shown below in Table 1. All the constructs achieved a Cronbach's alpha of over 0.7. The Sensing and Transforming constructs are achieving over 0.8. Heale & Twycross (2015) recommend a Cronbach of 0.7 and above as an indicator of the quality of the research instrument. In this case, respondents answered consistently to the research questionnaire for all constructs. Therefore, the research questionnaire achieved reliability across all five constructs in the survey. While reliability is achieved, the researcher notes that the lowest Cronbach Alpha value in the assessment relates to CP, with a value of 0.76.

Table 1: Reliability Statistics

Construct	**No of Questions**	**Cronbach's Alpha**
Digital Transformation	5	0.777
Sensing (Dynamic Capabilities)	5	0.842
Seizing (Dynamic Capabilities)	4	0.789
Transforming (Dynamic Capabilities)	5	0.853
Competitive Performance	5	0.763

Source: Researchers' own compilation

5.5. Factor Analysis

This session focuses on exploratory factor analysis of the research instrument to simplify the set of variables per construct. Beavers et al. (2013) argue, in their practical guidance on exploratory factor analysis, that there are wide recommendations and academic debates on the appropriate approach to exploratory factor analysis. Analysis of validity in this research will follow the recommendations made by Beavers et al. (2013), namely:

- Correlational value assessment
- Bartlett's test for sphericity testing to see if the observed correlation matrix is not factorable
- Kaiser-Meyer-Olkin (KMO) sampling adequacy measured.

The researcher has adopted practical recommendation made by Beavers et al. (2013) and Palland (2020) on the criteria. Table 2 shows the criteria adopted on the assessment to allow the researcher to make consistent decisions on validity.

Table 2: Criteria for Validity

Type of assessment	Criteria
Correlational value assessment	Manually analyse the correlation matrix to see if all the variables have at least one correlation above 0.3 (Pallant, 2020).
Bartlett's test for sphericity	P-value (or sig. value) < 0.05, reject the null hypothesis and confirm that factor analysis is appropriate (Beavers et al., 2013).
Kaiser-Meyer-Olkin (KMO) value and interpretation	Classification of KMO values (Beavers et al., 2013): - 0.90 – 1.00 ➔ Marvellous - 0.80 – 0.89 ➔ Meritorious - 0.70 – 0.79 ➔ Middling - 0.60 – 0.69 ➔ Mediocre - 0.50 – 0.59 ➔ Miserable - 0.00 – 0.49 ➔ Don't Factor
Eigenvalues interpretation	The number of factors in the constructs will be determined by factors of Eigenvalues above 1 (Pallant, 2020).

Source: Researchers' own compilation

For this research project, a KMO value below 0.5 (i.e., the "Don't factor" classification as suggested by Beavers et al. (2013)) has been chosen to require adjustment of the construct statements to ensure a higher quality of results.

5.5.1. Independent variable – Digital Transformation

To analyse factors in the DT construct, a partial factor analysis was conducted following the steps prescribed in Section 5.5 above. In the first step, the inter-item correlation matrix was analysed for the DT construct. Analysing each item on the DT instrument, each item/statement had at least one correlation above 0.3 (please see the Appendix 7 for the Inter-item correlation matrix of DT items). Here, the first step of the factor analysis was considered successful for exploratory factor analysis.

The second step is to analyse the Bartlett's test for sphericity. The sig./p-value (shown in KMO and Bartlett's Test below) is less than 0.05, meaning that the null hypothesis is rejected and factor analysis is appropriate on the datasets.

The third step is to assess the KMO measure for sampling adequacy. Table 3 below shows the KMO score of 0.79 and is classified as 'Middling' as per the guidance in the section 5.5 above. This is considered acceptable for this research.

Lastly, assessing total variance explained based on the Eigenvalues (shown in Table 4) with the criteria specified in section 5.5. It is only Factor 1 with an Eigenvalue above 1. This means the researcher can group the five questions on the DT construct into one group or factor for analysis.

Table 3: Digital Transformation KMO and Bartlett's Test

KMO and Bartlett's Test (Digital Transformation)		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy		**0.793**
Bartlett's Test of Sphericity	Approx. Chi-Square	276.693
	df	10
	Sig.	0.000

Source: Researchers' own compilation

Table 4: Digital Transformation Total Variance Explained

Total Variance Explained (Digital Transformation)						
	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Factor	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2.666	53.325	53.325	2.130	**42.606**	42.606
2	0.833	16.658	69.983			
3	0.584	11.688	81.671			
4	0.533	10.659	92.330			
5	0.384	7.670	100.000			

Source: Researchers' own compilation

5.5.2. Mediating variable – Sensing (Dynamic Capabilities)

Following similar analysis conducted for DT above and using the criteria in section 5.5. These observations were made: (1) the intercorrelation matrix validated that factor analysis could be considered appropriate for the construct, since each item had at least one correlation value above 0.3 (see Appendix 7 for inter-item correlation matrix for Sensing). Analysing Bartlett's test for sphericity, the sig. or p-value is less than 0.05, and factor analysis is appropriate on the construct. The KMO measure for sampling adequacy shows a value of 0.83, classifying the Sensing construct results in the 'Meritorious' category (shown in Table 5). This is considered acceptable in this research. In the last step, the Eigenvalue in Table 6 shows that there is one factor on the Sensing construct.

Table 5: Sensing KMO and Bartlett's test

KMO and Bartlett's Test (Sensing - Dynamic Capabilities)		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy		**0.834**
Bartlett's Test of Sphericity	Approx. Chi-Square	398.282
	df	10
	Sig.	0.000

Source: Researchers' own compilation

Table 6: Sensing Total Variance Explained

Total Variance Explained (Sensing - Dynamic Capabilities)						
	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Factor	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	3.073	61.468	61.468	2.604	**52.077**	52.077
2	0.641	12.813	74.280			
3	0.505	10.100	84.380			
4	0.450	9.008	93.388			
5	0.331	6.612	100.000			

Source: Researchers' own compilation

5.5.3. Mediating variable – Seizing (Dynamic Capabilities)

In analysing the intercorrelation matrix, the factor analysis approach was considered appropriate for the construct, as each item on the Seizing instrument had at least one correlation value above 0.3 (see Appendix 7 for the inter-item correlation matrix for Seizing). Analysing Bartlett's test for sphericity, the sig. or p-value is less than 0.05, and factor analysis is appropriate on the construct. The KMO measure for sampling adequacy shows a value of 0.736, classifying Seizing construct results in the ‘Middling’ category (please see Table 7). This is considered acceptable in this research. In the last step, the Eigenvalue (in Table 8) show that there is one factor on the Seizing construct.

Table 7:Seizing KMO and Bartlett's test

KMO and Bartlett's Test (Seizing - Dynamic Capabilities)		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy		**0.736**
Bartlett's Test of Sphericity	Approx. Chi-Square	252.283
	df	6
	Sig.	0.000

Source: Researchers' own compilation

Table 8: Seizing Total Variance Explained

Total Variance Explained (Seizing - Dynamic Capabilities)						
	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Factor	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2.452	61.289	61.289	1.940	**48.506**	48.506
2	0.731	18.269	79.558			
3	0.428	10.707	90.265			
4	0.389	9.735	100.000			

Source: Researchers' own compilation

5.5.4. Mediating variable – Transforming (Dynamic Capabilities)

The intercorrelation matrix results confirmed that the factor analysis approach is appropriate for the construct, since each item on the Transforming instrument had at least one correlation value above 0.3 (see Appendix 7 for inter-item correlation matrix for Seizing). The Bartlett test for sphericity, the sig. or p-value is less than 0.05, and factor analysis is appropriate on the construct. The KMO measure for sampling adequacy shows a value of 0.855, classifying Transforming construct results in the Meritorious category (please refer to Table 9). This is considered acceptable in this research. In the last step, the Eigenvalue shows that there is one factor on the Transforming construct (please refer to Table 10).

Table 9: Transforming KMO and Bartlett's test

KMO and Bartlett's Test (Transforming - Dynamic Capabilities)		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy		**0.855**
Bartlett's Test of Sphericity	Approx. Chi-Square	424.354
	df	10
	Sig.	0.000

Source: Researchers' own compilation

Table 10: Transforming Total Variance Explained

Total Variance Explained (Transforming - Dynamic Capabilities)						
	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Factor	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	3.156	63.114	63.114	2.709	**54.174**	54.174
2	0.584	11.689	74.802			
3	0.498	9.963	84.765			
4	0.434	8.686	93.452			
5	0.327	6.548	100.000			

Source: Researchers' own compilation

5.5.5. Dependent variable – Competitive Performance

Looking at the dependent variable, the factor analysis approach is appropriate for the construct since each item on the CP instrument had at least one correlation value above 0.3 (see appendix 7 for inter-item correlation matrix for CP). The Bartlett test for sphericity, the sig. or p-value is less than 0.05, and factor analysis is appropriate on the construct (Please see Table 11). The KMO for CP is 0.70 (rounded up), classified as middling. The Eigenvalue (shown in Table 12) highlight that there is one factor on the CP construct.

Table 11: Competitive Performance KMO and Bartlett's test

KMO and Bartlett's Test (Competitive Performance)		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy		**0.696**
Bartlett's Test of Sphericity	Approx. Chi-Square	374.693
	df	10
	Sig.	0.000

Source: Researchers' own compilation

Table 12: Competitive Performance Total Variance Explained

Total Variance Explained (Competitive Performance)						
	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Factor	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2.641	52.816	52.816	2.249	**44.985**	44.985
2	0.935	18.708	71.524			
3	0.714	14.286	85.810			
4	0.533	10.667	96.477			
5	0.176	3.523	100.000			

Source: Researchers' own compilation

Further analysis of the Factor Matrix (shown in Table 13 below) highlighted that the item “Compared with our competitors, we have better product,” has a loading factor of 0.32. Pallant (2020) notes that the factor matrix shows the loading of each item against the factor and recommends that the value is above 0.4. Analysis of all constructs shows that all items load strongly (i.e., above 0.4) except for the above-mentioned item. In this case, a decision was taken to remove this item, more so given that it is related to a dependent variable. Additional context on removed item will be provided in the discussion chapter.

Given the removal of the question or item, a rerun of Cronbach's alpha on the construct was conducted, and the Cronbach's alpha moved from 0.76 to 0.79. A rerun of the KMO and Bartlett’s test was conducted on the adjusted instrument and showed a slight drop from 0.696 to 0.691. The total variance explained increased from 44.99% to 53.21%.

Table 13: Competitive Performance Factor Matrix

Factor Matrix[a/b]	**Untreated**	**Treated**
	Factor	Factor
	1	1
Compared with our competitors, we have higher profit growth rate	0.874	0.861
Compared with our competitors, we have higher sales revenue growth rate	0.890	0.909
Compared with our competitors, we have lower operating costs	0.412	0.421
Compared with our competitors, we have better product quality	0.316	**Item removed**
Compared with our competitors, we have increasingly higher market share	0.651	0.638
	Extraction Method: Principal Axis Factoring.	Extraction Method: Principal Axis Factoring.
	a. 1 factors extracted. 7 iterations required.	a. 1 factors extracted. 10 iterations required.

Source: Researchers' own compilation

5.6. Descriptive statistics on Demographics

The questionnaire had eight questions relating to the demographics of the respondents, allowing the researcher to provide context to the research outcomes and to provide for control variables in the study. The demographic questions were relevant to the mining industry and the research topic relating to DT, dynamic capabilities, and CP in the mining industry.

5.6.1. Age of respondents

The sample showed an even split between respondents who are below 40 years old and those above 40 years old (i.e., 51% of respondents were greater or equal to 40 years old) (Please see Table 14). The largest single category was between 30 and 39 years old, with 45% of respondents in this category, followed by individuals between 40 and 49 years old with 30% of the respondents.

Table 14: Age split across the total respondents (n=212)

		Frequency	Percent
Valid	20-29 years	7	3.3
	30-39 years	95	44.8
	40-49 years	64	30.2
	50+ years	46	21.7
	Total	212	100.0

Source: Researchers' own compilation

5.6.2. Gender of respondents

The sample showed that 70% of respondents were male compared to 30% female respondents (Figure 3 below). Therefore, there is a strong bias towards male respondents in the survey. The mining industry is known to still have more male than female employees (Intergovernmental Forum, 2023), and the survey shows a similar distribution of females in the survey.

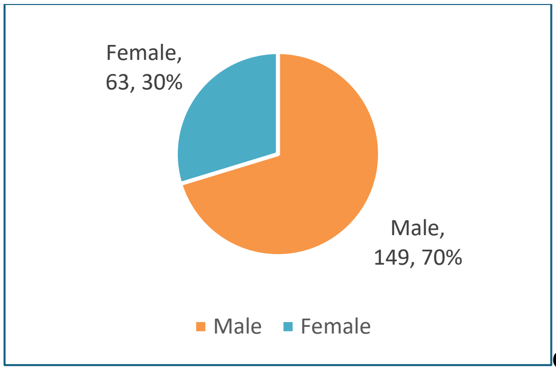

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Figure 3: Gender split across total respondents (n=212)

Source: Researchers' own compilation

5.6.3. Level of education of respondents

Majority of the participants had a postgraduate degree (67%), followed by respondents with an undergraduate degree (23%) (Results in Table 15). The results show that a high number of respondents had at least an undergraduate degree (92% of respondents). The researcher also used his own network, and they may be biased towards a similar profile of the researcher. The use of LinkedIn may also have led to more professional individuals working in the mining industry besides the frontline execution roles.

Table 15: Education level across all respondents (n = 212)

		Frequency	Percent
Valid	High school	3	1.4
	Diploma or advanced certificate	15	7.1
	Undergraduate degree	49	23.1
	Postgraduate degree (up to Master's level)	141	66.5
	Doctoral degree	4	1.9
	Total	212	100.0

Source: Researchers' own compilation

5.6.4. Years of employment in the mining organisation

The highest number of respondents had been with their organisation for more than one year but less than or equal to five years (30%), followed by respondents who had been with their organisations for more than 10 years but less than or equal to 15 years (19%). Results are shown in Table 16. It is worth noting that 64% of respondents had at least five years' experience in their organisation.

Table 16: Respondents years of employment in the mining organisation

		Frequency	Percent
Valid	Less than 1 year	13	6.1
	> 1 but ≤ 5 years	63	29.7
	> 5 but ≤ 10 years	39	18.4
	> 10 but ≤ 15 years	41	19.3
	> 15 but ≤ 20 years	24	11.3
	More than 20 years	32	15.1
	Total	212	100.0

Source: Researchers' own compilation

5.6.5. Disciplines where respondents work

Respondents noted that they worked across over 50 disciplines in their response to the survey. To analyse the different disciplines captured by the respondent, over 50 disciplines were grouped into 11 groups (Please see the appendix 4 for the full list of respondents and the groupings). The top three areas where respondents worked are: (1) Operations and Productions, (2) Innovation, Technology & Data Management, and (3) Engineering and Technical functions. These three disciplines accounted for 65% of respondents. Results are shown in Figure 4.

