Enabling firm performance through data driven decision making in maintenance management: A dynamic capabilities view

Kuben Kullenda

19388111

A research project proposal 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.

1 December 2020

ABSTRACT

Maintenance management is seen as a “necessary evil”, rather than a profit contributing resource that could intensify competitive advantage for the organisation. With the world facing the fourth industrial revolution, a radical increase in the reshaping of companies and competition within asset intensive industries is being observed. Organisations in these industries are being forced to rethink traditional ways of working and gearing the workforce with higher and more diversified competency profiles. This suggests that the traditional way of executing maintenance management, being predominantly reactive with the lack of data driven decision making, is certainly inadequate for a sustainable competitive advantage. An improved way of managing maintenance should be through developing and applying dynamic capabilities within the maintenance domain of the organisation.

This research draws on theories of dynamic capabilities (DC), decision making performance (DMP), business process performance (BPP) and firm performance (Fper), in the context of data driven decision making in organisations heavily reliant on good maintenance management practices. The aim of this study was to explore and understand the relationships between these constructs, for insight into further improvement and development of a competitive advantage.

The findings presented a statistically significant relationship between DC and Fper, DC and BPP, DC and DMP, but most importantly, a multiple full indirect mediation role was observed, which provides insights for both business and for further studies in academia.

Keywords

Data Driven Decision Making, Dynamic Capabilities, Business Process Performance, Decision Making Performance, Firm Performance

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.

____

Kuben Kullenda

01 December 2020

TABLE OF CONTENTS

List of Tables

List of Figures

Chapter 1: Introduction

1.1. Introduction

The current state of the economic ecology surrounding organisations today, is characteristic of competitive chaos. Wherein, competitive advantage and differentiation is based on both intrinsic and extrinsic subsystems or principles that govern the cascading choices that organisations need to act upon. Yet, we find that some industries have certain advantages over others. An organisations competitive advantage can be characterised by factors such as speed, quality, price and consistency (Pinjala, Pintelon, & Vereecke, 2006). Since maintenance management is an integral part in the operation of these industries, the decisions made to employ specific maintenance strategies to specific assets can affect the competitive advantage of the company, either positively or negatively (Pinjala et al., 2006). However, in asset intensive industries, maintenance is seen as a "necessary evil", rather than a profit contributing resource that has the ability to intensify competitive advantage for the organisation (Salonen & Bengtsson, 2011).

Data driven decision making capabilities within the maintenance domain could enable organisations to forge and sustain a competitive advantage (Ruschel, Santos, & Loures, 2017). However, the path to achieving such a competitive advantage, within the context of maintenance management, is not properly understood.

1.2. Research problem and purpose

Data driven decision making has proven to be a "game changer" for many industries to a level were organisational strategy and value propositions are influenced by it (Mazzei & Noble, 2017). According to Brynjolfsson, Hitt and Kim (2011), data driven decision making can increase output and productivity by 5% to 6%. Therefore, the analysis of maintenance history is important for organisations as it serves as knowledge discovery of the past as a starting point to predict what may happen in the future, for appropriate decisions to be executed in order to eliminate or reduce the impact of the failure reoccurring (Karim, Westerberg, Galar, & Kumar, 2016). Firms in industries such as manufacturing, oil and gas, heavy engineering, mining, utilities and transportation are known as asset intensive organisations due to the large capital investment and long term reliance on these major assets for sustained organisational performance (Mardiasmo, Tywoniak, Brown, &

Burgess, 2008). Competitive advantage within a firm refers to the effectiveness of an organisations capabilities to respond to an event, in alignment with the organisations strategic intent (Raghavan, Jain, & Jha, 2013). In order for an organisation to be competitive in its respective industry, an organisation should be in a position to exploit its data resources, through data analytics, to enhance decision making through its dynamic capabilities that will derive benefits with regards to its organisational performance. The evidence of using internal and external data for competitive advantages, has been observed over the past two decades through the rise and fall of industry giants who were not capable of evolving, innovating and capitalising on data driven decision making. Although maintenance equipment data or maintenance history is being collected in various forms and from various sources in asset intensive organisations, this data is seldom being used to change or improve any practices or processes (Moore, 2015). With the importance of data being such a commodity to an organisations competitiveness and sustainability, the derivation and capitalisation of insights from maintenance data seems to be deficient.

According to Sharma, Mithas, and Kankanhalli (2014), the capabilities needed for an organisation to effectively utilise data analytics to derive improved organisational performance and the role that decision-making and its associated business processes play in these relationships, needs to be further investigated. Further to this, it is posited that higher order dynamic capabilities – sensing, seizing and transforming, are required in sustaining an organisations competitive advantage and improving organisational performance (Teece, 2014). This suggests that there is a research gap in the role that decision making and business processes play, in the relationship between dynamic capabilities and organisational performance.

The purpose of this study is to explore and understand the effects that dynamic capabilities have on firm performance, in the context of data driven decision making in maintenance management, and whether decision making performance and business process performance play a role within that relationship.

1.3. Scope of the research

The scope of the research is limited to the direct and indirect relationships between dynamic capabilities, decision making performance, business process performance and firm performance.

The scope of the research is bound by the following concepts:

- Maintenance Management in Asset Intensive Industries
  - Refers to the decision-making processes that are aligned to the strategic objectives of industries including manufacturing, oil and gas, heavy engineering, mining, utilities, and transportation for long term reliance on these major assets for sustained organisational performance
- Dynamic Capabilities
  - According to Teece (2014), the dynamic capabilities of an organisation is a construct that refers to a firm's ability to effectively adapt its strategy, by reconfiguring its resources to align with the context of the business environment for improved organisational performance. The three constructs for dynamic capabilities of an organisation are sensing, seizing, and reconfiguring (Teece, 2014).
- Decision making Performance
  - Refers to the measures of quality, effectiveness and efficiency in decision making within an organisation (Ghasemaghaei, Ebrahimi, Hassanein, 2018)
- Business Process Performance
  - Refers to the aspects of the organisational and operational activities that have transactional inputs to, and transactional outputs from, various business processes within the organisation (Aydiner, Tatoglu, Bayraktar, & Zaim, 2019a)
- Firm Performance
  - A financial performance construct based on the research conducted by Wamba, Gunasekaran, Akter, Ren, Dubey & Childe (2017), which consists of an amalgamation of metrics of the firm's financial and market performance.

1.4. Business Rationale

Applying suitable maintenance practices can significantly enhance an organisations competitiveness through productivity, value and profitability advantages (Alsyouf, 2009). According to Rastegari and Mobin (2016), research in maintenance decision making has concluded that decision support systems in computerised maintenance management software is often missing and that data that is being collected in these organisations are underutilised. This leaves decision makers to intuitively make decisions that are rarely beneficial for the organisation. Further to this, in current maintenance organisations, further research is needed to identify and analyse competency and capabilities gaps to execute the analytics needed for decision making (Bokrantz, Skoogh, Berlin, & Stahre, 2017). This research study is of significance to business as it can highlight practical implications of the results to be used in creating urgency for the use of data driven decision making in asset intensive industries in order to nudge asset intensive organisations into developing strategies to future proof their organisations by applying measures for decision making that may catapult them into a better competitive advantage position than their peers.

1.5. Academic Rationale

The concept that dynamic capabilities has a relationship with competitive advantage has been a popular research topic in the IT research field (Mikalef, Krogstie, Pappas, & Pavlou, 2020). According to Newbert (2007), the relationship that dynamic capabilities has with competitive advantage, leads to improved firm performance. Further to this, it is posited that business process performance and decision making performance perform mediating roles between the relationship between dynamic capabilities and firm performance (Aydiner, Tatoglu, Bayraktar, & Zaim, 2019a). Due to these theoretical views, the researcher intends on contributing to academic theory by exploring whether there exists and relationship between dynamic capabilities and firm performance, and whether business process performance and decision making performance have any mediating roles between the aforementioned relationship, utilising the context of maintenance management.

1.6. Document structure

The research problem, purpose, and scope are outlined in this introductory chapter, together with contribution objectives to business and academia. The second chapter introduces a literature review that unpacks and explains the relationships of the constructs presented. The third chapter synthesises theoretical positions from the literature review into research questions to be tested. The fourth chapter details the research design methods adopted in this research. The fifth chapter presents the results of the statistical analysis conducted based on the research design methods and analysis approaches. The sixth chapter discusses results obtained through the statistical analysis. Lastly, chapter seven concludes the study.

Chapter 2: Literature review

2.1. Introduction

The literature review in this research is directed at illustrating the outlook of data driven decision making and the need for its integration with dynamic capabilities in the current operating environment, and its impact on firm performance. According to Kump, Engelmann, Kessler and Schweiger (2019), there seems to be a recurring theme of enabling of dynamic capabilities to create new value and forge a path to success. However, the road to success is often complex, as data driven decision making entwined with dynamic capabilities, within the context of maintenance management, is not properly understood. To address these points of view, the researcher unpacks these concepts to explain the distinct interplay between dynamic capabilities theory in a data driven ecosystem of maintenance management, and its effects on firm performance.

The initial discussion will focus on defining the key concepts within this research, thereafter, introducing leading views on data driven decision making and its relationship to dynamic capabilities. The central argument of this section aims to unpack how dynamic capabilities primes an organisation towards improved firm performance. This is then followed by literature on maintenance management and illustrates why an inherent dynamic capability within the maintenance management domain is needed for improved firm performance.

2.2. Data driven decision making

Data driven decision making has proliferated over the past ten years, where companies in various industries have adapted to explore and exploit their respective internal and external big data to bring about new competitive advantages that has transformed the way business is being done. Data refers to the representation of facts, numbers, concepts or instructions that are collected to be processed and analysed for communication and interpretation (Checkland & Holwell, 1998). In the context of maintenance, some sources of the data include online machinery health monitoring, control systems history, Internet of Things (IoT) smart devices, machine history and equipment failures, geo positioning systems (GPS) location system information, spares consumption and operational costs (Akhtar, Frynas, Mellahi & Ullah, 2019; Bokrantz, Skoogh, Berlin & Stahre, 2017).