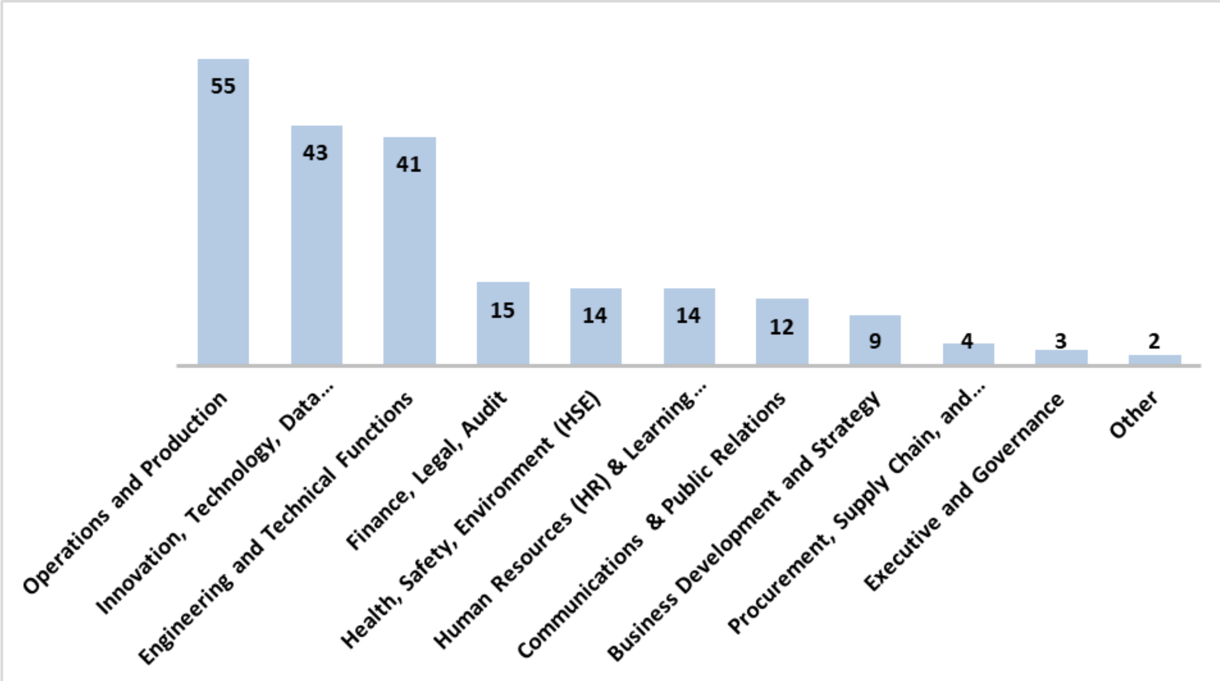

Figure 4: Disciplines where respondents work

Source: Researchers' own compilation

5.6.6. Management Level of respondents in their organisation

The majority of respondents (77%) were in middle management and above in their organisation (shown in Figure 5). Given that the sampling method used was a mixture of purposive, volunteer, and convenience sampling, there might be bias, since the researcher is in the senior level of management within the mining organisation.

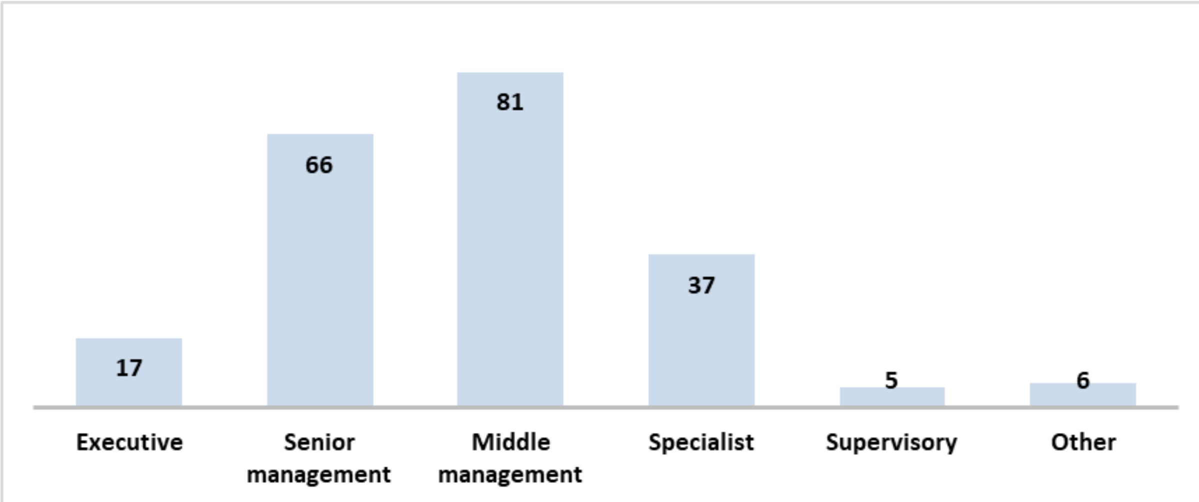

Figure 5: Respondents management level

Source: Researchers' own compilation

5.6.7. Size of mining organisation where respondents work

The highest number of respondents work for mining organisations with more than 20000 employees (45%), followed by organisations with 10001 to 20000 employees. Results are shown in Table 17.

Table 17: Aggregated view of respondents' organisation size

		Frequency	Percent
Valid	1 - 500 employees	14	6.6
	501 - 1000 employees	11	5.2
	1 001 - 5 000 employees	34	16.0
	5001 - 10 000 employees	20	9.4
	10 001 - 20 000 employees	37	17.5
	More than 20 000 employees	96	45.3
	Total	212	100.0

Source: Researchers' own compilation

5.6.8. Geographical region of respondents

When assessing the geographical region where respondents work, majority of respondents work in the Southern Africa region (75% of total respondents shown in Figure 6). This is followed by respondents in South America (12% of respondents) and then Australia/Oceania (5% of respondents). The researcher is based in South Africa and is currently studying at GIBS in South Africa, and the research results may reflect the bias towards Southern Africa as the researcher used a mixture of purposive, volunteer, and convenience sampling methods. It is noted that all continents/regions were represented in the research results, still showing a significant global reach of the research questionnaire, but with a bias in Southern Africa.

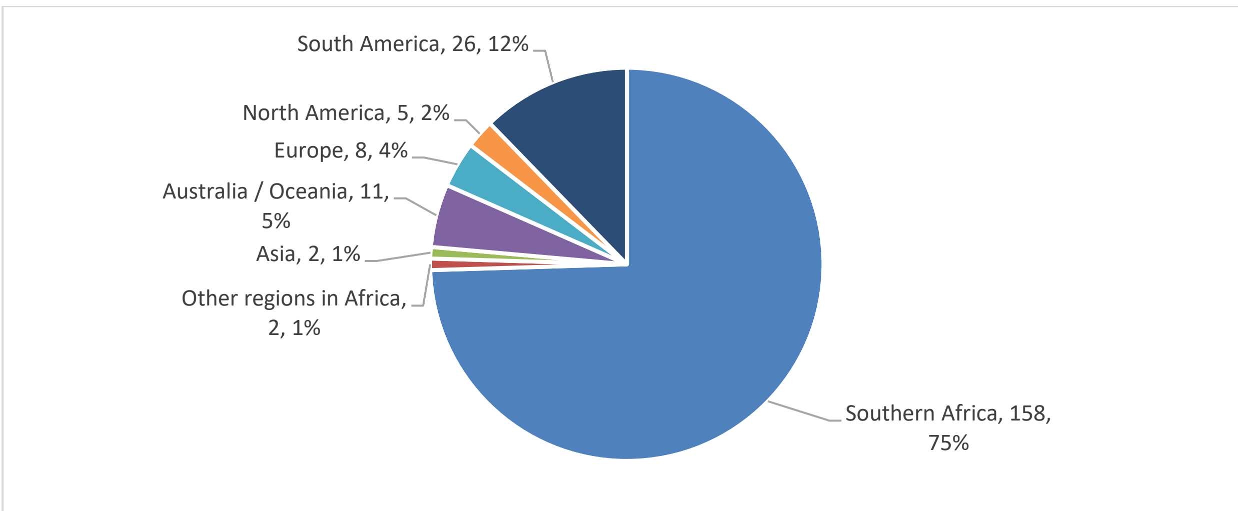

Figure 6: pie chart showing where respondents primarily work (n = 212)

Source: Researchers' own compilation

5.7. Descriptive Statistics on constructs

This section presents descriptive statistics on the construct within the research project, namely: DT, DCs (Sensing), DCs (Seizing), DCs (Transforming), and Competitive Performance.

5.7.1. Digital Transformation

The respondents responded with a high level of agreement on questions relating to DT in their organisations (results shown in Figure 7). Aggregating the “Strongly Agree” and “Agree” statements, most respondents indicated that they digitally upgrade existing offerings from manual to automated digital systems (86%). Similarly, most respondents indicated that their organisations implement a digital platform-based business model (67%). Lastly, a majority (74%) indicated that their organisations establish decision-making based on data analysis. It is worth noting that mixed results (less than 50% aggregated score between “Strongly Agree” and “Agree”) were received on whether respondents felt they develop intelligent offerings (i.e. AI AI-based tools) and whether the organisations flexibly adjust their structure or functional departments.

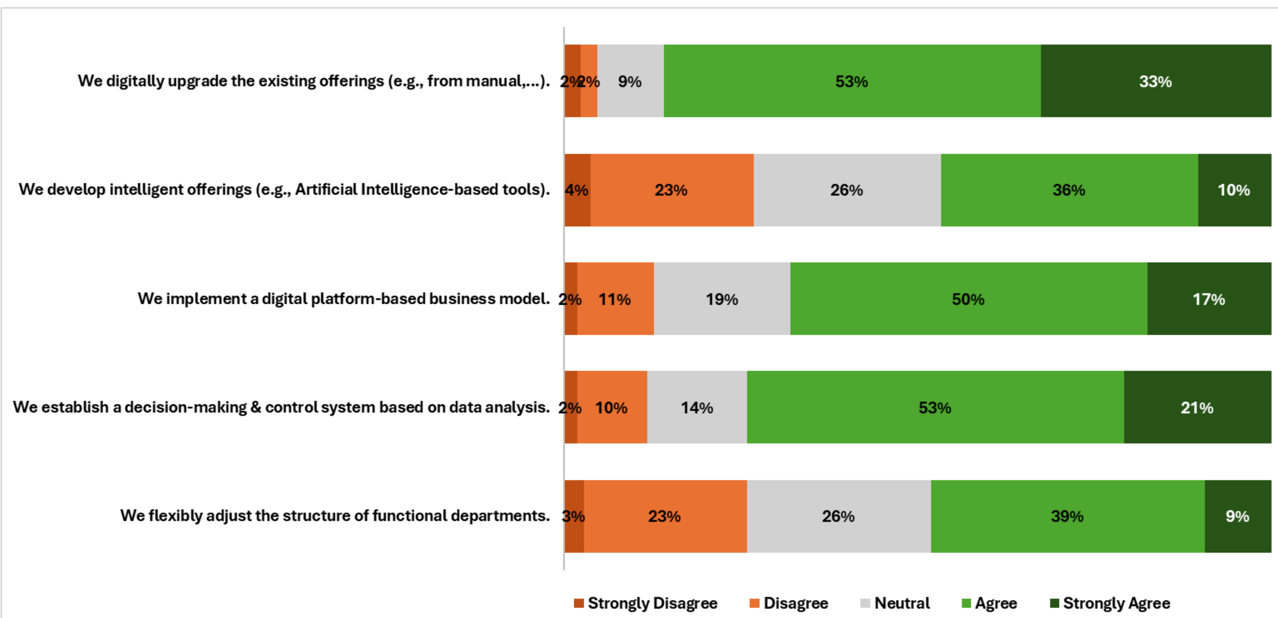

Figure 7: Digital Transformation Likert Scale Summary View

Source: Researchers' own compilation

5.7.2. Sensing (Dynamic Capabilities)

Most respondents agreed with statements relating to Sensing within dynamic capabilities (results shown in Figure 8). By combining “Agree” and “Strongly agree” responses, most respondents strongly agreed with all statements within dynamic capabilities, with the lowest combined scores ("agree" and "Strongly agree") of 64% on the statement of whether the company had an eye on competitor activities. Excluding the above-mentioned statement, the remaining statements on Sensing were more than or equal to 75% when combining "Agree" and "Strongly agree" statements. This shows strong agreement from respondents on statements relating to Sensing.

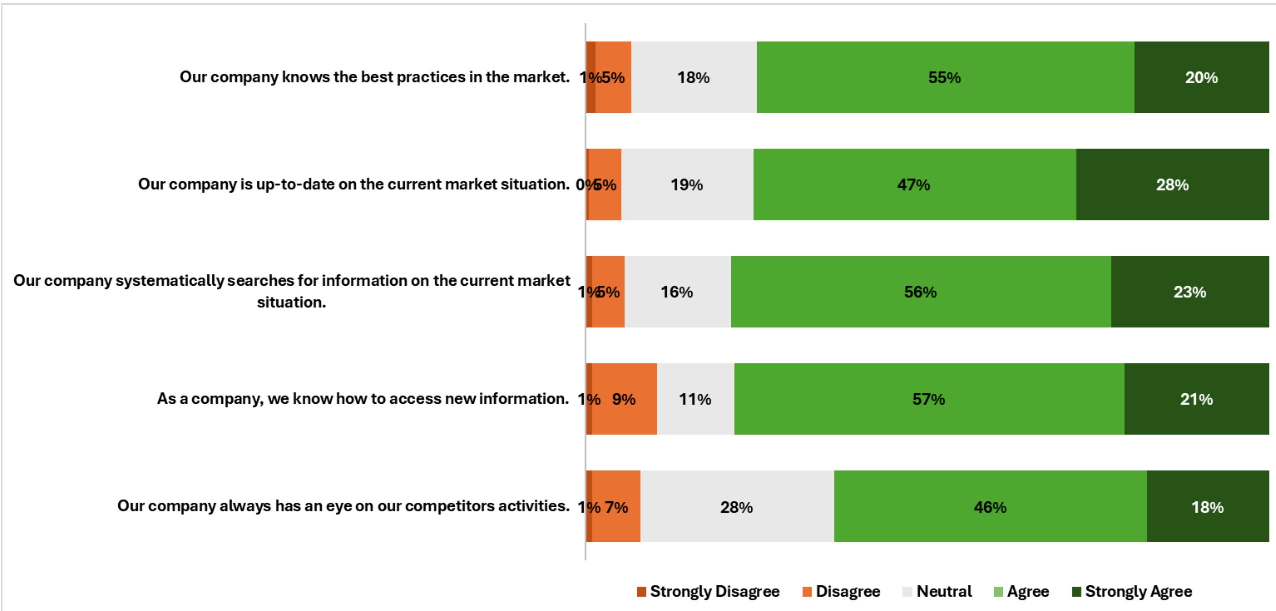

Figure 8: Sensing Likert Scale Summary

Source: Researchers' own compilation

5.7.3. Seizing (Dynamic Capabilities)

Most respondents agreed with statements on Seizing (results shown in Figure 9). When aggregating "Agree" and "Strong Agree" statements, most respondents agreed with all the statements relating to Seizing on the survey. Most respondents (76%) agreed ("strongly agreed" and "agreed") that their organisation was able to recognise what new information could be used within it. Similarly, statements relating to: (1) how "the company can relate to new information", (2) the organisation being "capable of turning new technological knowledge into process and product innovation", and (3) "current information leading to development of new products or services", received agreements from most respondents with 63%, 60% and 57% respectively.