According to Mcabee, Landis, and Burke (2017), data driven decision making refers to the deliberate objective to enhance organisational decision making capability through the collection and analysis of data. Further to this definition, Contreras and Salamo (2020), postulates that data-driven decision making is the practice of basing decisions fortified by data analytics, rather than purely relying on human intuition. In alignment with this definition, data driven decision making refers to the degree to which internal and external data can be collected and analysed to develop insights for making decisions effectively and efficiently, which is necessary for applications that are intended to enhance human experience based decision making (Bokrantz, Skoogh, Berlin, Wuest, & Stahre, 2020). This suggests that data analytics should be used in conjunction with human intuition, which is based on experience, to derive better decisions within an organisation for value creation and improved performance.

However, value creation from data analytics remains a major challenge for businesses in their quest for a competitive advantage due to the number of additional resources that are critical to eventually leading to an enhance organisational performance (Sena, Bhaumik, Sengupta & Demirbag, 2019). This orchestration of resources to establish a data driven decision making skillset is a key ingredient as to how an organisation can build a competitive advantage (Gupta & George, 2016). This suggests that for company to derive benefit from there data analytics, the organisation needs to focus on a resource-based view (RBV). The resource-based view posits that an organisation's competitive advantage stems from the resources within the company and that this is not easily replicated (Barney, 1991). This perspective explains the differences in competitive performance between organisations as the inherent competitive advantage is embedded in their resources which exhibit characteristics that are Valuable, Rare, Imperfectly Inimitable and Non-substitutable (VRIN), where Valuable refers to resources that can be exploited in order to create sustainable value, Rare refers to resources that are scarce, Imperfectly Inimitable refers to resources that are not easily duplicated or reproduced and Non-substitutable refers to resources that have no equivalent re-engineering (Barney, 1991; Wade & Hulland, 2004; Wojcik, 2015).

However, according to Wade & Hulland (2004), "the RBV as currently conceived fails to adequately consider the fact that resources rarely act alone in creating or sustaining competitive advantage" (p. 123). This position was further reiterated by research conducted by (Bhandari, Rana, Paul & Salo, 2020). According to Gupta and George

(2016), organisations need to develop on a data analytic capability by combining and utilising several organisational resources to be able to improve their decision making capability and improve their competitive advantage. This leads to the suggestion that there must be an analytical, dynamic capability within the resources for data driven decision making to derive a sustainable competitive advantage within the organisation.

2.3. Dynamic Capabilities entanglement with the Resource-based View and its effect of firm performance

Dynamic Capabilities in IT research has become a popular research field among scholars over the years as a crucial topic of interest in the strategic management and technology domains due to its potential to enhance the probability of a competitive advantage, and possibly resulting in positive performance outcomes within organisations (Kump et al., 2019; Mikalef, Krogstie, Pappas & Pavlou, 2020; Teece, Pisano & Shuen, 2009). According to Teece, Pisano and Shuen (1997), within continuously changing operating environments, dynamic capabilities refer to the approach in an organisation to emphasise the importance of exploiting both internal and external competencies in response to the change. Consequent to this, dynamic capabilities are described as the "organisational and strategic routines by which firms achieve new resource configurations as markets emerge, collide, split, evolve and die" (Eisenhardt & Martin, 2000, p. 1107). Helfat and Peteraf (2003), argued that the theory of dynamic capabilities needs to include a resource-based view in order to encompass all organisational capabilities. As a result of this, Helfat, Finkelstein, Mitchell, Peteraf, Singh, Teece and Winter (2007), included the resource based view, stating that dynamic capabilities and the resource-based view are entangled in the position of an organisation within its rapidly changing environment, to decisively shape and enhance its resource capabilities, tangible and intangible resources, that may be in the organisations control. These definitions are the most influential definitions of dynamic capabilities and through evolution of the theory, and have been seen to be complementary to each other (Kump et al., 2019). The idea of reinforcing dynamic capabilities with the resource-based view further evolved into the definition that dynamic capabilities were described as an organisations ability to effectively and efficiently adapt its strategy, by the reconfiguration of its resources to align with the context of the organisations operating environment, to strengthen performance (Teece, 2014). Due to the evolution of the theory of dynamic capabilities to incorporate and explain the entanglement between the two theories, the researcher has therefore adopted the view as posited by Teece (2014), going forward.

Firm performance is described as the organisation's ability to derive enhanced performance regarding their financial position through data driven decision making over the past three years, that distinguishes them from their competitors (Aydiner, Tatoglu, Bayraktar, & Zaim, 2019a; Torres, Sidorova & Jones, 2018). According to research conducted by Newbert (2007), it was postulated that there exists a relationship between the dynamic capabilities and competitive advantage of an organisation which results in firm performance, through the strategic organising of VRIN and core competencies within the organisation. This has been re-iterated according by Teece (2014), who posited that dynamic capabilities have the potential to deliver on these competitive advantages in order to improve firm performance. In research conducted by Kump et al. (2019), it was posited that dynamic capabilities are strong predictors of organisational performance. Contrary to these perspectives, research has also shown that dynamic capabilities alone are not sufficient to contribute to a competitive advantage for an organisation. In some cases, dynamic capabilities does not necessarily lead to better firm performance due to the fact that these capabilities are often costly for the organisation to implement which may lead to financial losses before the benefits are realised (Wilden, Gudergan, Nielsen & Lings, 2013). In research conducted by Wamba, Gunasekaran, Akter, Ren, Dubey and Childe (2017), it was concluded that data analytics dynamic capabilities have both direct and indirect positive effects on firm performance. Further to this, according to Mikalef et al. (2020), dynamic capabilities in analytics are necessary but not sufficient in order to derive a competitive advantage for an organisation. Their research posited that together with dynamic capabilities, the organisation also needs strong organisational capabilities such as marketing and technological capabilities to derive a competitive advantage.

Capabilities within and organisation in a competitive environment are categorised between ordinary capabilities which include skilled resources, operating assets, technical information and administrative coordination, and dynamic capabilities which include the ability to analyse and identify opportunities, capitalise on opportunities identified and continuously transform the organisation to ensure that value is enhanced through those opportunities (Teece, 2014). According to Teece (2014), the dynamic capabilities theory consists of three constructs which are sensing, seizing and transforming. It is posited by Wilden et al. (2013), that in order for dynamic capabilities to derive a competitive advantage, opportunities first need to be sensed, then the organisation needs to seize those opportunities, thereafter transforming the organisation to sustain the competitive advantage. This suggests that the dynamic capability of sensing, seizing, and transforming is inherently sequential and each construct complements or is a pre-requisite of the following construct. This also suggests that each of the constructs cannot be interchangeable or left out of the dynamic capability theory (Wilden et al., 2013). Birkinshaw, Zimmermann and Raisch (2016), further argues that these three dynamic capability constructs can be paralleled in meaning within an organisation to "sensing" equating to a lower order capability of exploration, "seizing" equating to a lower order capability of exploitation and "transforming" equating to a higher order capability which enables the organisation to be flexible enough to improve and adapt to remain competitive in a changing environment. However, this argument is further elaborated on as sensing, seizing and transforming is viewed as all being higher-order capabilities that need to exist in different levels of an organisation (Teece, 2018). The researcher adopted this view in the research study as this can be interpreted as an organisation using best practises in data driven decision making for the sensing, seizing capabilities and transforming capabilities at all operational, tactical and strategic levels for improving on these best practises and improving on the organisations business processes/business models to sustain the competitive advantage.

2.3.1 Sensing

The construct of sensing in dynamic capabilities refers to the organisations ability to identify opportunities internally and externally for enhancing the firm's competitive advantage (Teece, 2014). Sensing is also viewed as a dynamic capability within an organisation that refers to the exploration of data through analytics (Birkinshaw et al., 2016). Kump et al. (2019) posited that an organisation that inherently possesses and applies the sensing capability, is able to efficiently and reliably source information that is strategic to the attainment of the business objectives from both internal and external sources. Consequently, applying the sensing construct in their research, Kump et al. (2019), concluded that the sensing construct is a strong predictor of overall business performance. According to Torres, Sidorova, and Jones (2018), sensing can be aligned to the business strategy term of "diagnosis" and involves the sifting and rearranging of volumes of data, thus reducing the time and cognitive stress needed to derive insights by the organisations decision makers. Possessing good sensing analytics capabilities can enable an organisation to identify focus areas such as inefficiencies in processes, quality controls and best practices, which is critical for continuous improvement (Gupta & George, 2016). According to Sharma, Mithas and Kankanhalli (2014), there lies a complex relationship between data, the analytical tools that processes it, and the human element of sense making. Their research mentions that due to the organisational structure of a company, it often ensues that the resources responsible for sense making are also the ones selecting the data and this could hamper the quality of the insight derived, which may not be beneficial for enhancing the competitive advantage of the firm. Therefore, the sensing capability alone cannot derive firm performance but it does serve as facilitator for the seizing capability, as it can reduce the impact of uncertainty in the decision making process (Torres et al., 2018). Further to this, in research conducted by Garrido, Kretschmer, Vasconcellos and Goncalo (2020), it was concluded that the sensing construct presented to have a negative impact on some performance measures due to the investments needed for researching and analysis of information that did not derive immediate benefits, however the importance of its role in the dynamic capabilities construct is evident. This confirms that the sensing construct could have both positive and negative relationships to firm performance, thus creating paradox views on the significance of the sensing capability.