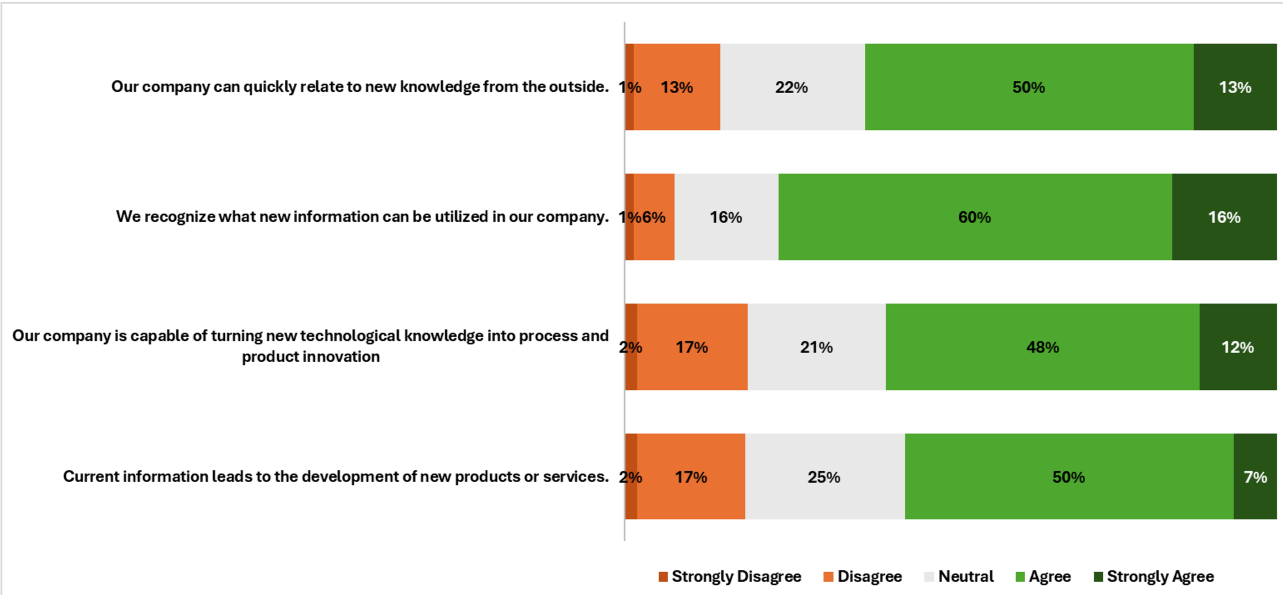

Figure 9: Seizing Likert Scale Summary

Source: Researchers' own compilation

5.7.4. Transforming (Dynamic Capabilities)

When analysing responses on Transforming, most respondents agreed with all the statements except for the statement saying that during unforeseen interruptions, change projects are seen through. This suggests that the majority do not fully agree that change projects are carried through during unforeseen interruptions. Results are shown in Figure 10.

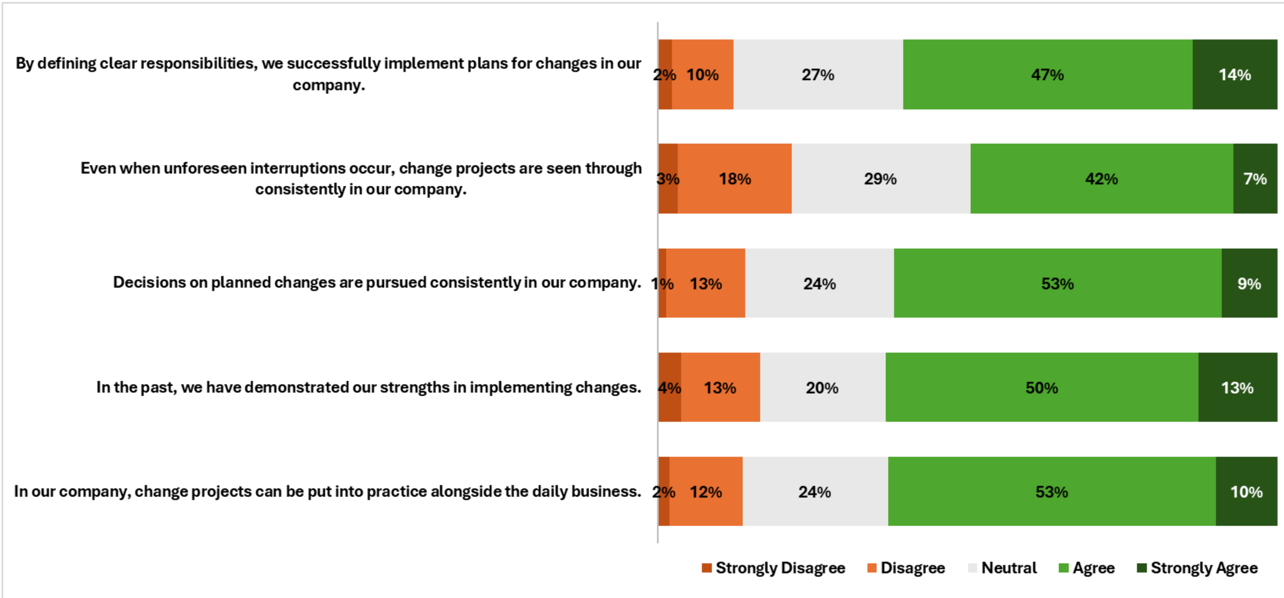

Figure 10: Transforming Likert Scale Summary

Source: Researchers' own compilation

5.7.5. Competitive Performance

Looking at CP, most respondents agreed with the statement that their organisation has better product quality compared to competitors (results shown Figure 11). This is the only statement where most respondents had an aggregated score of “Strong Agree” and “Agree” that is over 50%. Except for this preceding statement, the rest of the statements relating to CP, the aggregate score of “Strongly Agree” and “Agree” was below 50% indicating that the majority were not in agreement with CP. It is also notable that in all statements, over 30% of respondents selected neutral on all the statements. This indicates that the results were mainly mixed.

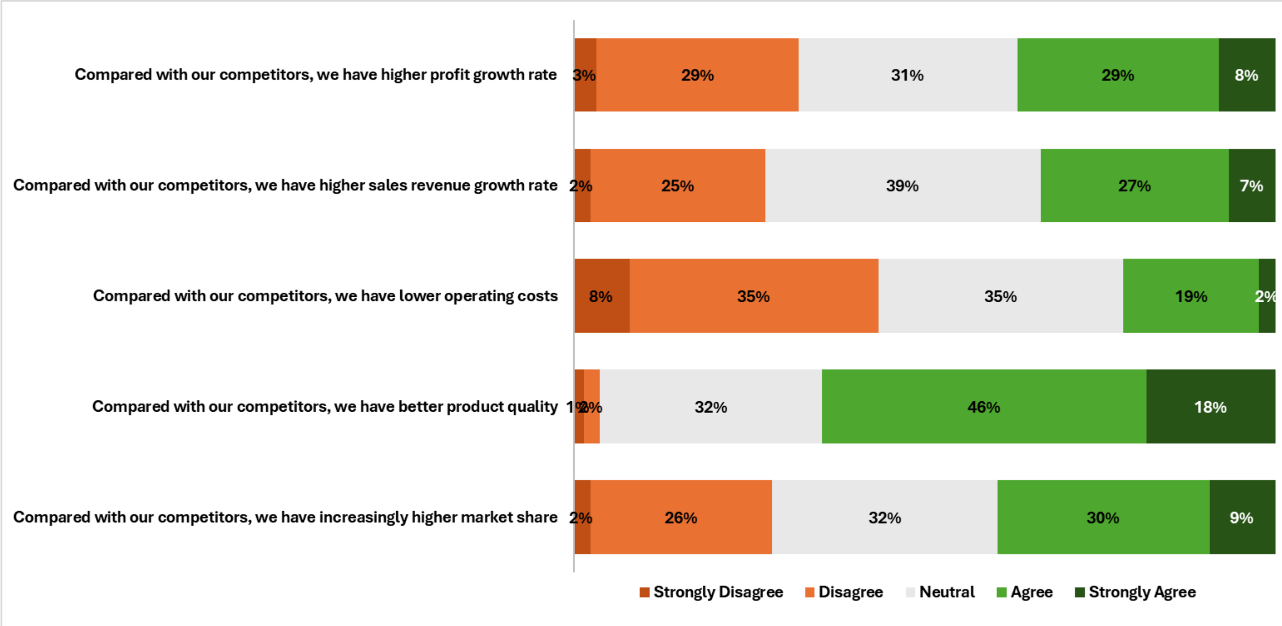

Figure 11: Competitive Performance Likert Scale Summary

Source: Researchers' own compilation

5.8. Hypothesis testing

This subsection covers the tests conducted on all seven hypotheses in the research projects. The subsection begins with testing for underlying assumptions for the Hierarchical Multiple Regression statistical test selected. Orientation of the hypothesis testing model is provided to give context to the results.

5.8.1. Checking for outliers

Manual observation of the box and whisker plots showed extreme outliers. Looking at box and whisker plots for Sensing (DCs), Seizing (DCs), and Transforming (DCs), row 141 was an outlier with an average value of 1 across all 3 mediating variables. An example of a box whisker plot showing this is shown in Figure 12 below. Manual inspection of row 141 showed the respondent simply had strongly disagreed with 22 of the 24 statements across all five constructs. This means that in most of the questions, respondents simply selected strongly disagree. This row was then removed from further statistical inferential analysis. The outlier was removed before conducting the hypothesis tested given that it was an extreme outlier, and the 22 out of 24, “Strongly Disagree” selection was viewed with suspicion. This meant that the total sample for inferential statistics was now reduced to 211 from 212.

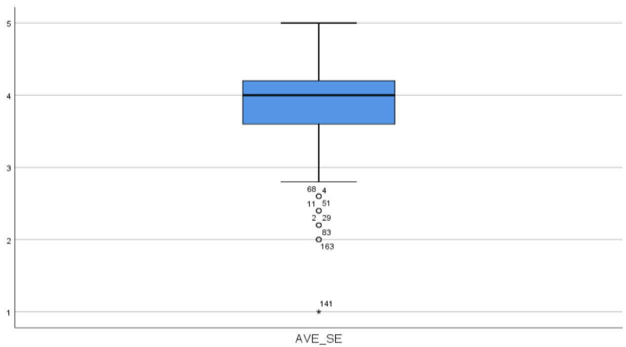

Figure 12: Sensing box and whisker plots for outliers analysis

Source: Researchers' own compilation

5.8.2. Test for normality

A test was conducted to for normality across all the factors, namely DT, Sensing (DCs), Seizing (DCs), Transforming (DCs), and CP. Looking at Skewness and Kurtosis across all variables (shown in Table 18). The values lie between -2 and 2, meaning that normality for Likert scale data is assumed (Bonanomi et al., 2021). Appendix 6 shows the histogram for the five factors and the bell shape for all factors. Looking at the Normality Q-Q Plot of five factors, the points fall along a straight-line, indicating normality of data.

Table 18: Normality - Skewness and Kurtosis

Descriptives			
		Statistic	Std. Error
AVE_DT	Mean	3.6436	0.04771
	Skewness	-0.441	0.167
	Kurtosis	0.764	0.333
AVE_SE	Mean	3.8957	0.04379
	Skewness	-0.466	0.167
	Kurtosis	0.233	0.333
AVE_SZ	Mean	3.6066	0.04735
	Skewness	-0.581	0.167
	Kurtosis	0.080	0.333
AVE_TF	Mean	3.5299	0.04961
	Skewness	-0.599	0.167
	Kurtosis	0.422	0.333
AVE_CP	Mean	3.0367	0.05191
	Skewness	-0.012	0.167
	Kurtosis	-0.673	0.333

Source: Researchers' own compilation

5.8.3. Final dataset used for hypothesis testing

Descriptive statistics were conducted on all completed interview surveys once the inappropriate or non-mining responses were cleaned, resulting in 212 responses. Then, quality testing of responses from a reliability and validity was conducted and resulting in the removal of the statement on the CP construct ("Compared with our competitors, we have better product quality"), given a low factor loading of 0.32 (less than the 0.4 threshold). Normality and outlier assessment were then conducted, and one row was removed, given it was an outlier, and 22 out of 24 statements across all constructs were simply marked as strongly disagree, raising concerns around the quality of the response. This resulted in a 211-sample population and one item or question removed from the CP construct ahead of hypothesis testing.

5.8.4. Hypothesis testing structure and orientation

Section 4.3.6 contains details on the Hierarchical Multiple Regression test. A brief orientation is provided to assist readers with the interpretation of results. In hypothesis testing, the Hierarchical Multiple Regression model, with three steps classified, was developed. The first step tested the relationship between the independent variable (Digital Transformation) and the dependent variable (Competitive Performance). The second step, linear regression, was conducted between DT and mediators (either Sensing, Seizing, or Transforming). Please see below a table of the hypothesis and test conducted. The third step tested the relationship between the independent variable (Digital Transformation) and the dependent variable (Competitive); however, in the third step, a mediator was added. These tests were repeated across all three mediators.

Table 19:Hypothesis and tests conducted on SPSS

Hypothesis	**Test conducted in SPSS**
H1: There is a positive relationship between Digital Transformation (DT) and Competitive Performance (CP) in the context of the mining industry.	Hierarchical Multiple Regression – Step 1
H2(a): Digital Transformation (DT) has a positive impact on Sensing (Dynamic Capabilities).	Linear Regression – Step 2
H2(b): Digital Transformation (DT) has a positive impact on Seizing (Dynamic Capabilities).	Linear Regression – Step 2
H2(c): Digital Transformation (DT) has a positive impact on Transforming (Dynamic Capabilities).	Linear Regression – Step 2
H3(a): Sensing mediates the relationship between Digital Transformation and Competitive Performance in the mining industry.	Hierarchical Multiple Regression – Step 3 (Sensing)
H3(b): Seizing mediates the relationship between Digital Transformation and Competitive Performance in the mining industry.	Hierarchical Multiple Regression – Step 3 (Seizing)
H3(c): Transforming mediates the relationship between Digital Transformation and Competitive Performance in the mining industry.	Hierarchical Multiple Regression – Step 3 (Transforming)

Source: Researchers' own compilation

5.8.5. Hierarchical Multiple Regression results for H1, H2(a) and H3(a)

To simplify the interpretation of Hierarchical Multiple Regression results presentation, a similar presentation layout of results is adopted from Urban & Maswabi (2021). Results of the Hierarchical Multiple Regressions for H1, H2(a), and H3(a) are summarised in the table below in Table 20. Key Beta results are greyed out with bold font for easier interpretation of the results. The p-value/sig. values are presented by the number of stars (*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$). For detailed results, please refer to Appendix 10.

Beta for the relationship between DT and CP is 0.24 (H1), meaning that for each unit increase in DT, CP only increases by 0.24. The p-value is less than 0.05, which means that the results are statistically significant.

Looking at the impact of DT on Sensing, the Beta value is 0.388 (H2(a)), showing a higher impact of DT on sensing. The results are statistically significant with a p-value of less than 0.05.

Looking at the mediating effects of Sensing on the relationship between DT, with mediating effects, the Beta for DT drops to 0.139 (H3)(a). However, the test does not achieve statistical significance, since the p-value of 0.051 is not less than the research study threshold of 0.05. Here, Sensing has a higher Beta (0.251) than DT when mediation effects are introduced.

Table 20: Regression Results (DT>CP & DT>SE) and Mediation Results (Sensing)

	Step 1 > H1: DT > CP			**Step 2 > H2(a)**: DT > SE			**Step 3 > H3(a)**: DT + SE > CP		
	B	Std. Err	β	B	Std. Err	β	B	Std. Err	β
Intercept	2.099	0.271					1.325	0.343	
DT	0.257	0.073	**0.237*****	0.356	0.059	**0.388*****	0.151	0.077	**0.139***
SE							0.298	0.084	**0.251*****
F	12.389***			37.024***			12.808		
R^2	0.056			0.15			0.11		

B = unstandardised parameters, β = standardised parameters, *** p < 0.01, ** p < 0.05, * p < 0.10.

Source: Researchers' own compilation

5.8.6. Hierarchical Multiple Regression results for H1, H2(b) and H3(b)

Table 21 shows the results Hierarchical Multiple Regression for H1, H2(b) and H3(b). On the impact of DT on Seizing, the Beta value of 0.515 is achieved (statistical significance is achieved with a p-value of less than 0.05). When mediation of Seizing is introduced, Beta of DT drops to 0.07 from the prior value of 0.24 without mediating effects. However, the Beta of 0.07 is not statistically significant given the p-value of 0.35, which is not less than the research study threshold of 0.05.

Table 21: Regression Results (DT>SZ) and Mediation Results (Seizing)

	Step 1 > H1: DT > CP				**Step 2 > H2(b)**: DT > SZ				**Step 3 >H3(b)**: DT + SZ > CP		
	B	Std. Err	β		B	Std. Err	β		B	Std. Err	β
Intercept	2.099	0.271							1.481	0.298	
DT	0.257	0.073	**0.237*** **		0.511	0.059	**0.515*** **		0.077	0.082	**0.070**
SZ									0.354	0.083	**0.323*** **
F	12.389***				75.287***				15.897		
R^2	0.056				0.265				0.133		
B = unstandardised parameters, β = standardised parameters, *** p < 0.01, ** p < 0.05, * p < 0.10.											

Source: Researchers' own compilation

5.8.7. Hierarchical Multiple Regression results for H1, H2(c) and H3(c)

Table 22 shows Hierarchical Multiple Regression results for H1, H2(c), and H3(c). Looking at the impacts of Digital Transformation on Transforming, the Beta level is 0.47, meaning that for a unit increase in DT, the impact on Transformation is 0.47 (results are statistically significant a p-value of less than 0.05). When analysing Transformation mediation effects on the relationship between DT and CP, the Beta for DT drops to 0.071 from the prior value of 0.24 without mediating effects. Meanwhile, the Beta for Transforming is 0.35. It is notable that at the Transformation, mediation is introduced, the Beta results become statistically significant, given the p-value of 0.33, which is not less than the research study threshold of 0.05

Table 22: Regression Results (DT>TF) and Mediation Results (Transforming)

	Step 1 > H1: DT > CP				**Step 2 >H2(c)**: DT > TF				**Step 3 >H3(c)**: DT + TF > CP		
	B	Std. Err	β		B	Std. Err	β		B	Std. Err	β
Intercept	2.099	0.271							1.463	0.290	
DT	0.257	0.073	**0.237*** **		0.492	0.063	**0.473*** **		0.077	0.079	**0.071**
TF									0.366	0.076	**0.35*** **
F	12.389***				69.350***				18.48		
R^2	0.056				0.224				0.151		
B = unstandardised parameters, β = standardised parameters, *** p < 0.01, ** p < 0.05, * p < 0.10.											

Source: Researchers' own compilation

5.8.8. Hypothesis Testing Summary

A summary of the hypothesis testing results is presented below in Table 23.

Table 23: Hypothesis testing results summary

Hypothesis	Summary of Results
H1: There is a positive relationship between Digital Transformation (DT) and Competitive Performance in the context of the mining industry.	Results show a Beta of 0.24 on the relationship between Digital Transformation and CP, and the results are statistically significant.
H2(a): Digital Transformation (DT) has a positive impact on Sensing (Dynamic Capabilities).	Results show a Beta of 0.39 on the relationship between Digital Transformation and Sensing. This means that 39% percent movement of Sensing can be explained by 1 unit movement of DT. Results are statistically significant.
H2(b): Digital Transformation (DT) has a positive impact on Seizing (Dynamic Capabilities).	Results show a Beta of 0.52 on the relationship between Digital Transformation and Seizing, and the results are statistically significant.
H2(c): Digital Transformation (DT) has a positive impact on Transforming (Dynamic Capabilities).	Results show a Beta of 0.47 on the relationship between Digital Transformation and Transforming, and the results are statistically significant.
H3(a): Sensing mediates the relationship between Digital Transformation and Competitive Performance (CP) in the mining industry.	While the reduction of Beta is notable (from 0.24 to 0.14) when Sensing is added to the relationship between DT and CP, the results are not classified as statistically significant, as the p-value is slightly above 0.05.
H3(b): Seizing mediates the relationship between Digital Transformation and Competitive Performance in the mining industry.	Significant reduction of Beta is noted (from 0.24 to 0.07) when Seizing is added to the relationship between DT and CP; however, results are not classified as statistically significant since the p-value is higher than the threshold of 0.05.
H3(c): Transforming mediates the relationship between Digital	Significant reduction of Beta is noted (from 0.24 to 0.07) when Transforming is added to the relationship between DT and CP; however, results are not

Transformation and Competitive Performance in the mining industry.	classified as statistically significant, since the p-value is higher than the threshold of 0.05.

Source: Researchers' own compilation

5.9. Results Summary

This chapter presented the results of the research study, starting with validity and reliability assessments, wherein all the items across the research instruments were declared valid. Additionally, reliability assessment per constructs was conducted, and the research instrument was classified as reliable, since all constructs achieved a Cronbach Alpha of over 0.7, confirming the quality of the research instrument based on the collected data. Factor analysis also showed that each construct had one factor based on the KMO and Bartlett's Test and the Eigenvalues. One item or question was removed from the research instrument based on a low loading factor (less than 0.4) to improve the quality of the research instrument.

The chapter then presents the descriptive statistics covering demographics to offer context and orientation on the participants. A global reach of the research results was obtained, with all continents and regions represented; however, a strong bias towards Southern Africa was seen. Most respondents had more than five years of experience working in their organisation. Bar charts were used to present results from each construct in the research instrument, with several respondents responding with a high level of agreement to DT questions, Sensing questions, Seizing, and Transforming; however, CP received mixed results with an aggregated agreement score (Strongly agree and agree) below 50% on four out of five questions in the CP instrument.

Hypothesis testing was then conducted, and the results were presented. The first part of hypothesis testing focused on assessing the data for outliers, and the box and whisker plot showed one respondent being an outlier. Detailed assessment of the respondents' data showed that 22 out of 24 questions were simply marked as "Strongly Disagree" and this data was then removed before conducting hypothesis testing. Normality tests were then conducted using Normality QQ and the Skewness and Kurtosis results. Hypothesis testing was conducted using Hierarchical Multiple Regressions, and results show there is a positive relationship between DT and CP (Beta 0.24) and that DT has a positive impact on Sensing, Seizing, and Transforming with Beta values of 0.39, 0.51, and 0.47, respectively. The tests for mediation did not achieve the level of significance required to conclude that mediating effects results were observed.

CHAPTER SIX: DISCUSSION OF RESULTS

6.1. Introduction

Organisations are facing disruptions due to a constant wave of DT (Mele et al., 2024) and the mining industry (traditionally seen as slow to innovate) faces prospects of significant disruption (Fernandez, 2021). In this regard, the research project focused on studying the impact of DT on mining company performance and the role of dynamic capabilities.

Insights from literature highlight the importance of DT given the current technological disruptions (Verhoef et al., 2021). More calls have been made to increase research in DT and Dynamic Capabilities (Mele et al., 2024). Arguments have been put forward on the limited and narrow view (in academic research) regarding DT, and a call has been made to broaden the scope of DT, given the impact (Verhoef et al., 2021).

Porter (2008a) argues that competition is a key driver for company performance. An alternative view on CP is the resource-based view, which argues that organisation may have unique and hard to imitate resources that offer a competitive advantage (Barney, 1991). For this research project, analysis of the literature on the Dynamic Capabilities was presented, and sub-elements of Dynamic Capabilities (Sensing, Seizing, and Transforming) were outlined.

The literature review highlighted the impact of DT on CP, given the development of new business models, which support CP (Bhatti et al., 2021). On the relationship between DCs and CP. Teece (2018) argues that stronger dynamic capabilities lead to the development of new business models, which in turn advance CP. Lastly, the role of DT on dynamic capabilities was presented in Chapter 2. Digital technologies, such as big data analytics support (1) market analysis and (2) rapid prototyping, which enables Sensing and Seizing, respectively (Teece, 2023).

This chapter focuses on the discussion of the results presented in the preceding chapter. Attention is placed on grounding the discussion of the results in academic theory that has been analysed in Chapter 2. The objective of the research focused on understanding the role that dynamic capabilities play in the relationship between DT and CP. The research project aimed to study the (1) relationship between DT and CP and (2) the mediating effects of DCs on the relationship between DT and CP. This chapter initiates by providing an overview discussion on descriptive statistics across all constructs (Digital Transformation, Sensing, Seizing, Transforming, and Competitive Performance). The chapter then discusses, in detail, the hypothesis testing results.

6.2. Overview of descriptive statistics

The first part of the research questionnaire included eight demographic questions relating to the demographics of the respondents. These demographic questions (age, gender, education level, employment years, discipline, management level, org size, and geography) assisted in providing more insights and context to the respondents to the survey. These demographic questions supported the analysis of the results and identified trends in subgroups in the results.

Looking at Gender, the results showed a male-to-female participation ratio of 70% and 30% respectively. The results show a lower representation of women compared to men among the participants. Ellix et al. (2021) confirm that women are underrepresented in the mining sector, noting that 8 to 17% of the employees in the mining industry are female. While the sample shows higher women representation, 26% of participants in this research were in core operations and production disciplines, which are, by implication, based on site. Intergovernmental Forum (2023) notes that a larger share of women (in the mining industry) is based in urban headquarters or offices compared to remote mining operations, where production activities take place. The notably higher representation of female participants in this research (when compared to industry estimates) possibly aligns with the off-site representation of participants, given more female representation on off-site locations, as highlighted above.

The two largest categories, in terms of age, were 30-39 and 40-49, and when combined, the group represented 75% of respondents. Respondents older than 30 years represented 97% of the total respondents. These results, coupled with the years of employment in mining organisation (whereby 64% of respondents had been employed in the mining industry for more than 5 years), show the depth of experience of the participants. Additionally, 77% of respondents were in middle management and above. Eliciting feedback from senior respondents provides richer feedback, given the depth of experience. Receiving experienced feedback matters, as Dynamic Capabilities are differentiated from ordinary capabilities (day-to-day activities). Dynamic capabilities are higher-order capabilities that usually rely on top management capabilities in Sensing, Seizing, and Transforming (Teece, 2014). In this case, senior respondents' inputs offer richer insights given the focus on higher-order dynamic capabilities rather than day-to-day ordinary capabilities.

While most respondents (75%) in this research were based in Southern Africa, insights were received from respondents working across all seven continents/regions, and the research results show a global reach. Having a global perspective on dynamic capabilities, DT, and CP offers deeper insights, given the differences in operating contexts of mining organisations in different parts of the world. Zahra et al. (2022b) argues that international businesses operate in different and global contexts that would require tailoring when developing dynamic capabilities within international business. The research project offers a more representative sample to cater to international businesses regarding dynamic capabilities in the mining industry.

6.2.1. Digital Transformation

When analysing statements on the DT construct, most respondents had higher agreement ratings to the statements except for "we develop intelligent offering (e.g., artificial intelligence-based tools)" and "we flexibly adjust the structure of functional department". These statements received mixed results from respondents. The first statement's mixed results highlight some opportunities in the mining industry regarding the adoption of artificial intelligence. This confirms the view by Maroufkhani et al. (2022) that the resource and energy sectors are lagging behind retail and manufacturing in DT. The mixed results of the second statement also highlight further opportunities in the mining industry to consider reviewing the structures of functional departments during DT. This highlights the view that the mining industry is rather slow to change (Fernandez, 2021).

6.2.2. Sensing

When analysing data from the Likert scale on the Sensing construct, the majority of respondents agreed with all statements. This highlighted that respondents have a strong response rate, Sensing highly within the mining organisations that were part of the sample. The stronger Sensing capabilities in the mining industry are interesting and perhaps align with the long-term nature of the mining industry, as it takes a long time to develop a mining operation. Here, the ability to identify future mineral demands and trends in the market is innate to how the mining organisations function. Mencarini et al. (2024) argues that, given the large capital requirements, it is important for mining organisations to predict potential future cost outlays and have a firm grasp of initial project assessment, as errors could be costly in the future.

6.2.3. Seizing

Looking at the Seizing construct, most of the respondents agreed with all the statements in the Seizing construct. This shows that Seizing capabilities within sampled mining organisations have built capabilities to direct resources to exploiting new opportunities. These results are counterintuitive, given the view that historically, mining companies were seen as slow to change and innovate (Fernandez, 2021).

6.2.4. Transforming

Looking at Likert scale data on the Transforming construct, mixed results were received on the statement “Even when unforeseen interruptions occur, change projects are seen through…” indicating that respondents had mixed views on the ability of mining organisations to persist with necessary changes during disruptions. For all four other statements, most respondents agreed with the survey statements within the Transforming construct.

The mean Likert scores for Sensing, Seizing, and Transforming were 3.90, 3.61, and 3.53, respectively. This reduction in scores across Sensing, Seizing, and Transforming highlights the argument made by Zahra et al. (2022a), while Sensing is important for identifying threats and opportunities, it is important to move beyond Sensing to Seizing and Transforming, where organisations can truly leverage opportunities identified in Sensing.

6.2.5. Competitive Performance

Looking at the CP construct, Likert scale results show that most respondents agreed with the following statement: “Compared with our competitors, we have better product quality”. For the rest of the statements, mixed results were obtained without a clear majority either agreeing or disagreeing. Further evidence of mixed results and respondents not being clear is shown by over 30% of respondents selecting neutral across all statements within the CP construct. Given that CP is a dependent variable within the research model, the mixed results prompted further analysis.

Analysis of the loading factor of all statements across all constructs showed that the statement “Compared with our competitors, we have better product quality” had a loading factor of 0.32 and Pallant (2020) had recommended a loading factor value of above 0.4. The statement, “Compared with our competitors, we have better product quality”, was removed ahead of conducting hypothesis testing. While there are increasing product differentiation factors relating to ESG and sustainability when it comes to mining products, the minerals and metal products are considered commodities (Recabarren et al., 2024). Porter (2008a) notes that industries that do not have product differentiation (such as mining), production innovation either does not happen at all or happens very fast. In this regard, the question around having a better product quality in the commodity business may have been impacted by the interpretation of the question, given the lack of product differentiation in the commodities space.

6.3. Discussion on hypothesis

This section discusses the results of the seven hypotheses proposed as part of the research project. The reference to the theory is given to provide context for the findings.

6.3.1. Hypothesis 1: Digital Transformation and Competitive Performance

The first hypothesis was formulated to study the relationship between DT and CP within the mining industry context. This hypothesis was proposed following a review of DT (Bhatti et al., 2021; Chatterjee & Mariani, 2024; Mele et al., 2024). The literature highlights the importance of DT in new business models and the impact of DT in driving operational excellence and CP. Verhoef et al. (2021) challenges the research community, arguing that research on DT is rather muted in recent periods and current research is narrow and does not appreciate the multidisciplinary view of DT.

> *H1: There is a positive relationship between Digital Transformation (DT) and competitive performance in the context of the mining industry.*

Using the Hierarchical Multiple Regression method, the results presented in the section 5.8.5 shows that the Beta value of the independent variable in the relationship between DT and CP is 0.24. Given that the p-value is less than 0.05, the results are statistically significant. This means that the variation on the dependent variable (Competitive Performance) of 0.24 is explained by a unit movement of DT. This shows there is a positive relationship between DT and CP in the mining industry. Results show that Hypothesis 1 is supported.

The results obtained on Hypothesis 1 confirm Maroufkhani et al. (2022) view that digital technologies (e.g, artificial intelligence, big data analytics) can have significant contributions to operational efficiencies and that may enhance CP within the resource and energy industry. These findings also confirm Ciampi et al. (2022) analysis that researchers estimate an 80% increase in profit for organisations that adopt digital technologies. Since (1) the mining industry has high innovation potential (Korbel & Grabbert, 2024) and (2) mining organisations have lagged in innovation and adoption of new technologies (Fernandez, 2021b; Maroufkhani et al., 2022). These results highlight the urgent need for mining companies to place emphasis on DT, given the upside potential.

The Beta coefficient is the marginal rate of change (Pallant, 2020) and given that the value of Beta for DT is less than one, it means that higher movement of DT is required to explain variation in CP. The results show a positive relationship between DT and CP, aligning with research question 1. While Hypothesis 1 is supported, the higher movement of DT to explain CP confirms Li (2022) view that there are other variables such as organisational inertia that could minimise the impact of DT.