2.3.2 Seizing

The construct of seizing in dynamic capabilities refers to the coordination of resources to capture value through evidence-based decision-making (Teece, 2014). Seizing is also viewed as a dynamic capability within an organisation that refers to the exploitation of data through analytics (Birkinshaw et al., 2016). According to Torres, Sidorova and Jones (2018), "seizing involves the integration and interpretation of information in order to arrive at a decision to act, as well as planning the commitment of resources to support that action" (p. 825). Their research highlighted the importance of the seizing capability in the firm, in order to realise value from the investments made in introducing this capability and also underlines the importance of analytical seizing capabilities in the enhancement for quality decision making. According to research conducted by Kump et al. (2019), it was postulated that an organisation that inherently possesses and applies a high level of seizing capability will be successful in deciding whether there lies potential value in information gathered and be able to transform the valuable information into opportunities that benefit the organisation. This suggests that the organisation needs to have a good sensing analytics capability, before it can utilise its seizing analytics capability to capitalise on opportunities. The sensing capability reinforces the seizing capability with insights that are based on empirical evidence (Gupta & George, 2016). This view is in alignment with the perspective that the sensing capability is a facilitator for the seizing capability, as posited by Torres et al. (2018). Applying the seizing construct in their research, Kump et al. (2019), concluded that the seizing construct is a strong predictor of overall business performance and had the highest predictive power on performance indicators out of all the other dynamic capability constructs. It is posited that this could be due to the strong decision making capability inherent in the seizing construct that is aligned to strategy translation in an organisation (Kump et al., 2019). This view on the seizing construct presenting strong positive relationships with firm performance, due to its strategic nature, was also acknowledge by research conducted by Garrido et al. (2020).

2.3.3 Transforming

According to Teece (2014), the transforming construct may also be referred to as “reconfiguration”, which will entail some capability of recombining or modification of existing resources. The construct of reconfiguration is necessary in organisations to allow for flexibility of their managers to make evidence-based decisions (Teece, 2014). This view is further developed on as the transforming construct, within dynamic capabilities theory, is viewed as the capability of continuously renewing a firms tangible and intangible assets towards sustaining a competitive advantage for an organisation in a changing environment (Birkinshaw et al., 2016). The linear sequence of the dynamic capabilities is viewed as equating sensing (exploration) and seizing (exploitation) as lower order capabilities pursued in the lower levels of an organisation, such as the operational levels, while transforming is viewed as a higher order capability pursued in the higher levels of the organisation which coordinates the sensing and seizing capabilities and transforms the firm based on the optimal strategy created for competitiveness (Birkinshaw et al., 2016). This view was however enhanced to include sensing, seizing and transforming capabilities as all presenting higher order capabilities that need to exist in all levels of an organisation (Teece, 2018). In research conducted by Kump et al. (2019), it is posited that an organisation that inherently possesses and actively applies the transforming capability is consistently renewing activities, knowledge and resource configurations to capitalise on opportunities, effectively and more efficiently than their competitors. They concluded that the transforming construct has a significant positive effect on business performance. Contrary to this observation, Garrido et al. (2020), found that the transforming construct, although having a critical role in the relationship with sensing and seizing in the dynamic capabilities construct, presented to have a negative relationship with firm performance. They posited that this could be due to the negative characteristics related to the industry that was surveyed. This suggests that the transforming construct could have both negative and positive effects on business, depending on the industry context of the selected population group.

2.4. The promise of data driven decision making

Within organisations today, it has been observed that leaders are looking into new opportunities to collect and analyse data in order to enhance their decision making capabilities for improved performance (Brynjolfsson & McElheran, 2016). With the vast amount of data being collected from many different sources, companies in various industries have taken the opportunity of exploiting that data, as their new competitive advantage (Provost & Fawcett, 2013). This perspective is due to the realisation that the application of data analytics to derive insights in support of decision making within organisations, leads to better quality and improved credibility in the decision being made (Fredriksson, 2018). Further to this, the insights derived from the analysis of the data offer an enhanced form of acumen that can be exploited in the decision making process to solve complex problems to reduce costs, increase productivity and increase profits within organisations (Fredriksson, 2018). Therefore, organisations that embrace opportunities derived from initiatives involving exploration of big data and deriving at decisions by acting on insights obtained from it, are realising improved performance on a tremendous scale (Mazzei & Noble, 2017). Further to this, the strategic and effective application of data driven decision making can improve an organisations operating margins by 60% (Akter et al., 2016), and the further companies delve into the realm of being data driven, the better the position to achieve goals with regards to financial and operational performance (McAfee & Brynjolfsson, 2012). Consequent to this, there is an ever growing trend of leaders shifting from purely intuition based decision making, to being more data driven, thus enhancing their capability in their respective decision making activities (Brynjolfsson & McElheran, 2016; Gupta & George, 2016; Mcafee & Brynjolfsson, 2012).

However, to exploit these benefits of data driven decision making, it is postulated that the organisation needs to inherently possess and apply dynamic capabilities (Birkinshaw et al., 2016; Gupta & George, 2016; Kump et al., 2019; Wilden et al., 2013). Further to this, it is also posited that dynamic capabilities alone are not sufficient to derive a competitive advantage, and with it, improved firm performance (Mikalef et al., 2020; Mikalef & Pateli, 2017; Wamba et al., 2017; Wilden et al., 2013). Kump et al. (2019), posited that there is a need to further expose the dynamic capabilities theory to other organisational processes that may have been previously overlooked.

Sharma, et al. (2014), researched in the information systems field and proposed to explore the impacts of analytical capabilities on organisations through decision-making processes. Their research posited that due to the complex nature of business (an ecosystem), the trajectory of analytical capabilities towards positive organisational performance is complex and further research should be conducted to investigate the roles of decision making and business processes on the path to organisational performance. Further to this, Kim, Shin, Kim and Lee (2011), posits that a firms ability to improve and adapt their business processes enables it to sustain a competitive advantage in a rapidly changing operating context and is an indication of firms propensity to capitalise on its inherent dynamic capabilities. Similarly, a firms use of data analytics can improve its decision making performance which potentially results in an associated competitive advantage (Ghasemaghaei et al., 2018). Subsequently, this introduces two organisational processes, business process performance and decision-making performance that both posit a relationship to competitive advantages that could lead to improved firm performance.

2.5. Business Process Performance

It is postulated that a firm that has the ability to transform, improve and integrate its business processes, which inherently is an important indicator of dynamic capabilities, has a potential competitive advantage to react more effectively in changing environments, which could lead to better firm performance (Kim et al., 2011). Business process performance (BPP) measures a combination of inter-related (Hasan et al., 2019) aspects of the organisational and operational activities that have transactional inputs to, and transactional outputs from, various business processes within the organisation (Aydiner, Tatoglu, Bayraktar, & Zaim, 2019a). Superior business process performance, in the context of production and operations, is the extent to which production throughput, productivity of labour and utilisation of equipment is improved or enhanced (Gu & Jung, 2013). However, firms should be cautious in thinking that improved or enhanced business processes will automatically result in better firm performance because the benefits of process improvement may be diluted by the effect of the associated large investments, on their financial performance (Kim et al., 2011). With regards to business process performance in maintenance management, it is posited that full adherence to business processes in maintenance management will lead to continuous improvement of those business processes through identification and corrective action of strengths and weakness, which leads to better organisational performance (Abreu, Martins, Fernandes, & Zacarias, 2013).

Research found that business process capabilities are positively associated with functional performance and functional performance is positively associated with firm performance (Torres et al., 2018). Similarly, Aydiner, Tatoglu, Bayraktar and Zaim (2019), concluded that business process performance supported a mediation role between data analytics and firm performance. This suggests that in the operations context, business process performance is integral for functional performance which leads to better firm performance. Further to this, according to Wamba et al. (2017), business process capabilities have been found to be a significant partial mediator between analytics capability and firm performance.

2.6. Decision-making performance

Decision making performance (DPM) refers to the measures of quality, effectiveness and efficiency in decision making within an organisation (Ghasemaghaei et al., 2018). The availability of data within an organisation, has the potential to enhance the organisation’s competitive advantage through the improved decision-making performance it potentially promises (Ghasemaghaei, Ebrahimi, & Hassanein, 2018). However, it is postulated that domain knowledge and analytical skills are fundamentally required by the individuals conducting data analytics, which will lead a higher level of decision making performance (Ghasemaghaei et al., 2018). In their research, Ghasemaghaei et al. (2018), concluded that there exists a relationship between the analytical capability and decision making performance within an organisation. Furthermore, according to research conducted by Baum & Wally (2003), it was found that strategic decision making speed presented to have a mediating relationship effect between organisational factors of dynamism and firm performance. Subsequent to this, Aydiner et al. (2019a), posited that decision making performance is a mediating variable between information system capabilities and improved firm performance. However, their findings indicated that the mediation role between information system capabilities and firm performance was not supported, as there could be other variables at play, but suggested that this finding probably holds true in an organisation within an unstable environment.

Data analytics and strategic decision making in maintenance can be a major contributor to an organisations competitiveness due to the management insights derived (Jamkhaneh, Pool, Khaksar, Arabzab & Kazemi, 2018). This suggests that decision making performance may have a relationship with the data analytics capability which may lead to better firm performance.

2.7. Maintenance Management

The evolution of technology, brought about by the fourth industrial revolution, will see changes towards digital manufacturing and with it, astronomical changes to the way maintenance management is strategised and executed. The objectives of maintenance management is to develop and follow a maintenance strategy that aligns to operational requirements that production, engineering and safety have specified, to ensure optimum reliability and availability of plant and machinery, at a minimum cost (Kelly, 2006; Smith & Mobley, 2011). Maintenance management is concerned with keeping an asset in good working condition in order for it to create value through capacity assurance (Gulati, 2013). According to Fraser, Hvolby and Tseng (2015), maintenance management is an applied research field that over past decade, it has been seen to evolve into one of the most important improvement areas since maintenance decisions are strategically important to the competitiveness of every organisation. Further to this, maintenance management refers to “the decision-making processes that align maintenance delivery activities with corporate objectives and strategies”, (GFMAM, 2016, p. 5). This suggests that maintenance management is much more than ensuring reliability and availability of assets but consequently plays a strategic role in maximising the profitability of an organisation in the production operating environment, thus influencing the organisation’s competitiveness.

There are three most widely popularised models or philosophies for maintenance management which are Total Production Maintenance (TPM), Reliability Centred Maintenance (RCM) and Condition Based Maintenance (CBM) (Bokrantz et al., 2016; Fraser et al., 2015). Kelly (2006), argues that these models should not be focused on independently and needs to form part of an overall methodology for decision making through business centred maintenance (BCM). This proves the criticality of maintenance management in business, as all of these models have a synergic relationship geared towards cost optimisation of maintenance management through improving maintenance plans, reducing unplanned breakdowns and improving maintenance efficiency and effectiveness (i.e. maintenance processes) (Gulati, 2013; Moore, 2015; Mitchell, 2015).