An additional assessment will be presented to examine the mediating effects of testing on the relationship between the independent variable (Digital Transformation) and the dependent variable (Competitive Performance). However, before presenting results of mediating effects, the Hierarchical Regression method requires us to test the influence of an independent variable (Digital Transformation) on the mediators (Sensing, Seizing & Transforming): H2(a), H2(b), and H2(c).

6.3.2. Hypothesis 2(a): Digital Transformation and Sensing

Hypothesis 2(a) was proposed to study the DT impacts on mining organisations Sensing capabilities. Jenkinson et al. (2024) argues that big data analytics capabilities (BDAC) support Sensing in the organisation given that BDAC assists in understanding market and competitor trends, which allows organisation to be aware of opportunities and threats.

> *H2(a): Digital Transformation (DT) has a positive impact on Sensing (Dynamic Capabilities).*

Analysing the relationship between DT and Sensing, through simple regression analysis, the resultant Beta was 0.39 higher than the resultant Beta for H1. These results show there is a positive relationship between the independent variable (Digital Transformation) and the mediating variable (Sensing). This means that a 39% variation in movement on Sensing can be explained by one point movement in DT. The research results have found that DT positively affects or enables Sensing in the mining industry. These results confirm the Jenkinson et al. (2024) findings that big data analytics is a key enabler for

Sensing. Teece (2023) highlights that digital technologies heighten Sensing capabilities, given the ability to conduct rapid testing of opportunities and threats using technology.

6.3.3. Hypothesis 3(a): Mediating effects of Sensing

Sensing, within dynamic capabilities, enables the organisation to identify, interpret the future implications of trends in the markets and generate options for growth before they are apparent to all (Teece et al., 2016). Hypothesis 2(a) was developed to understand how DT (independent variable) influences CP (dependent variable) through Sensing as a mediator. The overall interest is to understand the underlying effect of Sensing on the relationship between DT and CP.

> *H3(a): Sensing mediates the relationship between Digital Transformation and Competitive Performance in the mining industry.*

Using Hierarchical Multiple Regression analysis for testing mediation on the relationship between DT and CP, the resultant Beta value with mediation effects on DT is reduced to 0.14. However, the p-value for the test is now 0.051 and is no longer less than 0.05, and the test cannot be considered statistically significant given the threshold of 95% confidence applied to the research. But the Beta value for the mediator is 0.25 with a p-value of less than 0.05, and the test is statistically significant. These results offer interesting insights. Results show that when a mediator (Sensing) is introduced, the relationship between the independent variable (Digital Transformation) and dependent variable (Competitive Performance) is affected significantly. This indicates that when the mediator (Sensing) is introduced (in the Hierarchical Multiple Regression analysis), the mediator now plays a more significant role in explaining the variation observed in the dependent variable (Competitive Performance) compared to the DT. Sensing overpowers DT when introduced as a mediator in the relationship between DT and CP. These findings are similar to the argument made by Li et al. (2022), where an analysis of digitisation and firm performance was conducted, and the resultant argument was that relying solely on digitisation capabilities may be limiting in improving firm performance. In this case role of a mediator becomes important. Results have practical implications as they suggest that, in a resource constrained environment, it may be more prudent to prioritise Sensing capabilities as the relationship between Sensing and CP supersedes DT and CP.

With results from H1, H2(a), and H3(a), the full Hierarchical Multiple Regression results have been collated for the mediating effects of Sensing on the relationship. Following guidance from Baron & Kenny (1986) on conditions to be met for a variable to function as a mediator, the following results have been observed:

Table 24: Hierarchical Multiple Regression results - Sensing as a mediator:

Conditions to be met for a variable to function as a mediator (Baron & Kenny, 1986)	**Results – Sensing as mediator**
(a) Independent variable accounts for variation in mediator.	Variation of DT accounts for variation in Sensing with a Beta value of 0.39. – H2(a)
(b) Variation in the mediator explains variation in the dependent variable.	With Sensing added as a mediator, Sensing accounts for variation in CP with a Beta value of 0.25. – H3(a)
(c) With (a) and (b) above under control, the previous relationship between the independent variable and dependent variable is no longer significant.	While Beta drops significantly from 0.24 to 0.14 on the relationship between DT and CP (when the mediator Sensing is introduced), the p-value of 0.051 does not support the statistical significance.

Source: Researchers' own compilation

Results in Table 24 above indicate that the first two conditions for mediation are met under the Hierarchical Multiple Regression method. The third condition while the reduction of Beta drops significantly, the p-value of 0.051 leads to questionable results when a 95% confidence interval is applied.

6.3.4. Hypothesis 2(b): Digital Transformation and Seizing

Studies have shown that DT impacts Dynamic Capabilities (Chatterjee & Mariani, 2024; Mele et al., 2024; Teece, 2023). More specifically, Ancillai et al. (2023) argues that DT leads to business model innovation, and as Teece (2023) notes, Seizing is concerned about how the company generates revenue.

> *H2(b) Digital Transformation (DT) has a positive impact on Seizing (Dynamic Capabilities).*

Using regression to analyse the relationship between DT and Seizing, the Beta value of 0.52 was achieved, showing a higher explanation of the resultant variation of Seizing due to DT movements. The p-value achieved was less than 0.05, indicating that the results are statistically significant. Compared with the results from Sensing (H2(a)), DT has higher effects on Seizing than Sensing. These results strongly confirm the impact of DT on business model innovation (Ancillai et al., 2023). Seizing focuses on business model Transformation (Teece, 2023).The findings support the significant increase in DT and business model innovation research (Caputo et al., 2021).

6.3.5. Hypothesis 3(b): Mediating effects of Seizing

Seizing focuses on getting things done by mobilising resources to exploit opportunities and ensuring value delivery (Teece et al., 2016). Hypothesis 3(b) was proposed to study how DT influences CP through Seizing as a mediator. The focus is to understand the underlying effect of Seizing on the relationship between DT and CP.

> *H3 (b) Seizing mediates the relationship between Digital Transformation and Competitive Performance in the mining industry.*

Using the Hierarchical Multiple Regression technique to test for mediation effects, when Seizing is added to the analysis on the relationship between DT and Competitive, the Beta value for Seizing is 0.32. The p-value was less than 0.05, and the results were statistically significant. The Beta results for Seizing as a mediator are higher than when

Sensing was the mediator in Hypothesis 3(a). This means that Seizing performs better as a mediator compared to Sensing on the relationship between DT and CP.

When Seizing is introduced as a mediator, the Beta for DT drops from 0.24 to 0.07. This drop is even higher compared to when Sensing was introduced as a mediator. This shows that Seizing as a mediator performs better than Sensing on the relationship between DT and CP. However, the p-value is 0.35, and this is even higher compared to the p-value when Sensing was a mediator. This test, therefore, is classified as statistically insignificant. These results are even more interesting since for Sensing, the p-value was 0.051 and closer to the required threshold, but with Seizing, the p-value was far from being acceptable.

With H1, H2(b), and now H3(b) analysed individually, the full results of Seizing as mediator can be presented.

Table 25: Hierarchical Multiple Regression results - Seizing as a mediator

Conditions to be met for a variable to function as a mediator (Baron & Kenny, 1986).	**Results – Seizing as mediator**
(a) Independent variable accounts for variation in mediator.	Variation of DT accounts for variation in Seizing, with a Beta value of 0.52. – H2(b).
(b) Variation in the mediator explains variation in the dependent variable.	With Seizing added as a mediator, Seizing accounts for variation in CP with a Beta value of 0.32. – H3(b).
(c) With (a) and (b) above under control, the previous relationship between the independent variable and the dependent variable is no longer significant.	While Beta drops significantly from 0.24 to 0.07 on the relationship between DT and CP (when the mediator Seizing is introduced), the p-value of 0.35 does not support the statistical significance.

Source: Researchers' own compilation

Results in Table 25 above, indicate that the first two conditions for mediation are met under the Hierarchical Regression method for Seizing. The third condition while the reduction of Beta drops significantly, the p-value of 0.35 leads to questionable results if a 95% confidence interval is applied. Here, results do not support mediation effects of Seizing on the relationship between DT and CP in the mining industry.

6.3.6. Hypothesis 2(c): Digital Transformation and Transforming

Soluk & Kammerlander (2021) highlights that during business model innovation (driven by digitalisation), organisations can drive Transformation within their organisational structures. This subsection focuses on DT and the Transforming subconstruct of dynamic capabilities.

> *H2(c) Digital Transformation (DT) has a positive impact on Transforming (Dynamic Capabilities).*

Using regression to analyse the relationship between DT and Transforming, the Beta value of 0.47 was achieved, showing a higher explanation of resultant variation of Seizing due to the DT movement. The p-value less than 0.05 was achieved, indicating that the results are statistically significant. Compared with the results from Sensing and Siezing (H2(a) and H2(b) respectively), DT has higher effects on Transforming than Sensing, however, less than Seizing. With the three relationships between DT and Dynamic Capabilities subconstructs analysed, the order is Seizing, Transforming, and Sensing regarding the impact of DT.

6.3.7. Hypothesis 3(c): Mediating effects of Transforming

Transforming capabilities focus on the organisations ability to continuously renew itself amidst a constantly changing environment (Teece et al., 2016). Hypothesis 3(c) was proposed to study how DT influences CP through Transforming as a mediator. The research design was to understand the underlying effect of Transforming on the relationship between DT and CP.

> *H3(c): Transforming mediates the relationship between Digital Transformation and Competitive Performance in the mining industry.*

When Transforming is added to the Hierarchical Multiple Regression analysis on the relationship between DT and Competitive, the Beta value for Transforming is 0.35. The p-value of less than 0.05 was achieving showing that the results are statistically significant. The Beta results for Transforming as a mediator are higher than when Sensing or Seizing was the mediator in Hypothesis 3(a) and Hypothesis 3(b), respectively. This means that transform performs better as a mediator compared to either Sensing or Seizing on the relationship between DT and CP.

In the Dynamic Capabilities theory, Teece (2018) contends that in business model Transformation, adjustment and fine-tuning are required to achieve desired results, and the flexibility of a start-up organisation makes it easier to undergo fine-tuning compared to a larger organisation with set procedures. In the research, many respondents were from large mining organisations (63% of respondents were from large organisations with over 10000 employees). In this case, having Transformation as a better mediator in the relationship between DT and CP provides interesting insights into the mining industry's ability to transform. In part, the cyclical nature of the mining industry and volatile commodity prices (Sellschop et al., 2025) suggest that Transformation capabilities are well practiced and the organisations needs to be flexible and adjust to respond to price movements.

When Transforming is introduced as a mediator, the Beta for DT drops from 0.24 to 0.07. This is similar to when Seizing was introduced as a mediator. However, as earlier discussed, the Beta for DT when Sensing is a mediator is 0.14. The researcher notes that Transforming as a mediator between DT and CP performs better than Sensing and Seizing. The p-value for the test is, however, 0.33, and this is a similar p-value to when Seizing was a mediator. The results show that the statistical significance is not achieved when Transforming is a mediator.

With H1, H2(c), and now H3(c) analysed individually, the full results of Seizing as mediator can be presented.

Table 26: Hierarchical Multiple Regression results - Transforming as a mediator

Conditions to be met for a variable to function as a mediator (Baron & Kenny, 1986)	**Results – Transforming as a mediator**
(a) Independent variable accounts for variation in mediator.	Variation of DT accounts for variation in Transforming with a Beta value of 0.47. – H2(c).
(b) Variation in the mediator explains variation in the dependent variable.	With Transforming added as a mediator, Transforming accounts for variation in CP with a Beta value of 0.35. – H3(c).
(c) With (a) and (b) above under control, the previous relationship between the independent variable and dependent variable is no longer significant.	While Beta drops significantly from 0.24 to 0.07 on the relationship between DT and CP (when the mediator Seizing is introduced), the p-value of 0.33 does not support a statistically significant result.

Source: Researchers' own compilation

Results in Table 26 above, indicate that the first two conditions for mediation are met under the Hierarchical Multiple Regression method for Transforming. The third condition while the reduction of Beta drops significantly, the p-value of 0.33 leads to questionable results if a 95% confidence interval is applied. Similarly, Transforming had a p-value of 0.35, indicating that the test for mediation was also statistically unreliable. At a 95% confidence level, the mediation could not be supported across all three mediators.

The question as to why such a significant difference in reliability across the three constructs became apparent (sensing had a p value of 0.051). While further quantitative analysis could not be pursued, a number of insights are provided to aid future studies. Li (2022) argues that organisational inertia has an opposite effect compared to dynamic capabilities. Zahra et al. (2022a) indicates that research is shifting towards Seizing and Transforming given the focus on adjusting business models and delivering goals from Sensing. As a possible area for further analysis is the impact of inertia on sensing, seizing and transforming. Ancillai et al. (2023) also highlights that the impact of digital technologies on business models differs across industries. Lastly, Li et al. (2022) also cautions against solely relying on digitalisation capabilities may be limiting in improving firm performance. These possible further research avenue will be discussed in the subsequent chapter.

6.3.8. Summary of Hypothesis Results

A summary of the hypotheses' results is shown in Table 27 below, showing that all but the mediation hypotheses are supported. In this regard, DT has an impact in CP and that that DT has an impact on DCs (Sensing, Seizing and Transforming).

Table 27: Summary of Hypothesis results - acceptance or rejection

Hypothesis	Results
H1: There is a positive relationship between Digital Transformation (DT) and competitive performance in the context of the mining industry.	Hypothesis supported.
H2(a): Digital Transformation (DT) has a positive impact on Sensing (Dynamic Capabilities).	Hypothesis supported.
H2(b): Digital Transformation (DT) has a positive impact on Seizing (Dynamic Capabilities).	Hypothesis supported.
H2(c): Digital Transformation (DT) has a positive impact on Transforming (Dynamic Capabilities).	Hypothesis supported.
H3(a): Sensing mediates the relationship between Digital Transformation and Competitive Performance in the mining industry.	Hypothesis not supported.
H3(b): Seizing mediates the relationship between Digital Transformation and Competitive Performance in the mining industry.	Hypothesis not supported.
H3(c): Transforming mediates the relationship between Digital Transformation and Competitive Performance in the mining industry.	Hypothesis not supported.

Source: Researchers' own compilation

6.4. Summary

This chapter focused on the discussions around the results that have been contained. The chapter uses literature to give context to the findings. The purpose of the study was to understand the role of dynamic capabilities in the relationship between DT and CP within the mining industry.

Using Hierarchical Multiple Regression, the study found that there is a relationship between DT and CP. The study also found that there is a relationship between DT and proposed mediators (Sensing, Seizing, and Transforming). However, the study could not conclusively support the mediating effects of the mediators (Sensing, Seizing, and Transforming) on the relationship between DT and CP within the mining industry. While it was clear that Seizing and Transforming mediation results were conclusively insignificant, the p-value of 0.051 for Sensing raises a question about whether a slightly lower confidence interval for the research project would arrive at a different conclusion.

Discussion around the mediation results also demonstrated the order of strength of the relationship between DT and mediators. DT had the biggest impact on Seizing, followed by Transforming, and lastly Seizing. In the following chapter, the principal findings of the research project are presented.

CHAPTER SEVEN: CONCLUSION AND RECOMMENDATIONS

7.1. Introduction

The mining industry is seen as an industry likely to face significant disruption due to DT, more so as the industry has high potential for automation (Korbel & Grabbert, 2024). The mining industry has historically been seen as slow to innovate (World Economic Forum, 2025). Given this high potential for disruption, the research project focuses on Digital Transformation, Dynamic Capabilities, and Competitive Performance. Organisations that are strong in: (1) scanning new technological or market opportunities (Sensing), (2) translating these opportunities into revenue models (Seizing), and adjusting their organisation (Transforming) are likely to have a competitive advantage (Teece, 2014).