Although there has been much development in the maintenance management domain to realise the benefits, many companies still find themselves unable to realise these benefits due to their inherent traditional way of thinking (Mitchell, 2015). Maintenance management in these companies has notoriously been reactive (fix it when it breaks), which has created a culture that makes it difficult to transition into a cost optimised mindset of being more proactive or preventive (Gulati, 2013; Ylipää et al., 2017). According to Jamkhaneh et al. (2018), it is the organisational factors such as capabilities and exceptional resources that are needed in the decision making structure that can derive organisational strategies for maintenance management, which enables an organisation to remain competitive.

2.7.1 Key Elements of a Maintenance Management System

According to Kelly (2006), there are eight key elements of the maintenance management system, which are intended to be highly integrated, that are required to effectively manage the maintenance management process within the organisation. These key elements include:

- Budgetary control – which has its main function of controlling maintenance costs
- Maintenance performance measurement and control – which is needed to measure actual performance and highlight any deviations within the maintenance process
- Plant reliability control – assists in identifying focus areas for improvement using costs and failure data

- Maintenance organisational efficiency control – used to manage the efficient use of key maintenance resources (artisans, special equipment)
- Short-term maintenance work planning and control – has its main function of planning, scheduling, allocating and controlling work orders required for jobs to be executed
- Long-term maintenance work planning and control - has its main function of planning, scheduling, allocating and controlling work orders required for major shutdowns and equipment replacements
- Equipment spares management – has its main function of controlling and issuing of spares that are needed for work execution
- Maintenance documentation – this refers to the information system that serves as an integration point for all the other maintenance systems to interact

Currently, information for maintenance management is increasingly being collected, analysed and reported on via computerised maintenance management systems (CMMS), which serves as the maintenance documentation system for effective data driven decision making, as described above. According to Jamkhaneh, Pool, Khaksar, Arabzad, and Kazemi (2018), CMMS can be seen as a major contributor to an organisations competitiveness due to the management insights derived and therefore CMMS should be managed as a strategic asset to attain world class performance. Using this data, effectively, in an analytical way that has “line of sight” to the development of improved maintenance strategies which are aligned to organisational goals, can be of much value to an organisation as the development of a data led strategy leads to the ability for the organisation to enable rapid innovation and as a result, a competitive advantage through new value creation (Mazzei & Noble, 2017). According to Torres, Sidorova, and Jones (2018), a company found that by transforming the business intelligence and analytics of its maintenance capabilities, showed an increase in availability and reduced preventive maintenance costs, which resulted in higher profits with regards to firm performance. Jamkhaneh et al. (2018) further posits that a CMMS does not necessarily cater for maintenance decision making capabilities, but instead, provides for a platform that can be used as an enabler for better decision making, using the maintenance history information that is stored in a structured way, for optimisation of the maintenance management discipline.

2.7.2 Optimisation in Maintenance Management

An organisations competitive advantage in their respective markets are, but not limited to, factors such as speed, quality, price, and consistency (Pinjala et al., 2006). All of these are related to the approach to maintenance management practices that the organisation adopts, and optimisation is key in sustaining their respective competitive advantage (Pinjala et al., 2006). Optimisation in maintenance management requires maintenance decision making capabilities, which are data driven in nature, and has a direct influence on the management of organisations in the production environment (Ruschel et al., 2017). Further to this, problem solving and continuous improvement leads to continuous learning in the organisation's maintenance capability, which reinforces the knowledge base and sustains incremental improvements in maintenance cost while leading the organisation towards achieving their organisational goals (Ansari et al., 2016). It is argued that analysis and improvement tools that lie in Lean Manufacturing, SixSigma practices, and technology, fundamentally needs to be incorporated into the maintenance management domain, in order to reduce costs and develop a competitive advantage within an organisation (Gulati, 2013; Mitchell, 2015; Moore, 2015). Consequent to this, these continuous improvement initiatives have proliferated over the past two decades (Gutierrez-Gutierrez & Antony, 2020). Lean Manufacturing practices uses problem solving and continuous improvement techniques to reduce wastes such as delays, downtimes and excessive inventory in the maintenance discipline (Moore, 2015). Similarly, SixSigma practices uses problem solving and continuous improvement techniques to reduce variability in the maintenance discipline (Gulati, 2013). Due to the inter-relations and complementary tools that exist between these two practices, has resulted in both of these practices often being combined into "LeanSixSigma" in operating environments (Gutierrez-Gutierrez & Antony, 2020; Mitchell, 2015). Further to this, there are also maintenance root cause analysis tools that are critical for continuous improvement within an organisation (Bokrantz et al., 2016; Gulati, 2013). Table 1 lists some of the tools required for optimised maintenance management (Gulati, 2013).

Table 1: List of Continuous Improvement Tools

Tool	Description	LeanSixSigma	Maintenance Root Cause Analysis

VSM	Value Stream Mapping	x	
TOC	Theory of Constraints	x	
DMAIC	Structured problem solving and Continuos Improvement (Define, Measure, Analyse, Improve, Control)	x	
Pareto	Pareto Analysis (80/20 Principle)	x	
RCA	Root Cause Analysis	x	x
Fishbone	Cause and Effect (Fisbone Diagram)	x	x
FMEA	Failure Modes and Effects Analysis		x
Fault Tree	Fault Tree Analysis		x

Adapted from "Maintenance and Reliability Best Practices," by R. Gulati, 2013, Industrial Press Inc., 2nd edition, p. 357-399. Copyright 2013 by Industrial Press Inc., New York.

According to research conducted by Anand, Ward, Tatikonda and Schilling (2009), it was affirmed that continuous improvement initiatives in an organisation may be considered as a potential dynamic capability. Further to this, it was argued that since LeanSixSigma has a positive effect on strengthening organisational business processes, as it has a positive relationship to the improvement of dynamic capabilities within the organisation (Gowen, McFadden & Settaluri, 2012). Similarly, Hansen and Møller (2016), argued that the concept of implementing continuous improvement initiatives in an organisation, is directly linked to developing dynamic capabilities. This suggests that implementing continuous improvement activities within the maintenance management activities, leads into an analytical capability that reinforces maintenance management into a dynamic capability, that will potentially lead to improved firm performance.

Further to this, strategic decision making (Jamkhaneh et al., 2018) and full adherence and improvement of business processes (Abreu et al., 2013), using the maintenance management dynamic capability, leads to competitive advantages that will improve firm performance. This suggests that business process performance and decision-making performance has a relationship with the maintenance capability and play a role in leading the organisation towards improved firm performance.

However, there exists many challenges that organisations experience in implementing data driven decision making through continuous improvement tools and initiatives, within the maintenance management domain (Bokrantz et al., 2016).

2.7.3 Challenges in implementation of data driven decision making in maintenance management

In the implementation of data driven decision making, organisations face the challenge of collection, storage and the analysis of the data which inherently demands new technical capabilities and competencies which come at massive investment costs (Mazzei & Noble, 2017). This leads to further questions within the organisation of what data should be collected and stored, how data should be collected and stored, and how insights can be derived from the data (Mazzei & Noble, 2017). Further to this, Bokrantz, Skoogh, Berlin, Wuest and Stahre (2020), argue that even in the event that the data collected is of high quality, it does not automatically lead to a state where decisions are deemed to be data driven since large amounts of data within an organisation can remain unused, which regresses the decision making to human intuition and experience.

Another clear challenge that emerges is that the methods and tools that are required for continuous improvement, as illustrated in Table 1, are seldom used in the maintenance management domain in many organisations (Bokrantz et al., 2016). Further to this, the maintenance domain in organisations being predominantly experience based, which signifies that lack of an analytical capability and data driven decision making (Ylipää et al., 2017). This suggests that these companies may be experiencing a diminished firm performance, due to the lack of a potential sustained competitive advantage through the absence of a dynamic “continuous improvement” capability in the maintenance management domain.

A combination of employee domain knowledge and analytical skills is required to for an organisation to reap the benefits of the data analytics investment to improve firm performance (Ghasemaghaei et al., 2018). However, according to Bokrantz et al. (2020), a work dilemma arises due to maintenance employees not being accustomed to higher order capabilities such as data analytics which results in a lack in their capability of communicating information effectively to data scientists for enhanced decision making to be derived from their experience and data. Further to this, Baglee & Marttonen (2015), it has been found that maintenance managers are reluctant to seize the benefits derived from data analytics for decision making, as there intuition is preferred, but this needs to be addressed, as it could relate to a competency gap. Furthermore, CMMS software rarely offer decision making functions which reverts decision making to intuition and individual experience in maintenance, which often in turn, either causes an increase in the time for decisions to made or offers an inappropriate decision that may negatively impact the organisation (Ma, Ren, Xiang, & Turk, 2020).

According to Kitchens, Dobolyi, Li, & Abbasi (2018), a major challenge in large organisations is to successfully leverage and integrate both internally and external relevant data across different departments. This is re-affirmed in the research in maintenance management where according to Baglee & Marttonen (2015), information from different unstructured and unrelated databases are collected and this makes it difficult to model and analyse, sometimes even manually, in order to derive to decisions that could be worthwhile for the organisation.

These challenges can obstruct the organisation's continuous improvement initiatives and as a result, erode the prospects of developing a competitive advantage through potential dynamic capabilities within the maintenance management domain.