This chapter outlines the principal findings of the research project by revisiting the research questions that were outlined. Theoretical and business contributions are then presented, and lastly, limitations and recommendations for future studies are also discussed.

7.2. Principal findings of the research project

The research project sought to answer the following two questions. First, what is the role of DT on CP in the mining industry? Second, what role do dynamic capabilities play in the relationship between DT and CP in the mining industry? Results summarised in the overall resultant research model in Figure 13.

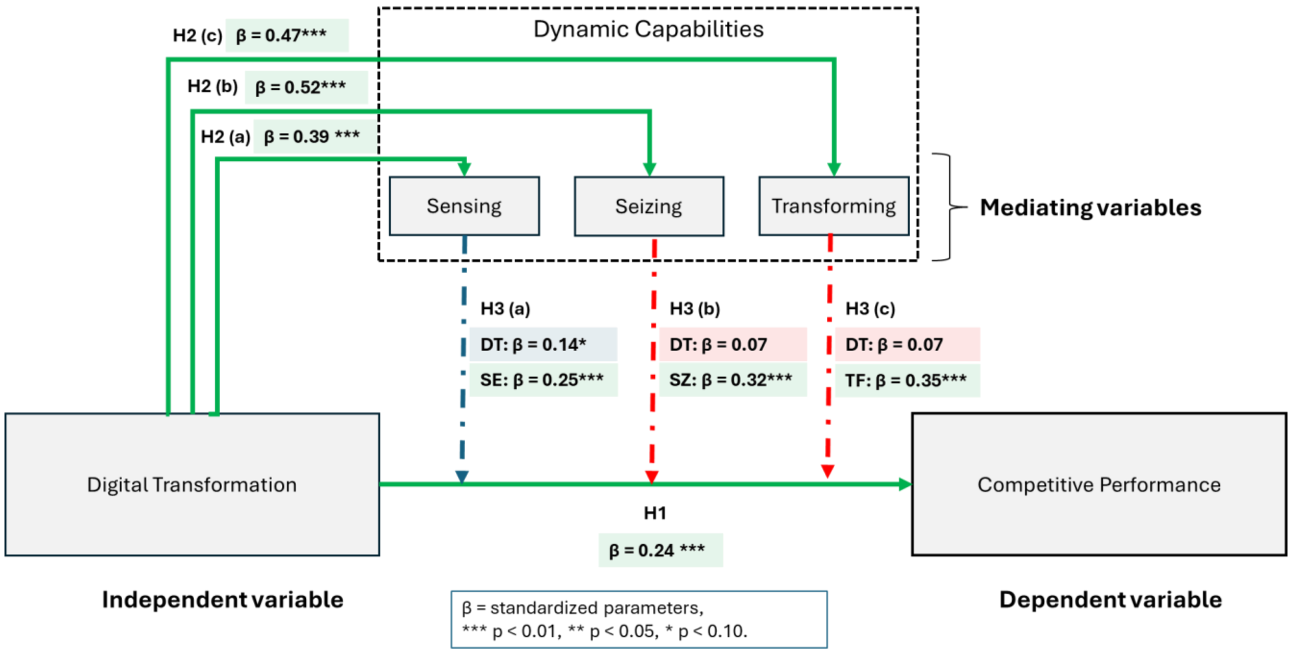

Figure 13: Resultant Research Model

Source: Researchers' own compilation

7.2.1. Question 1: Digital Transformation and Competitive Performance

To respond to the first question, the research project studied the relationship between DT and CP within the mining industry context. The following hypothesis was then developed (step 1):

> *H1: There is a positive relationship between Digital Transformation (DT) and Competitive Performance (CP) in the context of the mining industry.*

Results show that there is a positive relationship between DT and CP (within the mining industry), with regression analysis showing a Beta of 0.24, and the results are statistically significant (H1 results shown with a green solid line in Figure 13). These results confirm the analysis by Ciampi et al. (2022) that there is an 80% potential profit uplift to organisations when they pursue digital technologies.

7.2.2. Question 2: Mediating effects of dynamic capabilities

To respond to the second question, the research project studied the role of dynamic capabilities (Sensing, Seizing, and Transforming) on the relationship between DT and CP within the mining industry context: several hypotheses were then developed to answer the question.

As a second step from H1, the researcher looked at the relationship between DT (Independent Variable) and Dynamic Capabilities (Proposed Mediators):

Step 2: Digital Transformation and Dynamic Capabilities

> *H2(a): Digital Transformation (DT) has a positive impact on Sensing (Dynamic Capabilities).*
>
> *H2(b): Digital Transformation (DT) has a positive impact on Seizing (Dynamic Capabilities).*
>
> *H2(c): Digital Transformation (DT) has a positive impact on Transforming (Dynamic Capabilities).*

Results show a positive relationship between DT and Sensing, Seizing, and Transformation, with resultant Beta values of 0.39, 0.52. 0.47 respectively. Results were statistically significant. Results are shown in Figure 13 with H2(a), H2(b), H2(c) being depicted with a green solid line. Results show a strong relationship between DT and Dynamic capacities subconstructs (Sensing, Siezing, and Transforming) in the mining industry. Results confirm that DT enhances Sensing capabilities through digital technologies, such as big data analytics, IoT, and artificial intelligence (Jenkinson et al., 2024; Teece, 2023). As Seizing is about how a business generates revenue from identified opportunities, results support the view from Ancillai et al. (2023) that DT leads to business model innovation. Additionally, the rapid prototyping enables testing of solutions using digital technologies (Teece, 2023).

With the relationship between DT and Dynamic Capabilities (Sensing, Seizing, Transformation) established, the third step looked at testing the mediation of Dynamic Capabilities on the relationship between DT and CP in the mining industry.

Step 3: Dynamic Capabilities mediation effects

H3(a): Sensing mediates the relationship between Digital Transformation and Competitive Performance in the mining industry.

H3(b): Seizing mediates the relationship between Digital Transformation and Competitive Performance in the mining industry.

H3(c): Transforming mediates the relationship between Digital Transformation and Competitive Performance in the mining industry.

While two out of three steps in the Hierarchical Multiple Regression tests succeeded for each dynamic capability mediator (Sensing, Seizing, Transforming), the third test could not be deemed statistically significant at a 95% confidence level. Hypothesis of Sensing, Seizing, and Transforming as a mediator on the relationship between DT and CP could not be supported. Results are shown with a dotted line in Figure 13 for H3(a), H3(b) and H(c). While mediation effects could not be supported, the test for Sensing as a mediator had a p-value of 0.051, slightly over the threshold of 0.05 (marked with a blue dotted line). Here, should the study have used a threshold of 90% confidence (p-value < 0.01); mediation would have been supported.

While mediation could not be supported, the resultant Beta value of Sensing, Seizing, and Transforming when added as mediator in the Hierarchical Multiple Regression method, the Beta for Sensing, Seizing, and Transforming were 0.25, 0.32, and 0.35, respectively (i.e., the Beta values are higher than 0.24 on the relationship between DT and CP). These tests were statistically significant. This demonstrated that Sensing, Seizing, and Transforming became dominant when added as a mediator meaning they explain more results in CP compared to DT. These results confirm the focus of Dynamic Capabilities on high payoff activities that ultimately transform business models (Teece, 2018). This finding has significant practical implications as it suggests that in a resource constraint environment, dynamic capabilities support a higher impact on CP compared to DT in the mining industry.

7.3. Research theoretical contributions

The research contributes to academic research, as it responds to several academic calls for increased research in Dynamic Capabilities and DT. For example, Mele et al. (2024) argues that literature on Dynamic Capabilities and DT is still limited despite the potential of the two areas. The research project offers an industry specific (instead of generic) view on DT, dynamic capabilities, and CP. The quantitative study also offers empirical results highlighting the impact of DT on mining company CP. The research project validates Ciampi et al. (2022) view of the upside potential of DT when it comes to CP. The quantitative research project also highlights the influence of dynamic capabilities (Sensing, Seizing, and Transforming) on CP and concludes that Dynamic Capabilities (when compared to DT) have more impact on Competitive Performance in the mining industry.

The research project contributed to the body of research by investigating the application of DT and DCs in the mining industry. The focus in the mining industry allowed for nuanced (instead of generic) views on the DT, DCs, and competitiveness within the mining industry. This contribution is important given Ancillai et al. (2023) argument that impact of digitalisation may differ across industries.

Recent academic research has a bias towards early adopters of DT (retail, banking, etc.) and often focuses on technical parts of DT (Soluk & Kammerlander, 2021). This research confirms Verhoef et al. (2021) view that it is important to consider a multidisciplinary view of Digital Transformation beyond just the technical scope. This research's non-technical (i.e. broader managerial) view of DT contributes to the body of research.

7.4. Research business contribution

While mediation effects of DCs on DT and competitive performance could not be established; the research project results showed the importance of DCs in mining company competitive performance. In this case, Sensing, Seizing, and Transforming capabilities are important for mining organisations given the prospects of future disruptions. Additionally, since these capabilities are higher-order capabilities with dependency on top management team (Teece, 2014), the findings of this research have practical considerations for top management teams in mining. How do top management teams in mining lead, develop, and institutionalise dynamic capabilities within their organisation given the significant role?

The research project found that Dynamic Capabilities' influence on Competitive Performance is higher than that of Digital Transformation. This has significant practical implications for mining organisations. In a resource constrained environment, prioritisation of focus areas becomes important for leaders. Additionally, Teece (2014) states that dynamic capabilities need to be built and cannot be easily bought. This has practical implications for top management teams as they would need to invest time in building dynamic capabilities internally. Given the dominant impact of DC's (when compared with DT) on competitive performances, leaders need to find a balance between pursing DT strategies while strengthening DCs to support DT.

7.5. Limitations of the research project

The study had several limitations and these added context to the findings. The research project relies on the views and opinions of participants via an anonymous survey, and no opportunity to prompt the respondents on their responses. Here, the survey relies on perceptions and views of participants. While due care was undertaken, there is inherent risk in an online survey. For instance, during the analysis of outliers (conducted in the section 5.8.1), one respondent simply had "Strongly Disagree" on 22 out of the 24 statements across all five constructs. This was an outlier and resulted in the row being removed post the outlier analysis.

While the global geographic reach of the respondents was encouraging on the global applicability of the research project (all continents/regions were represented), the respondents were skewed towards Southern Africa. Debates in academia on the nuances of Dynamic Capabilities to international businesses that operate in several regions, which have different operating contexts that may require tailoring of Dynamic Capabilities (Zahra et al., 2022b).

The study only focused on Digital Transformation and Dynamic Capabilities' influence on Competitive Performance in the mining industry. Other contributory factors (such as organisational inertia) were not considered in the study. The focus in the mining industry was a deliberate focus to ensure industry specific analysis; however, exclusion of industries also limits the generic applicability of results to other industries.

7.6. Future studies recommendation

Considering these limitations, several potential future studies are recommended. As the study is limited to the mining industry, there is an opportunity to expand the research project across multiple industries and examine whether the results are consistent across various sectors.

Results suggested differences in mediating effects between Sensing, Siezing, and Transforming on the relationship between DT and CP. There is an opportunity to continue research in this area to understand the differences and antecedents to dynamic capabilities (sensing, seizing and transforming) that could explain the differences.

Another potential future study area is to extend the study to include organisational inertia construct to conduct empirical research on the extent organisational inertia influences the overall competitive performance. This would allow researchers to understand mixed effects of DCs and organisational inertia.

7.7. Conclusion

The mining industry faces prospects of significant disruption, and the ability for mining organisation to be dynamic in the face of technological and market changes will be important. The research project focused on the mining to understand the nuances of DT, DCs, and CP. Results of this project show that there is a relationship between DT and CP. The study also showed a strong impact of DT on Dynamic Capabilities (Sensing, Seizing, and Transforming). The results confirmed the importance of digital technologies in Sensing, Seizing, and Transforming capabilities for the mining organisation. While the mediation effects of DCs could not be supported, the importance of DCs on CP within the mining industry context has been elucidated.

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APPENDIX 1 – RESEARCH INSTRUMENT

Table 28: Research instrument with Cronbach's alpha values

Construct	Indicator Code / Question No	Item	Description	Loading	Cronbach’s alpha
	Section A - Demographic information				
N/A	Q1	Do you work in the mining industry?	Yes	N/A	N/A
			No **Thank the individual and complete the survey**		
	Q2	How old are you?	20-29 years		
			30-39 years		
			40-49 years		
			50+ years		
	Q3	Gender identity	Male		
			Female		
			Non-binary		
			Transgender		
			Prefer not to reply		
			Other		
	Q4	What is your highest level of education?	High school		
			Diploma or advanced certificate		
			Undergraduate degree		
			Postgraduate degree (up to Masters level)		
			Doctoral degree		
	Q5		Less than 1 year		

		How many years have you been with your organisation?	> 1 but ≤ 5 years		
			> 5 but ≤ 10 years		
			> 10 but ≤ 15 years		
			> 15 but ≤ 20 years		
			More than 20 years		
	Q6	Which discipline do you work in?	Operations / production		
			Finance		
			Human Resources		
			Information Technology		
			Projects		
			Procurement and supply chain		
			Community relations and corporate social responsibility		
			Other (specify)		
	Q7	Which level in the organisation are you on?	Supervisory		
			Specialist		
			Middle management		
			Senior management		
			Executive		
			Other		
	Q8	What is the size of your organisation?	1 - 500 employees		
			501 - 1000 employees		
			1 001 - 5 000 employees		
			5 001 - 10 000 employees		
			10 001 to 20 000 employees		

			More than 20 000 employees		
	Q9	In which geographical region do you primarily work?	Southern Africa		
			Other regions in Africa		
			Europe		
			North America		
			South America		
			Asia		
			Australia / Oceania		
	Section B - Digital Transformation				
	Indicate the degree to which you agree with the following statement, where 1 = strong disagree and 5 = Strongly agree.				
Digital Transformation (Rahman et al., 2025)	DT1	We digitally upgrade the existing offerings (e.g., from manual, paper-based processes to automated digital systems and workflows powered by software, cloud computing, mobile technology, and data analytics).	Strongly disagree	0.84	0.896
			Disagree		
			Neutral		
			Agree		
			Strongly agree		
	DT2	We develop intelligent offerings (e.g., Artificial Intelligence-based tools).	Strongly disagree	0.845	
			Disagree		
			Neutral		
			Agree		
			Strongly agree		
	DT3	We implement a digital platform-based business model.	Strongly disagree	0.839	
			Disagree		
			Neutral		