2.8. Conclusion

The literature review confirms the importance of dynamic capabilities (Teece, 2014), within the maintenance management domain, to utilise data driven decision making as a competitive advantage (Birkinshaw et al., 2016; Gupta & George, 2016), towards improved firm performance. The literature review further elaborated on potential relationships between dynamic capabilities and business process performance (Aydiner, Tatoglu, Bayraktar, Zaim, et al., 2019; Kim et al., 2011), and the potential relationship between dynamic capabilities and decision-making performance (Aydiner, Tatoglu, Bayraktar, & Zaim, 2019a; Ghasemaghaei et al., 2018), in the maintenance management domain. Moreover, the literature review indicated the possible mediation roles of business process performance (Aydiner, Tatoglu, Bayraktar, Zaim, et al., 2019) and decision-making performance (Aydiner, Tatoglu, Bayraktar, & Zaim, 2019a; Baum & Wally, 2003), between dynamic capabilities and firm performance, in the operating environment of maintenance management. The above-mentioned relationships between these constructs have not specifically been established through quantitative analysis, although the theory presented could infer these relations to be true. The findings and concepts presented in this literature review will form the basis of the research questions that will be used to test hypotheses, within the maintenance management context.

Chapter 3: Research questions

3.1. Introduction

The previous chapters highlighted the main objectives of understanding the value that data driven decision making presents to an organisation and how this relates to the dynamic capabilities that are needed in the maintenance management domain for the potential improvement of the firm performance. Drawing on recent literature in dynamic capabilities, a conceptualised framework is proposed for this research shown in Figure 1. This study aims to investigate firstly, whether there is a positive relationship between dynamic capabilities and firm performance, secondly, whether dynamic capabilities have a positive relationship to business process performance and decision making performance, and thirdly, whether business process performance and/or decision making performance play any role to mediate the proposed relationship between dynamic capabilities and firm performance.

3.2. Research questions

The research questions proposed for this study have been hypothesised as five individual hypotheses as discussed below:

3.2.1 Research question 1

Is there a positive relationship between Dynamic Capabilities and Firm Performance in the maintenance management domain of an organisation?

Research question 1 aimed to confirm pragmatic evidence of a direct relationship between the second order construct Dynamic Capabilities (independent variable) and Firm Performance (dependent variable). Preceding literature proposed Dynamic Capabilities Theory to be the differentiating factor in competitive advantages between organisations (Birkinshaw et al., 2016; Kump et al., 2019; Mikalef & Pateli, 2017; Teece et al., 2009; Teece & Leih, 2016).

A review of the literature confirmed a significant, positive relationship between Dynamic

Capabilities and Firm performance (Kump et al., 2019).

The first research question was hypothesised as:

H_1: Dynamic Capabilities has a significant positive relationship with Firm Performance.

3.2.2 Research question 2

Is there a positive relationship between Dynamic Capabilities and Business Process Performance in the maintenance management domain of an organisation?

Research question 2 aimed to confirm pragmatic evidence of a direct relationship between the second order construct Dynamic Capabilities and Business Process Performance. Preceding literature proposed Dynamic Capabilities Theory to have a significant effect on Business Process Performance (Aydiner, Tatoglu, Bayraktar, Zaim, et al., 2019; Kim et al., 2011).

A review of the literature confirmed a significant, positive relationship between Dynamic Capabilities and Business Process Performance (Aydiner, Tatoglu, Bayraktar, Zaim, et al., 2019).

The second research question was hypothesised as:

H_2: Dynamic Capabilities has a significant positive relationship with Business Process Performance.

3.2.3 Research question 3

Is there a positive relationship between Dynamic Capabilities and Decision-Making Performance in the maintenance management domain of an organisation?

Research question 3 aimed to confirm pragmatic evidence of a direct relationship between the second order construct Dynamic Capabilities and Decision-Making Performance. Preceding literature proposed Dynamic Capabilities Theory to have a significant effect on Decision Making Performance (Aydiner, Tatoglu, Bayraktar, & Zaim, 2019a; Ghasemaghaei et al., 2018).

A review of the literature confirmed a significant, positive relationship between Dynamic Capabilities and Decision Making Performance (Aydiner, Tatoglu, Bayraktar, & Zaim, 2019a).

The third research question was hypothesised as:

H_3: Dynamic Capabilities has a significant positive relationship with Decision Making Performance.

3.2.4 Research question 4

Does Business Process Performance mediate the relationship between Dynamic Capabilities and Firm Performance in the maintenance management domain of an organisation?

Research question 4 aimed to confirm pragmatic evidence of a mediation role of Business Process Performance between Dynamic Capabilities and Firm Performance. Preceding literature proposed Business Process Performance to have a mediating role between Dynamic Capabilities and Firm Performance (Aydiner, Tatoglu, Bayraktar, Zaim, et al., 2019; Wamba et al., 2017).

A review of the literature confirmed a significant full mediation (Aydiner, Tatoglu, Bayraktar, Zaim, et al., 2019) and a significant partial mediation (Wamba et al., 2017), relationship for Business process performance between Dynamic Capabilities and Firm Performance.

The fourth research question was hypothesised as:

H_4: Business Process Performance mediates the relationship between Dynamic Capabilities and Firm Performance

3.2.5 Research question 5

Does Decision-Making Performance mediate the relationship between Dynamic Capabilities and Firm Performance in the maintenance management domain of an organisation?

Research question 5 aimed to confirm pragmatic evidence of a mediation role of Decision-Making Performance between Dynamic Capabilities and Firm Performance. Preceding literature proposed Decision-Making Performance to have a mediating role between Dynamic Capabilities and Firm Performance (Aydiner, Tatoglu, Bayraktar, & Zaim, 2019a; Baum & Wally, 2003).

A review of the literature confirmed that strategic decision making speed presented to have a mediating relationship effect between organisational factors such as dynamism and firm performance (Baum & Wally, 2003).

The fifth research question was hypothesised as:

H_5: Decision-Making Performance mediates the relationship between Dynamic Capabilities and Firm Performance

3.2.6 Research question 6

Does Decision-Making Performance and Business Process Performance act as multiple mediators in the relationship between Dynamic Capabilities and Firm Performance in the maintenance management domain of an organisation?

Research question 6 aimed to confirm pragmatic evidence of a multiple mediation role of Decision-Making Performance and Business Process Performance between Dynamic Capabilities and Firm Performance. Preceding literature proposed Decision-Making Performance to have a mediating role between Dynamic Capabilities and Firm Performance (Aydiner, Tatoglu, Bayraktar, & Zaim, 2019a; Baum & Wally, 2003). Preceding literature also proposed Business Process Performance to have a mediating role between Dynamic Capabilities and Firm Performance (Aydiner, Tatoglu, Bayraktar, Zaim, et al., 2019; Wamba et al., 2017). Research question 6 aims to combine these two views into a possible multiple mediation relationship.

The sixth research question was hypothesised as:

H_6: Decision-Making Performance and Business Process Performance combined, mediates the relationship between Dynamic Capabilities and Firm Performance

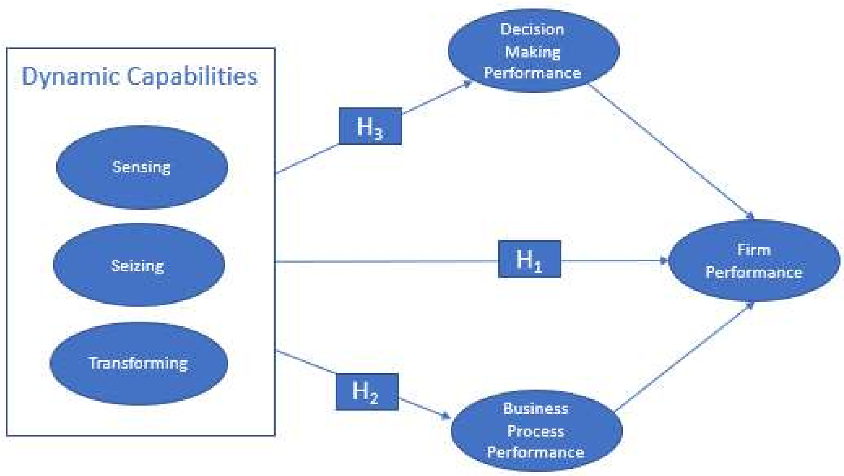

Figure 1: Model adapted from Aydiner, et al., (2019a) and Wilden, et al. (2013)

Chapter 4: Research methodology

4.1. Introduction

According to Williams (2007), research is an integrated approach that covers three systematic processes which include collection, analysis, and the interpretation of data in order to further understand a specific phenomenon. This section detailed the research design and methodology choices adopted by the researcher to test the proposed conceptual framework and the research questions identified in the previous chapter.

4.2. Research design

The purpose of research design is to enable the researcher to effectively address any predefined research problems, based on the body of evidence that has been collected (Bordens & Abbott, 2010). The research purpose of this study was to pragmatically evaluate the effect on firm performance (Fper) in the presence of the constructs, dynamic capabilities (DC), business process performance (BPP) and Decision making performance (DMP) in an organisation that were developed based on theoretical positions highlighted in Chapter 2. Chapter 3 highlighted the research questions that were developed to be tested by the researcher to empirically evaluate the relationships between DC, BPP, DMP, and their effect on Fper.

Considering that the research was based on measuring the impact of capabilities of an organisation, in the context of data driven decision making in maintenance, and its effect on the organisational performance of a firm, the nature of this research had its intent on building hypotheses, collecting quantifiable evidence using a questionnaire, and testing them statistically in order to identify any causal relationships between the constructs. Given this approach, the researcher therefore adopted a philosophy of positivism. A positivist philosophy is a highly structured method that values objectivity in phenomena and tends to measure relationships between variables to derive at a conclusion of either proving or disproving the hypotheses that are based on existing theory (Saunders & Lewis, 2018). Research conducted by Wamba, et al. (2017), which investigated the possible relationships between data analytics and firm performance, used a positivist philosophy to test their proposed research model.

The research study intended to develop a better understanding of DC and its relationships with BPP, DMP and Fper. Based on the literature review in Chapter 2, these constructs have previously been researched extensively. Given that theoretical positions and measures currently exist for these constructs, the researcher adopted a deductive approach to the study. A deductive approach refers to “the logical process of deriving a conclusion about a specific instance based on a known general premise or something known to be true” (Zikmund W. G., Babin, Carr, & Griffin, 2009, p. 44). According to Saunders & Lewis (2018), the deductive approach entails defining research questions, hypothesising relationships between variables, collecting and analysing data, then confirming or modifying the theory. Given that the researcher adopted a positivist philosophy, the questionnaire responses allowed for the hypotheses to be tested quantitively, using the deductive approach.

The researcher then used the results of the quantitative analysis to ascertain whether the results confirmed the proposed theory for dynamic capabilities relationship with firm performance or whether there was some modification of the theory required. Given that the research was based on a positivist philosophy and a structured deductive approach to prove or disprove hypotheses that were tested based on data that was collected by a single method using a questionnaire and then analysed in a statistical way, a mono method quantitative study was proposed, as the constructs were required to be objectively measured, using a questionnaire, which was a single data collection technique (Saunders & Lewis, 2018).

The research aimed to test and explain casual relationships between the constructs of DC, BPP, DMP and Fper. Research conducted by Aydiner, Tatoglu, Bayraktar, & Zaim (2019), Wilden, Gudergan, Nielsen, & Lings (2013), Ghasemaghaei, Ebrahimi, & Hassanein (2018) and Wamba, et al. (2017), also opted to statistically test the relationships of their proposed models and they all used questionnaires to collect the data neccesary for their research. The researcher therefore adopted an explanatory study. An explanatory study seeks to statistically test and explain the causal relationship and impacts between variables (Saunders & Lewis, 2018).

According to Saunders & Lewis (2018), a survey research strategy can be used for structured way of data collection and can be distributed to a sizeable population. Apart from being able to reach a larger population, the survey strategy is also cost effective. The survey strategy is also designed to be able to be administered via web-based means which will enabled the researcher to reach an even wider scale population (Bryman & Bell, 2011). A survey strategy was therefore used to collect data that was used to evaluate the constructs of DC, BPP, DMP and Fper. Based on literature reviews, Aydiner et al. (2019), Wilden et al. (2013) and Wamba et al. (2017), all used surveys to collect and analyse their data.

In alignment with studies that were conducted in research by Ghasemaghaei, Ebrahimi, & Hassanein (2018) and Wamba, et al. (2017), a cross-sectional study was therefore adopted. According to Zikmund W. G., Babin, Carr, & Griffin (2009), a cross-sectional study refers to data that has been collected at a single point in time. Saunders & Lewis (2018), refers to a cross-sectional study as a “snapshot of current thinking” (p. 130). According to Bryman & Bell (2011), a cross-sectional study is complemented by a survey research strategy. Although in the maintenance research domain, it would be beneficial to apply a longitudinal study to access the changes over time with regards to the adoption and evolution of dynamic capabilities, this however was not be feasible due to the time constraints.

The researcher administered electronic surveys which served as the research instrument in the form of a self-completed questionnaire (Bryman & Bell, 2011). The questionnaire was structured to measure the proposed constructs and related variables (Saunders & Lewis, 2018). The questionnaire was developed to encompass questions relating to each of the variables proposed within the constructs of DC, BPP, DMP and FPer. The questionnaire was designed to contain both questions to gain contextual understanding, as well as a five-point Likert scale of the questions relevant for statistical analysis of the relationships between the constructs.

4.3. Population

According to (Zikmund et al., 2009), the population refers to the comprehensive set of individuals, companies or industries that exhibit similar characteristics, was scoped for the research. The population for research was all asset intensive firms that use computerised maintenance management systems (CMMS) to collect and analyse maintenance related data that is meant to be utilised for decision making to improve their maintenance strategies. The population was not be limited to the size of the organisation, volume of data stored or whether the organisation owns the data infrastructure, as this can be outsourced.

The researcher targeted the responsible managers, users, and decision makers who are expected to be involved in CMMS data sensing, seizing, and reconfiguring within the business. This included senior and middle managers of the firm such as information technology and integration managers, technical engineering managers, reliability engineers, business analysts, maintenance planners and asset managers who are responsible for the day-to-day decision making, as well as the overall strategy of the organisation. Previous studies in the literature review did not cover this extent of roles and focused mainly on IT managers and business analysts (Aydiner, Tatoglu, Bayraktar, Zaim, et al., 2019; Wamba et al., 2017).

4.4. Unit of analysis

The unit of analysis is defined as an indication of "what or who should provide the data and at what level of aggregation" (Zikmund et al., 2009, p. 119). The researcher investigated characteristics DC, BPP, DMP and Fper, pertaining to the firm that has implemented a CMMS and utilises maintenance data analytics for decision making. In alignment with this notion, the researcher targeted individuals of asset intensive firms, where questions in the research instrument were posed to target data pertaining to the characteristics of their organisation, however, answered from an individual's perspective, that were then aggregated to the firm level. Therefore, the unit of analysis was the organisation, where responses were aggregated to firm level. Previous studies in dynamic capabilities, Aydiner et al. (2019), Wilden et al. (2013) and Wamba et al. (2017), as discussed in Chapter 2, all had their studies based on the individual's answers aggregated to the firm level.

4.5. Sampling method and size

Non-probability sampling refers to a technique where the complete list of the participants and the probability of any specific member being selected is unknown (Zikmund et al., 2009; Saunders & Lewis, 2018). Based on this criteria, non-probability sampling technique was used due to the research covering dynamic capabilities in asset-intensive firms, where a complete list of the of the desired population was unlikely to be obtained. Purposive sampling is a form of the non-probability sampling technique where the researcher aims to target specific attributes in individuals and organisations, in order to obtain the insights required for the research, based on the experience of the researcher (Zikmund et al., 2009; Saunders & Lewis, 2018; Bryman & Bell, 2011). The researcher adopted the purposive sampling technique to distribute the survey to specific firms and targeted individuals in the maintenance domain. Snowball sampling is also a form of the non-probability sampling technique where participants in the research are encouraged to identify further participants through referrals (Zikmund et al., 2009; Saunders & Lewis, 2018; Bryman & Bell, 2011). The snowball technique was used for individuals within a firm to transmit the survey between colleagues in their networks that are relevant to the research. The researcher also used the snowball technique to leverage colleagues in the maintenance industry that are involved in data analytics using CMMS data and CMMS software developing firms, to access their clients. These techniques had been chosen due to its cost effectiveness as well as due to the difficulty in accessing the correct target population. These sampling techniques had previously been used by Kump et al. (2019), in their research on dynamic capabilities of a firm.

Sample size is regarded as a key attribute when conducting the partial least squares Structural Equation Modelling (PLS-SEM) technique and a minimum sample size was estimated before data collection for analysis. According to Hair et al. (2019), the minimum sample size can be estimated by using the 10x rule. However, Roldán and Sanchez-Franco (2012), argued that the minimum sample needed to be calculated based on the effect size. The path coefficient from a mediated model was used in the calculation of minimum sample size and extracted from Wamba et al. (2017), where an effect size of 0.235 was reported. The results of both calculation methods are presented in Table 2.

Table 2: Minimum sample size required

Academic	Calculation Method	Sample size required
Hair et al. (2019)	10x rule	80*
Roldán & Sanchez-Franco (2012)	Effect size	~158
*Maximum Links for Latent variable Sensing (8 Links)		

The final sample size of the research was reported as 173 respondents, which was assumed adequate based on the required sample size calculation results in Table 2. The researcher originally anticipated a sample size of 200, as previous research conducted by Wamba, et al. (2017), Wilden, et al. (2013) and Aydiner, et al. (2019) yielded sample sizes of between 204 and 297 respondents.

4.6. Measurement instrument

The measurement instrument was in the form of a self-administered online questionnaire which was divided into seven sections and contained items that link to a specific construct. The data was collected using a five-point Likert scale (refer to Appendix A). In research conducted by Aydiner, Tatoglu, Bayraktar, & Zaim (2019), a five-point Likert scale ranging from 1 = "strongly disagree" to 5 = "strongly agree" was preffered as opposed to a seven-point Likert scale, as the five-point Likert scale seemed less cumbersome to complete and this was used to potentially increase the response rate of the participants. The first section consisted of ten questions that where intended for collecting demographic information, collecting some key characteristics of the firm, as well as one screening question that was intended for targeting the correct sample population. The screening question selected for the survey was - "*Does your company make use of a computerised maintenance management system (CMMS) or a maintenance management module in an Enterprise Asset Management System?".* The demographic information enabled the researcher to provide descriptive information, by executing descriptive analysis, to establish the sample diversity, whilst providing discovery into valuable insight on the type of respondent and firm characteristics.

The subsequent sections, sections two to seven, consisted of 39 questions covering six first order constructs of Sensing, Seizing, Transforming, Business Process Performance, Decision Making Performance and Firm Performance. To measure the sensing construct, the researcher used an eight item scale model adapted from measures established by Torres et al. (2018) and Akter et al. (2016). The seizing construct was measured using a six item scale model adapted from measures also established by Torres et al. (2018) and Akter et al. (2016). The transforming construct was measured using a five item scale model adapted from measures established by Torres et al. (2018). The decision-making performance construct was measured using a seven item scale adapted from measures established by Aydiner, Tatoglu, Bayraktar, & Zaim (2019a). The business process performance was measured using a seven item scale model adapted from measures established by Aydiner, Tatoglu, Bayraktar, & Zaim (2019a). The final construct, firm performance was measured using a six item scale adapted from measures established by Torres et al. (2018) and Akter et al. (2016).

The survey was uploaded and structured into SurveyMonkey® to begin a pre-test with a selected sample group from the researchers' network. It is recommended that a pre-test be conducted to reduce the potential of non-response (Zikmund et al., 2009), with a pre-test sample size of between 5 to 15 respondents being most prevalent in survey method research (Perneger, Courvoisier, Hudelson and Gayet-Ageron, 2015). Based on this view, the researcher embarked on a pre-test sample consisting of 10 respondents that were chosen to identify and report issues in the questionnaire relating to spelling and grammatical errors, question ambiguity, alignment with the maintenance management domain, order of items within a construct, completion time and length of the survey. Recommendations were collected and changes to the survey was made accordingly.