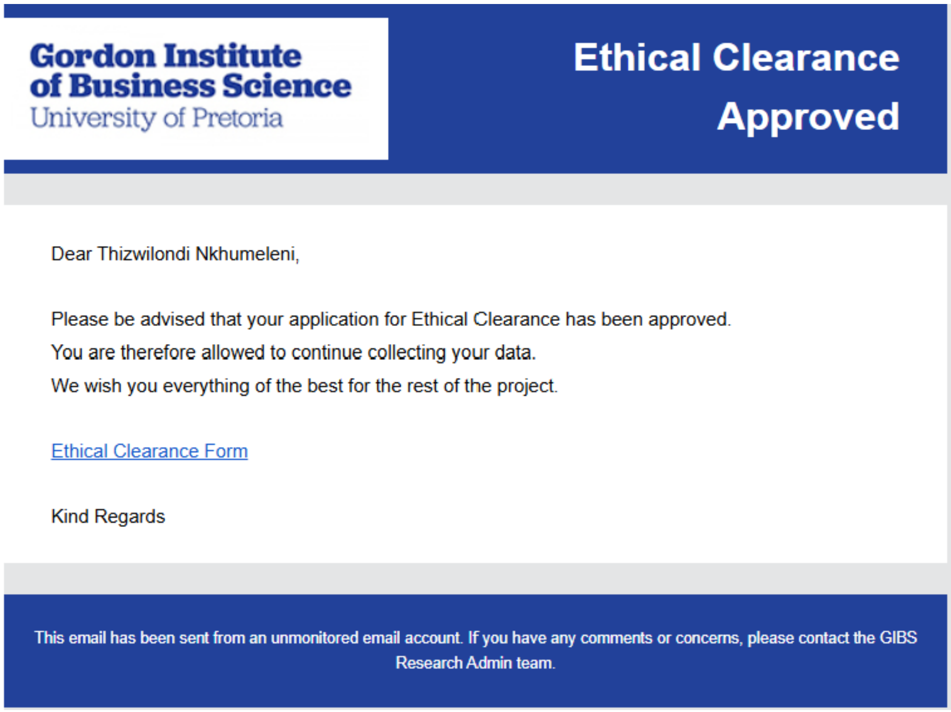
			Agree		
			Strongly agree		
	DT4	We establish a decision-making & control system based on data analysis.	Strongly disagree	0.833	
			Disagree		
			Neutral		
			Agree		
			Strongly agree		
	DT5	We flexibly adjust the structure of functional departments.	Strongly disagree	0.847	
			Disagree		
			Neutral		
			Agree		
			Strongly agree		
	Section C - Dynamic Capabilities				
Dynamic Capabilities (Sensing) (Kump et al., 2019)	SE1	Our company knows the best practices in the market.	Strongly disagree	0.72	0.88
			Disagree		
			Neutral		
			Agree		
			Strongly agree		
	SE2	Our company is up-to-date on the current market situation.	Strongly disagree	0.82	
			Disagree		
			Neutral		
			Agree		
			Strongly agree		
	SE3	Our company systematically searches for information on the current market situation.	Strongly disagree	0.95	
			Disagree		
			Neutral		
			Agree		
			Strongly agree		
	SE4	As a company, we know how to access new information.	Strongly disagree	0.83	
			Disagree		
			Neutral		
			Agree		

			Strongly agree		
	SE5	Our company always has an eye on our competitors' activities.	Strongly disagree Disagree Neutral Agree Strongly agree	0.7	
Dynamic Capabilities (Seizing) (Kump et al., 2019)	SZ1	Our company can quickly relate to new knowledge from the outside.	Strongly disagree Disagree Neutral Agree Strongly agree	0.87	0.83
	SZ2	We recognise what new information can be utilised in our company.	Strongly disagree Disagree Neutral Agree Strongly agree	0.72	
	SZ3	Our company is capable of turning new technological knowledge into process and product innovation	Strongly disagree Disagree Neutral Agree Strongly agree	0.84	
	SZ4	Current information leads to the development of new products or services.	Strongly disagree Disagree Neutral Agree Strongly agree	0.73	
Dynamic Capabilities (Transforming)	TF1	By defining clear responsibilities, we successfully implement plans for changes in our company.	Strongly disagree Disagree Neutral Agree Strongly agree	0.89	0.86

(Kump et al., 2019)	TF2	Even when unforeseen interruptions occur, change projects are seen through consistently in our company.	Strongly disagree Disagree Neutral Agree Strongly agree	0.9	
	TF3	Decisions on planned changes are pursued consistently in our company.	Strongly disagree Disagree Neutral Agree Strongly agree	0.62	
	TF4	In the past, we have demonstrated our strengths in implementing changes.	Strongly disagree Disagree Neutral Agree Strongly agree	0.6	
	TF5	In our company, change projects can be put into practice alongside the daily business.	Strongly disagree Disagree Neutral Agree Strongly agree	0.72	
	Section D - Competitive Performance				
Competitive performance (Behl et al., 2022; Jenkinson et al., 2024)	CP1	Compared with our competitors, we have higher profit growth rate	Strongly disagree Disagree Neutral Agree Strongly agree	0.84	0.82
	CP2	Compared with our competitors, we have higher sales revenue growth rate	Strongly disagree Disagree Neutral Agree Strongly agree	0.87	

	CP3	Compared with our competitors, we have lower operating costs	Strongly disagree Disagree Neutral Agree Strongly agree	0.62	
	CP4	Compared with our competitors, we have better product ~~and service~~ quality	Strongly disagree Disagree Neutral Agree Strongly agree	0.65	
	CP5	Compared with our competitors, we have increasingly higher market share	Strongly disagree Disagree Neutral Agree Strongly agree	0.82	

APPENDIX 2 – ETHICAL CLEARANCE



Gordon Institute of Business Science
University of Pretoria

Ethical Clearance Approved

Dear Thizwilondi Nkhumeleni,

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

Ethical Clearance Form

Kind Regards

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

Figure 14: Ethical clearance confirmation email

APPENDIX 3 – CODE BOOK

Table 29: Codebook for the SPSS data loading

No	0
Yes	1

20-29 years	1
30-39 years	2
40-49 years	3
50+ years	4

High school	1
Diploma or advanced certificate	2
Undergraduate degree	3
Postgraduate degree (up to Masters level)	4
Doctoral degree	5

Less than 1 year	1
> 1 but ≤ 5 years	2
> 5 but ≤ 10 years	3
> 10 but ≤ 15 years	4
> 15 but ≤ 20 years	5
More than 20 years	6

1 - 500 employees	1
501 - 1000 employees	2
1 001 - 5 000 employees	3
5001 - 10 000 employees	4
10 001 - 20 000 employees	5
More than 20 000 employees	6

Male	0
Female	1

Southern Africa	1
Other regions in Africa	2
Asia	3
Australia / Oceania	4
Europe	5
North America	6
South America	7

Strongly disagree	1
Disagree	2
Neutral	3
Agree	4
Strongly agree	5

Senior management	1
Middle management	2
Specialist	3
Executive	4
Other	5

Source: Researchers' own compilation

APPENDIX 4 – GROUPING OF DISCIPLINES

Table 30: Grouping of disciplines to consolidated disciplines

Discipline	Classification	Frequency	Total
Business Development	Business Development and Strategy	1	
Business development & technical projects	Business Development and Strategy	1	
Strategy	Business Development and Strategy	4	
Strategy and Business Improvement	Business Development and Strategy	2	
Strategy and Innovation	Business Development and Strategy	1	9
Communications	Communications & Public Relations	1	
Communications and PR	Communications & Public Relations	1	
Community relations and corporate social responsibility	Communications & Public Relations	10	12
Asset Management	Engineering and Technical Functions	1	
BI	Engineering and Technical Functions	1	
Business Improvement	Engineering and Technical Functions	5	
Business Improvement (Operational Excellence)	Engineering and Technical Functions	1	
Chemistry	Engineering and Technical Functions	1	
Corporate Technical Function	Engineering and Technical Functions	1	
Engineering	Engineering and Technical Functions	3	
Engineering & Maintenance	Engineering and Technical Functions	1	
Engineering/Planning department	Engineering and Technical Functions	1	
Operational Excellence	Engineering and Technical Functions	1	
Operational improvement	Engineering and Technical Functions	1	
Operations, Business Improvement, Projects, IT	Engineering and Technical Functions	1	
Projects	Engineering and Technical Functions	17	
Technical	Engineering and Technical Functions	4	
Technical and Strategy	Engineering and Technical Functions	1	

Technical and sustainability	Engineering and Technical Functions	1	41
Board Governance	Executive and Governance	1	
CEO	Executive and Governance	1	
Chief of Staff	Executive and Governance	1	3
Finance	Finance, Legal, Audit	12	
Intergrated risk and business continuity	Finance, Legal, Audit	1	
Internal Audit	Finance, Legal, Audit	1	
Legal	Finance, Legal, Audit	1	15
Corporate Safety, Ops Risk & Assurance	Health, Safety, Environment (HSE)	1	
Energy and Decarbonisation	Health, Safety, Environment (HSE)	1	
ESG	Health, Safety, Environment (HSE)	1	
Health and safety	Health, Safety, Environment (HSE)	1	
Health and Safety	Health, Safety, Environment (HSE)	1	
health safety and environment	Health, Safety, Environment (HSE)	1	
HSE	Health, Safety, Environment (HSE)	1	
Occupational Safety	Health, Safety, Environment (HSE)	1	
Occupational Safety, Health and Environment	Health, Safety, Environment (HSE)	1	
Safety	Health, Safety, Environment (HSE)	1	
Safety and risk management	Health, Safety, Environment (HSE)	1	
SHE	Health, Safety, Environment (HSE)	3	14
Human Resources	Human Resources (HR) & Learning Development	13	
Learning and Development	Human Resources (HR) & Learning Development	1	14
AI Delivery (Innovation team seperate to IT)	Innovation, Technology, Data Management	1	
Information Technology	Innovation, Technology, Data Management	42	43
Exploration	Operations and Production	1	
Maintenance	Operations and Production	1	

Mining operations	Operations and Production	1	
Operations / production	Operations and Production	52	55
Consulting	Other	1	
Document Control	Other	1	2
Procurement and supply chain	Procurement, Supply Chain, and Support Functions	4	4
		212	212

Source: Researchers' own compilation

APPENDIX 5 – VALIDITY: FACTOR MATRIX OF CONSTRUCTS

Table 31: Factor Matrix for Digital Transformation, Sensing and Seizing

Factor Matrix[a] **(Digital Transformation)**	
	Factor
	1
We digitally upgrade the existing offerings (e.g., from manual, paper-based processes to automated digital systems and workflows powered by software, cloud computing, mobile technology, and data analytics).	0.523
We develop intelligent offerings (e.g., Artificial Intelligence-based tools).	0.588
We implement a digital platform-based business model.	0.834
We establish a decision-making & control system based on data analysis.	0.672

Factor Matrix[a] **(Sensing - Dynamic Capabilities)**	
	Factor
	1
Our company knows the best practices in the market.	0.693
Our company is up-to-date on the current market situation.	0.723
Our company systematically searches for information on the current market situation.	0.788
As a company, we know how to access new information.	0.765

Factor Matrix[a] **(Seizing - Dynamic Capabilities)**	
	Factor
	1
Our company can quickly relate to new knowledge from the outside.	0.716
We recognise what new information can be utilised in our company.	0.638
Our company is capable of turning new technological knowledge into process and product innovation.	0.731
Current information leads to the development of new products or services.	0.697

We flexibly adjust the structure of functional departments.	0.604
Extraction Method: Principal Axis Factoring.	
a. 1 factors extracted. 9 iterations required.	

Our company always has an eye on our competitors' activities.	0.628
Extraction Method: Principal Axis Factoring.	
a. 1 factors extracted. 5 iterations required.	

Extraction Method: Principal Axis Factoring.
a. 1 factors extracted. 6 iterations required.

Source: SPSS output

Table 32: Factor Matrix for Transforming and Competitive Performance

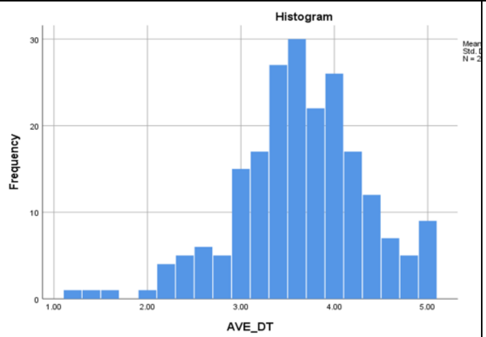
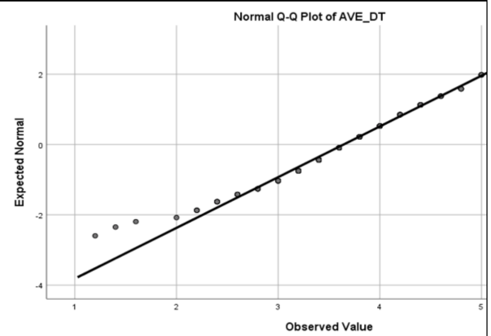
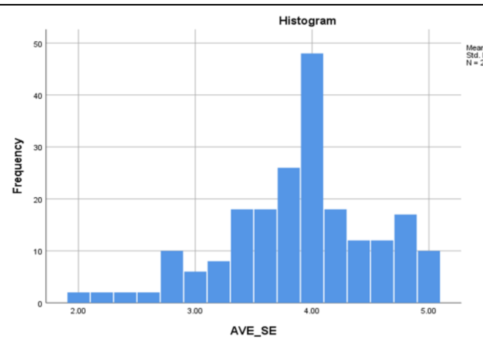
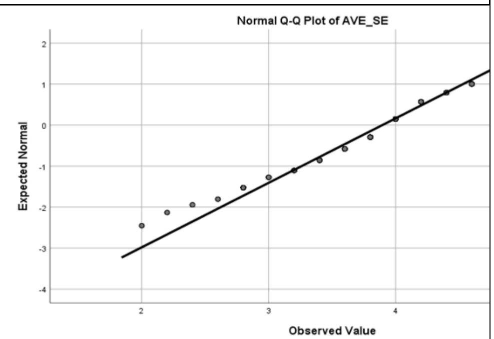
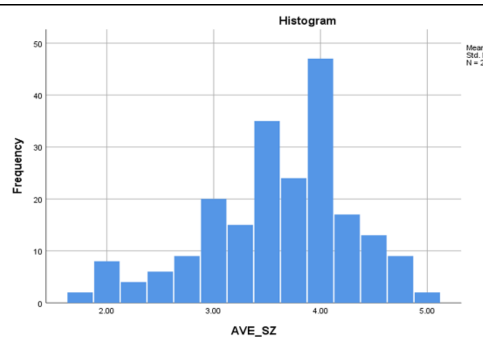
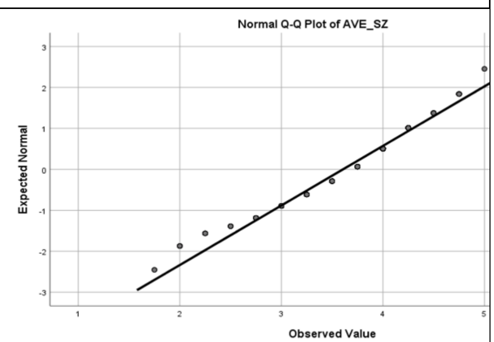
Factor Matrix[a] **(Transforming - Dynamic Capabilities)**	
	Factor
	1
By defining clear responsibilities, we successfully implement plans for changes in our company.	0.662
Even when unforeseen interruptions occur, change projects are seen through consistently in our company.	0.745
Decisions on planned changes are pursued consistently in our company.	0.673
In the past, we have demonstrated our strengths in implementing changes.	0.821
In our company, change projects can be put into practice alongside the daily business.	0.767
Extraction Method: Principal Axis Factoring.	
a. 1 factors extracted. 6 iterations required.	