4.7. Data gathering process

Once the survey was finalised, based on the recommendations reported by the pre-test sample, the final SurveyMonkey® weblink was distributed by the researcher via social networks such as WhatsApp, LinkedIn and email, and was live for a total of 16 days (25th September to 10th October). Aligning to the snowball sampling technique, respondents were asked to transmit the survey within their respective networks. Within the 16 days, the survey collected a total of 220 raw sample responses with a completion rate of 86%, in an average completion time of 9m:31s. Given that SurveyMonkey® is a cloud-based platform, the data was collected and collated in a format that could easily be extracted for analysis. Once the survey was closed, and the data was extracted in excel (XLS) format for analysis.

4.8. Analysis approach

A quantitative analysis was executed given that the data to be collected is of a categorical and ordinal nature (Wegner, 2016). According to Zikmund et al. (2009), data analysis process is preceded by data editing, data coding and data file preparation processes.

4.8.1 Data coding

Given that SurveyMonkey® could convert the data into numerical format for executing statistical analysis, data coding was executed first. Data coding is the process of assigning numerical scores to character symbols (Zikmund et al., 2009).

4.8.2 Data editing

According to Zikmund et al. (2009), data editing refers to the process of confirming consistency and completeness of the data. By following the editing process, the researcher observed missing data in the dataset. Missing data are a nuisance to researchers conducting statistical analysis, especially if the sample size is important, as in multivariate analysis (Hair et al., 2019). The problem of missing data can be solved by using the imputation method which is a statistically evaluated best guess value of the missing data that is based on other available data in the dataset (Zikmund et al., 2009). The missing data was handled by assuming that the data was systematic and missing at random (MAR), therefore applying the multiple imputation (MI) technique (Hair et al., 2019), on responses that were observed to have between 50% and 100% completion rate (Hair et al., 2010).

The dataset was sub-divided into groups based on industry, the mean value of each question was calculated for each group, and then imputed to the missing data of respondents of that specific industry (Hair et al., 2010). The raw dataset had initially 220 responses of which 24 were removed after the pre-screening question. This resulted in 196 responses being tested for completeness and missing data (Zikmund et al., 2009). A further 23 responses were rejected due to less than 50% completion (Zikmund et al., 2009). Thereafter three responses were imputed (Hair et al., 2010) and added to 170 completed responses. The total final sample size was 173 responses.

4.9. Statistical Analysis of data

The following section provides an explanation of the descriptive and inferential statistics conducted by the research on the edited dataset that was generated into XLS and CSV format and imported into IBM SPSS and SmartPLS for analysis.

4.9.1 Descriptive statistics

Descriptive statistics refers to the transformation of data into a form that can be used to describe certain characteristics of a sample dataset by analysing means, medians, modes, variances, ranges and standard deviations (Zikmund et al., 2009). Descriptive statistics was applied to responses from section one of the survey to analyse the frequency and percentage frequency of the sample and section two to seven was analysed to determine the mean values, standard deviation, kurtosis and skewness of the data, using IBM SPSS. Descriptive statistics were also applied in research conducted by Kump et al. (2019), Aydiner, Tatoglu, Bayraktar, and Zaim (2019a) and (Wamba et al., 2017).

4.9.2 Inferential statistics

Inferential statistics is a type of statistics that is used to derive inferences from a sample that could be applied to an entire population (Zikmund et al., 2009). To test the hypotheses and test for validity and reliability of the dataset, Multivariate Statistical Analysis (MSA) was used as the dataset contained more than three variables (Hair et al., 2019). Since the model, Figure 1, consisted of dependent variables that had to be predicted by independent variables through multiple relations, the dependance technique using the variance-based PLS-SEM as the MSA technique was chosen (Hair et al., 2011). SmartPLS 3.0 was used to analyse the PLS-SEM model. SmartPLS software was used in evaluating PLS structural models in research conducted by Akter et al. (2016), Ghasemaghaei et al. (2018) and Mikalef and Pateli (2017).

Prior to developing the structural model, the researcher conducted an Exploratory Factor Analysis (EFA) to understand and validate the factor structure of the 1st order constructs (Sensing, Seizing, Transforming, BPP, DMP and Firm Performance). The purpose of EFA is validate if the observed variables that are attached to a higher order variable can be grouped together (Pallant, 2007). In addition, the factorability was assessed using a Principle Component Analysis (PCA) in IBM SPSS, whereby the Kaiser-Meyer-Olkin (KMO) measure and the Bartlett's test for sphericity was assessed. Carpenter (2018) states that the KMO measure should exceed 0.5 and the significance of the Bartlett's test for sphericity should be less than 0.05. The final structures of the 1st order variables were modified based on the low inter-item correlations for Sensing, Seizing, DMP and BPP.

The conceptual research model was now ready to be modelled and assessed using the PLS-SEM technique. The researcher first conducted reliability and validity assessments for the PLS-SEM outer model. Internal consistency reliability is a critical pre-test to ensure the internal reliability and consistency of the measurement scale and observed variables relationships, with the respective 1st order linked variable (Zikmund et al., 2009). Although the Cronbach's Alpha is the most widely adopted score for evaluating internal consistency reliability in quantitative research, Chin (2010), states that the score tends to be underestimated in PLS-SEM conditions. Hair et al. (2017) further states that the Composite Reliability score should be adopted for PLS-SEM techniques where the minimum score reported should be greater than 0.8. The researcher tested both the Composite reliability and Cronbach's Alpha scores in this research where Hair et al., (2017) states that the threshold value for Cronbach's Alpha should be 0.7. Validity of the outer model was then conducted and analysed through two lenses – Convergent and Discriminant validity. Hair et al., (2017), states that convergent validity is critical to ensure that observed variables are related with other observed variables that aim to measure the same 1st order variable and discriminant validity is even more important in ensuring that observed variables do not exhibit a large relationship with other observed variables that measure other 1st order variables. Convergent validity is established when the factor loadings of each observed variable, on its respective 1st order variable, report a value greater than 0.7 and when the Average Variance Extracted (AVE) reported a score greater than 0.5 (Hair et al., 2017). On the other hand, Discriminant validity is measured through the Fornell-Larker criterion technique, whereby the associations of the observed variables should only be higher with itself and associated observed variables that report on a 1st order variable (Henseler, Ringle, Sarstedt, 2015). Once the data was analysed and found to be acceptable the researcher then adopted the six-step framework by Hair et al., (2017) as depicted in Figure 2.

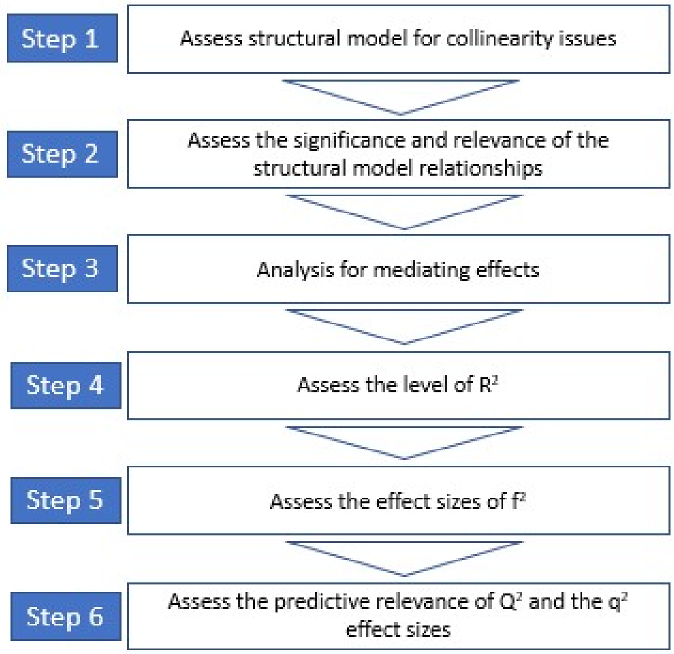

Figure 2: PLS model evaluation process. Adapted from “A primer on partial least squares structural equation modelling (PLS-SEM),” by J.A. Hair, G.T.M. Hult, C.M. Ringle and M. Sarstedt, 2017, Sage, edition 2, p. 202. Copyright 2017 J.A. Hair, G.T.M. Hult, C.M. Ringle and M. Sarstedt.

The inner model was then assessed for collinearity issues as in step 1 of Figure 2. Hair et al. (2017) recommends an upper threshold of 0.5 when reporting collinearity using the Variance Inflation Factor (VIF). These values were found to be acceptable in this research as all observed variables reported VIF scores less than 5.

The next step involved evaluating the structural model relationships which were the research hypotheses for the strength, magnitude, and significance at the 95% confidence level. These were conducted using the PLS algorithm and Bootstrap technique in SMARTPLS 3.0. The mediation tests were evaluated using the method proposed by Hair et al., (2017) as depicted in Figure 3.

The final step in the structural model assessment involved the analysis of the Coefficient if determination (R^2), effect sized (f^2) and the predictive relevancy of the model (Q^2 and SRMR). Hair et al., (2017) recommends that the R^2 should be more than 0.1, the Q^2 be in excess of 0.34 and the SRMR be less than 0.10.

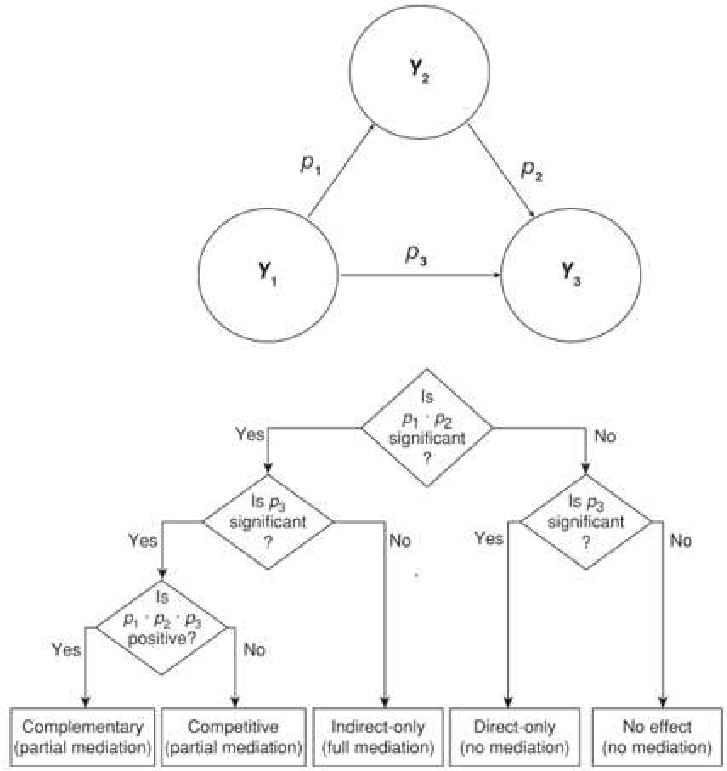

Figure 3: PLS-SEM Mediation Analysis Procedure. Adapted from “A primer on partial least squares structural equation modelling (PLS-SEM),” by J.A. Hair, G.T.M. Hult, C.M. Ringle and M. Sarstedt, 2017, Sage, edition 2, p. 233. Copyright 2017 J.A. Hair, G.T.M. Hult, C.M. Ringle and M. Sarstedt.