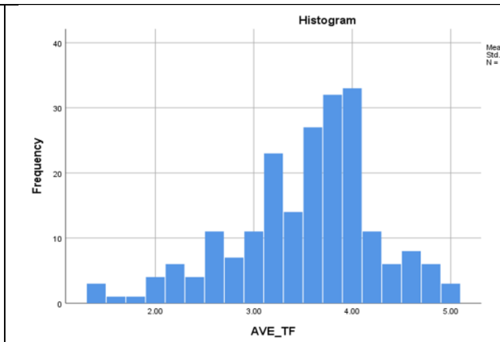
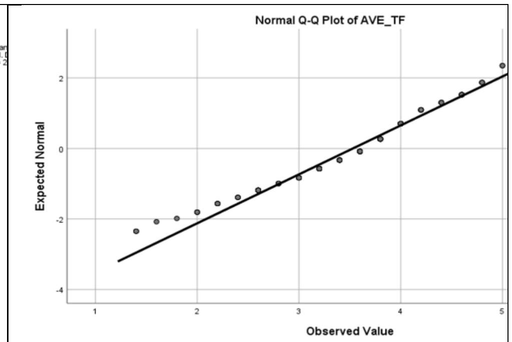
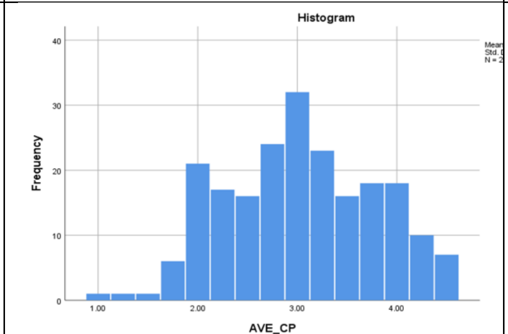
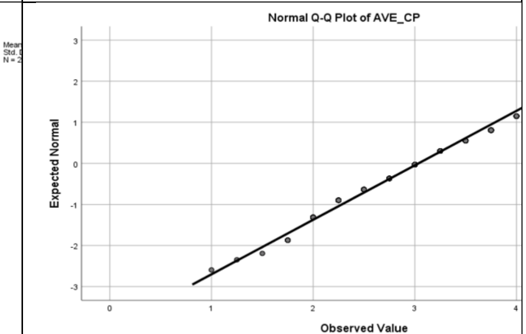
Factor Matrix[a] **(Competitive Performance)**	
	Factor
	1
Compared with our competitors, we have higher profit growth rate	0.874
Compared with our competitors, we have higher sales revenue growth rate	0.890
Compared with our competitors, we have lower operating costs	0.412
Compared with our competitors, we have better product quality	0.316
Compared with our competitors, we have increasingly higher market share	0.651
Extraction Method: Principal Axis Factoring.	
a. 1 factors extracted. 7 iterations required.	

Source: SPSS output

APPENDIX 6 – NORMALITY (HISTOGRAMS AND Q-Q PLOTS)

Table 33: Normality assessment - histograms and Q-Q plots for all variables

<table>
<tr><td>Variable</td><td>Histogram</td><td>Normal Q-Q Plot</td></tr>
<tr><td>Digital Transformation</td><td>
</td><td>
</td></tr>
<tr><td>Sensing (DCs)</td><td>
</td><td>
</td></tr>
<tr><td>Seizing (DCs)</td><td>
</td><td>
</td></tr>
</table>

Transforming (DCs)		
Competitive Performance		

Source: SPSS output

APPENDIX 7 – INTER-ITEM CORRELATION MATRICES

Table 34: Digital Transformation Inter-item correlation matrix

Digital Transformation Construct - Inter-Item Correlation Matrix					
	We digitally upgrade the existing offerings (…).	We develop intelligent offerings (e.g., Artificial Intelligence-based tools).	We implement a digital platform-based business model.	We establish a decision-making & control system based on data analysis.	We flexibly adjust the structure of functional departments.
We digitally upgrade the existing offerings (…).	1.000	0.415	0.439	0.283	0.282
We develop intelligent offerings (e.g., Artificial Intelligence-based tools).	0.415	1.000	0.477	0.359	0.321
We implement a digital platform-based business model.	0.439	0.477	1.000	0.579	0.494
We establish a decision-making & control system based on data analysis.	0.283	0.359	0.579	1.000	0.474
We flexibly adjust the structure of functional departments.	0.282	0.321	0.494	0.474	1.000

Source: SPSS output

Table 35: Sensing inter-item correlation matrix

Sensing - Inter-Item Correlation Matrix					
	Our company knows the best practices in the market.	Our company is up-to-date on the current market situation.	Our company systematically searches for information on the current market situation.	As a company, we know how to access new information.	Our company always has an eye on our competitorsâ€™ activities.
Our company knows the best practices in the market.	1.000	0.567	0.484	0.537	0.430
Our company is up-to-date on the current market situation.	0.567	1.000	0.593	0.513	0.400
Our company systematically searches for information on the current market situation.	0.484	0.593	1.000	0.614	0.524
As a company, we know how to access new information.	0.537	0.513	0.614	1.000	0.507
Our company always has an eye on our competitorsâ€™ activities.	0.430	0.400	0.524	0.507	1.000

Table 36: Seizing inter-item correlation matrix

Seizing - Inter-Item Correlation Matrix				
	Our company can quickly relate to new knowledge from the outside.	We recognize what new information can be utilized in our company.	Our company is capable of turning new technological knowledge into process and product innovation	Current information leads to the development of new products or services.
Our company can quickly relate to new knowledge from the outside.	1.000	0.566	0.479	0.447
We recognize what new information can be utilized in our company.	0.566	1.000	0.411	0.390
Our company is capable of turning new technological knowledge into process and product innovation	0.479	0.411	1.000	0.608
Current information leads to the development of new products or services.	0.447	0.390	0.608	1.000

Source: SPSS output

Table 37: Transforming inter-item correlation matrix

Transforming - Inter-Item Correlation Matrix					
	By defining clear responsibilities, we successfully implement plans for changes in our company.	Even when unforeseen interruptions occur, change projects are seen through consistently in our company.	Decisions on planned changes are pursued consistently in our company.	In the past, we have demonstrated our strengths in implementing changes.	In our company, change projects can be put into practice alongside the daily business.
By defining clear responsibilities, we successfully implement plans for changes in our company.	1.000	0.521	0.417	0.545	0.505
Even when unforeseen interruptions occur, change projects are seen through consistently in our company.	0.521	1.000	0.538	0.573	0.556
Decisions on planned changes are pursued consistently in our company.	0.417	0.538	1.000	0.559	0.498
In the past, we have demonstrated our strengths in implementing changes.	0.545	0.573	0.559	1.000	0.661
In our company, change projects can be put into practice alongside the daily business.	0.505	0.556	0.498	0.661	1.000

Source: SPSS output

Table 38: Competitive performance inter-item correlation matrix

Competitive performance - Inter-Item Correlation Matrix					
	Compared with our competitors, we have higher profit growth rate	Compared with our competitors, we have higher sales revenue growth rate	Compared with our competitors, we have lower operating costs	Compared with our competitors, we have better product quality	Compared with our competitors, we have increasingly higher market share
Compared with our competitors, we have higher profit growth rate	1.000	0.808	0.374	0.304	0.506
Compared with our competitors, we have higher sales revenue growth rate	0.808	1.000	0.323	0.240	0.588
Compared with our competitors, we have lower operating costs	0.374	0.323	1.000	0.068	0.339
Compared with our competitors, we have better product quality	0.304	0.240	0.068	1.000	0.263
Compared with our competitors, we have increasingly higher market share	0.506	0.588	0.339	0.263	1.000

Source: SPSS output

APPENDIX 8 – CONSTRUCT VALIDATION RESULTS

This appendices shows all correlations results per construct as evidence for the validity of the research instrument. Construct Validation Results

Table 39: Digital Transformation construct validation - correlations

Digital Transformation: Correlations

		Total_DT
We digitally upgrade the existing offerings (…).	Pearson Correlation	.644**
	Sig. (2-tailed)	0.000
	N	212
We develop intelligent offerings (e.g., Artificial Intelligence-based tools).	Pearson Correlation	.719**
	Sig. (2-tailed)	0.000
	N	212
We implement a digital platform-based business model.	Pearson Correlation	.819**
	Sig. (2-tailed)	0.000
	N	212
We establish a decision-making & control system based on data analysis.	Pearson Correlation	.740**
	Sig. (2-tailed)	0.000
	N	212
We flexibly adjust the structure of functional departments.	Pearson Correlation	.716**
	Sig. (2-tailed)	0.000
	N	212
Total_DT	Pearson Correlation	1
	Sig. (2-tailed)	
	N	212

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

Source: SPSS output

Table 40: Sensing construct validation - correlations

Sensing: Correlations		
		Total_SE
Our company knows the best practices in the market.	Pearson Correlation	.769**
	Sig. (2-tailed)	0.000
	N	212
Our company is up-to-date on the current market situation.	Pearson Correlation	.782**
	Sig. (2-tailed)	0.000
	N	212
Our company systematically searches for information on the current market situation.	Pearson Correlation	.817**
	Sig. (2-tailed)	0.000
	N	212
As a company, we know how to access new information.	Pearson Correlation	.813**
	Sig. (2-tailed)	0.000
	N	212
Our company always has an eye on our competitorsâ€™ activities.	Pearson Correlation	.734**
	Sig. (2-tailed)	0.000
	N	212
Total_SE	Pearson Correlation	1
	Sig. (2-tailed)	
	N	212
**. Correlation is significant at the 0.01 level (2-tailed).		

Source: SPSS output

Table 41: Seizing construct validation - correlations

Seizing: Correlations		
		Total_SZ
Our company can quickly relate to new knowledge from the outside.	Pearson Correlation	.795**
	Sig. (2-tailed)	0.000
	N	212
We recognise what new information can be utilised in our company.	Pearson Correlation	.738**
	Sig. (2-tailed)	0.000
	N	212
Our company is capable of turning new technological knowledge into process and product innovation	Pearson Correlation	.811**
	Sig. (2-tailed)	0.000
	N	212
Current information leads to the development of new products or services.	Pearson Correlation	.786**
	Sig. (2-tailed)	0.000
	N	212
Total_SZ	Pearson Correlation	1
	Sig. (2-tailed)	
	N	212
**. Correlation is significant at the 0.01 level (2-tailed).		

Source: SPSS output

Table 42: Transforming construct validation - correlations

Transforming: Correlations		
		Total_TF
By defining clear responsibilities, we successfully implement plans for changes in our company.	Pearson Correlation	.754**
	Sig. (2-tailed)	0.000
	N	212
Even when unforeseen interruptions occur, change projects are seen through consistently in our company.	Pearson Correlation	.807**
	Sig. (2-tailed)	0.000
	N	212
Decisions on planned changes are pursued consistently in our company.	Pearson Correlation	.752**
	Sig. (2-tailed)	0.000

	N	212
In the past, we have demonstrated our strengths in implementing changes.	Pearson Correlation	.847**
	Sig. (2-tailed)	0.000
	N	212
In our company, change projects can be put into practice alongside the daily business.	Pearson Correlation	.808**
	Sig. (2-tailed)	0.000
	N	212
Total_TF	Pearson Correlation	1
	Sig. (2-tailed)	
	N	212
**. Correlation is significant at the 0.01 level (2-tailed).		

Source: SPSS output

Table 43: Competitive performance construct validation - correlations

Competitive Performance: Correlations		
		Total_CP
Compared with our competitors, we have higher profit growth rate	Pearson Correlation	.850**
	Sig. (2-tailed)	0.000
	N	212
Compared with our competitors, we have higher sales revenue growth rate	Pearson Correlation	.840**
	Sig. (2-tailed)	0.000
	N	212
Compared with our competitors, we have lower operating costs	Pearson Correlation	.597**
	Sig. (2-tailed)	0.000
	N	212
Compared with our competitors, we have better product quality	Pearson Correlation	.497**
	Sig. (2-tailed)	0.000
	N	212
Compared with our competitors, we have increasingly higher market share	Pearson Correlation	.768**
	Sig. (2-tailed)	0.000
	N	212
Total_CP	Pearson Correlation	1
	Sig. (2-tailed)	

	N	212
**. Correlation is significant at the 0.01 level (2-tailed).		

Source: SPSS output

APPENDIX 9 – FACTOR ANALYSIS: FACTOR MATRICES

Table 44: Digital Transformation - Factor Matrix

Digital Transformation: Factor Matrix[a]	
	Factor
	1
We digitally upgrade the existing offerings (…).	0.523
We develop intelligent offerings (e.g., Artificial Intelligence-based tools).	0.588
We implement a digital platform-based business model.	0.834
We establish a decision-making & control system based on data analysis.	0.672
We flexibly adjust the structure of functional departments.	0.604
Extraction Method: Principal Axis Factoring.	
a. 1 factors extracted. 9 iterations required.	

Source: SPSS output

Table 45: Sensing Factor Matrix

Sensing: Factor Matrix[a]	
	Factor
	1
Our company knows the best practices in the market.	0.693
Our company is up-to-date on the current market situation.	0.723
Our company systematically searches for information on the current market situation.	0.788
As a company, we know how to access new information.	0.765
Our company always has an eye on our competitorsâ€™ activities.	0.628
Extraction Method: Principal Axis Factoring.	
a. 1 factors extracted. 5 iterations required.	

Table 46: Seizing Factor Matrix

Seizing: Factor Matrix[a]	
	Factor
	1
Our company can quickly relate to new knowledge from the outside.	0.716
We recognise what new information can be utilised in our company.	0.638
Our company is capable of turning new technological knowledge into process and product innovation	0.731
Current information leads to the development of new products or services.	0.697
Extraction Method: Principal Axis Factoring.	
a. 1 factors extracted. 6 iterations required.	

Table 47: Transforming Factor Matrix

Transforming: Factor Matrix[a]	
	Factor
	1
By defining clear responsibilities, we successfully implement plans for changes in our company.	0.662
Even when unforeseen interruptions occur, change projects are seen through consistently in our company.	0.745
Decisions on planned changes are pursued consistently in our company.	0.673
In the past, we have demonstrated our strengths in implementing changes.	0.821
In our company, change projects can be put into practice alongside the daily business.	0.767
Extraction Method: Principal Axis Factoring.	
a. 1 factors extracted. 6 iterations required.	

Source: SPSS output

APPENDIX 10 – HIERARCHICAL MULTIPLE REGRESSION MODEL RESULTS

Table 48: SPSS Output - Hierarchical Multiple Regression model results: Sensing as a mediator

Coefficients[a]								
		Unstandardised Coefficients		Standardised Coefficients			95.0% Confidence Interval for B	
Model		B	Std. Error	Beta	t	Sig.	Lower Bound	Upper Bound
1	(Constant)	2.099	0.271		7.741	0.000	1.564	2.634
	AVE_DT	0.257	0.073	0.237	3.520	0.001	0.113	0.402
2	(Constant)	1.325	0.343		3.865	0.000	0.649	2.000
	AVE_DT	0.151	0.077	0.139	1.959	0.051	-0.001	0.304
	AVE_SE	0.298	0.084	0.251	3.542	0.000	0.132	0.464
a. Dependent Variable: AVE_CP								

Source: SPSS output

Table 49: SPSS Output - Hierarchical Multiple Regression model results: Seizing as a mediator

Coefficients[a]								
		Unstandardised Coefficients		Standardised Coefficients			95.0% Confidence Interval for B	
Model		B	Std. Error	Beta	t	Sig.	Lower Bound	Upper Bound
1	(Constant)	2.099	0.271		7.741	0.000	1.564	2.634
	AVE_DT	0.257	0.073	0.237	3.520	0.001	0.113	0.402
2	(Constant)	1.481	0.298		4.974	0.000	0.894	2.068
	AVE_DT	0.077	0.082	0.070	0.935	0.351	-0.085	0.238
	AVE_SZ	0.354	0.083	0.323	4.287	0.000	0.191	0.517
a. Dependent Variable: AVE_CP								

Source: SPSS output

Table 50: SPSS Output - Hierarchical Multiple Regression model results: Transforming as a mediator

Coefficients[a]								
		Unstandardised Coefficients		Standardised Coefficients			95.0% Confidence Interval for B	
Model		B	Std. Error	Beta	t	Sig.	Lower Bound	Upper Bound
1	(Constant)	2.099	0.271		7.741	0.000	1.564	2.634
	AVE_DT	0.257	0.073	0.237	3.520	0.001	0.113	0.402
2	(Constant)	1.463	0.290		5.054	0.000	0.893	2.034
	AVE_DT	0.077	0.079	0.071	0.979	0.329	-0.078	0.233
	AVE_TF	0.366	0.076	0.350	4.822	0.000	0.216	0.516
a. Dependent Variable: AVE_CP								

Source: SPSS output