4.10. Limitations

A limitation to the proposed research could be the access to the correct respondents. Since the researcher has proposed non-probability sampling, which includes snowball sampling method, a disadvantage could be an induced sampling bias due to the similarities of characteristics of respondents (Zikmund W. G., Babin, Carr, & Griffin, 2009).

Another limitation to the research is that many organisations are still in the process of implementing their computerised maintenance management systems and may not have seen any benefits yet. Although a cross-sectional study was proposed, a longitudinal study may be better fit for this research (Wamba, et al., 2017), due to the time constraints of this study, a longitudinal study is not viable.

Chapter 5: Research results

5.1. Introduction

Chapter 5 presents the results of the research as described through the adopted research methodology and design described in the previous chapter. The chapter starts by first presenting the descriptive analysis with regards to the research sample and thereafter an analysis of the statistical analysis is presented which address the six research questions in Chapter 3.

5.2. Descriptive analysis of the sample data

5.2.1 Research sample

The researcher targeted a minimum of 200 responses as previously obtained by Wamba, et al. (2017), Wilden, et al. (2013) and Aydiner, et al. (2019). This anticipated size was to ensure that the researcher obtained the minimum sample size as required by the PLS statistical test as described in Chapter 4. The research survey attracted a raw sample of 220 responses of which 24 were removed after the pre-screening question – "*Does your company make use of a computerised maintenance management system (CMMS) or a maintenance management module in an Enterprise Asset Management System?".* The researcher then analysed the remaining 196 for completeness and verify any missing data input, as recommended by Zikmund et al. (2009). A further 23 responses were rejected as they reported a completion rate less than 50% (Zikmund et al., 2009). 170 responses displayed a 100% completion rate whilst three responses had a completion rate between 50 – 100%, the researcher conducted data imputation on these three by averaging the overall responses for each question. The sample results are summarised in Table 3.

Table 3: Summary of research sample data

	Total data set	% Total data
Raw data sample size	220	100
Pre-screening	24	10.9
Responses with less than 50% completion	23	10.5
Responses with 100% completion	170	77.3
Responses with >50% and <100% completion	3	1.4
Qualified responses	**173**	**78.6**

5.2.2 Descriptive characteristics of respondents

The researcher included a total of nine sample descriptive questions in the research survey. As illustrated in Table 4, there were significantly more respondents between the ages of 25 – 44 years. Majority of the respondents reported their age as being between 35 – 44 years (42.2%) which was followed by the 25 – 34 years group (38.2%). No qualified respondents where younger than 18 and older than 64 years of age.

Table 4: Respondent age groups

What age group are you in?		
Age Group	Frequency	Percent
18 - 24	3	1.7
25 - 34	66	38.2
35 - 44	73	42.2
45 - 54	20	11.6
55 - 64	11	6.4
Total	173	100.0

34.7% of the respondents indicated their principal industry as Mining and Quarrying, 11% reported that they work in the Engineering and professional services sector and 10.4% reported their principal industry as Oil and Gas (including retail). Table 5, summarised the industry coverage reported from the research sample.

Table 5: Summary of respondent industries

Which of the following best describes the principal industry of your organisation?		
Industry	Frequency	Percent
Airlines & Aerospace (including Defence)	3	1.7
Automotive Manufacturing (including Spares and Accessories)	3	1.7
Construction and Home Development	3	1.7
Chemical, Additive and Minerals Processing	6	3.5
Engineering Professional services	19	11.0
Food & Beverages (including processing and packaging)	16	9.2
Healthcare & Pharmaceuticals	4	2.3
Heavy Engineering, Metal Processing and Machine Building	8	4.6
Other Manufacturing and Processing	11	6.4
Paper and Pulp (including processing and packaging)	7	4.0
Mining and Quarrying	60	34.7
Transportation & Delivery	3	1.7
Textiles and Plastic Manufacturing	1	0.6
Utilities (Electricity, Water and Renewable Energy)	11	6.4

Oil and Gas (including Retail)	18	10.4
Total	173	100.0

Majority of the qualified respondents indicated that they have been in the field of maintenance management for over 5 years (74.6%). 30.1% reported that they were associated with maintenance management for between 6 – 9 years, 23.1% reported that they were associated with maintenance management for between 10 – 15 years whilst 9.8% indicated that they were associated with maintenance management for less than 2 years. Table 6, summarises the responses for which the qualified respondents indicated the tenure that they were associated in the field of maintenance management.

Table 6: Summary of maintenance management association

How long have you been associated with the field of maintenance management?		
Category	Frequency	Percent
0 - 2 years	17	9.8
3 - 5 years	27	15.6
6 - 9 years	52	30.1
10 - 15 years	40	23.1
> 15 years	37	21.4
Total	173	100.0

Table 7, provides a summary of the respondent's association with the field of data analytics. 29.5% of the respondents indicated that they were involved with data and analytics for between 3 – 5 years whilst 20.2% indicated an association with data analytics less than 2 years.

Table 7: Summary of tenure in field of data analytics

How long have you been associated with the field of data analytics?		
Category	Frequency	Percent
0 - 2 years	35	20.2
3 - 5 years	51	29.5
6 - 9 years	39	22.5
10 - 15 years	31	17.9
> 15 years	17	9.8
Total	173	100.0

The organisational tenure, Table 8, for the pursuit or application of data analytics was predominantly greater than 15 years (31.2 %). Less than 10% of the qualified respondents indicated that their organisation was actively pursuing or applying analytics in their business for less than 2 years whilst 19.7% reported this at between 6 – 9 years.

Table 8: Summary of organisational tenure in pursuit of data analytics

How long has your organisation actively pursued or applied data analytics to its business?		
Category	Frequency	Percent
0 - 2 years	17	9.8
3 - 5 years	37	21.4
6 - 9 years	34	19.7
10 - 15 years	31	17.9
> 15 years	54	31.2
Total	173	100.0

Table 9, summarises the qualified respondent's main association with the analytics capability within the organisation. 59.5% reported that they were users of analytics, 26.6% reported that they were processors of the data and 13.9% reported that they were involved with either the IT systems and data management.

Table 9: Summary of respondent's main association with data analytics

What is your main association with the analytics capability?		
Category	Frequency	Percent
User of analytics within business	103	59.5
Data analyst (Direct processor of data)	46	26.6
IT Systems or Infrastructure (Data Technology environment)	12	6.9
Big Data Management (Driving application of resources)	12	6.9
Total	173	100

In Table 10, the majority of the respondents indicated that their organisation had greater than 1000 employees (50.9%). 21.4% indicated their employee size between 500 – 999, 23.7% reported their organisation size between 100 – 499 and less than 3% reported their employee count of less than 100.

Table 10: Summary of respondent's organisation size

What is the approximate total number of employees within your organisation?		
Category	Frequency	Percent
1 - 99	4	2.3
100 - 499	41	23.7

500 - 999	37	21.4
> 1000	88	50.9
Do not know	3	1.7
Total	173	100.0

Table 11, summarises the qualified respondent's reported job role within their organisation. 35.8 % indicated they were middle management, 29.5% reported their role as being specialists in the organisation and 24.9% indicated that they were in senior management.

Table 11: Summary of current job levels

Which of the following best describes your current job level?		
Category	Frequency	Percent
Owner/Executive/C-Level	7	4.0
Senior Management	43	24.9
Middle Management	62	35.8
Specialist (including maintenance planners, schedulers and technical coordinators)	51	29.5
Junior/Entry Level	10	5.8
Total	173	100.0

The majority of the respondents reported the primary geographic location as being South Africa (94.8%). Of the other locations reported, most where from Africa as summarised in Table 12.

Table 12: Summary of respondent indicated country

In what country do you work?		
Country	Frequency	Percent
South Africa	164	94.8
Lesotho	2	1.2
Botswana	1	0.6
Canada	1	0.6
Madagascar	1	0.6
Mozambique	1	0.6
Namibia	1	0.6
Nigeria	1	0.6
Papua New Guinea	1	0.6
Total	173	100.0

5.3. Statistical tests

This section provides an analysis of the statistical tests as described in Chapter 4.

5.3.1 Reliability analysis

As described in Chapter 4, the PLS outer model was assessed for reliability through the Cronbach Alpha and Composite Reliability indices. Table 13, provides a summary of the reliability results.

Table 13: Summary of reliability analysis

Reliability Analysis		
Construct	**Cronbach's Alpha**	**Composite Reliability**
Sensing	0.82	0.87
Seizing	0.86	0.90
Transforming	0.88	0.91
Decision Making Performance	0.86	0.90
Business Process Performance	0.83	0.89
Firm Performance	0.94	0.95

As per the minimum scores required for the reliability indices above (0.7 – Cronbach Alpha and 0.8 for the Composite Reliability), all constructs reported adequate reliability scores. The researcher removed indicators for the following constructs due to low factor loadings (refer to Section 4.9.2):

- Sensing – Sensing 3, 6, and 7,
- Seizing – Seizing 2 and 6rc,
- Decision Making performance – DMP 1 and 6rc,
- Business Process performance – BPP 4, 5, 6.

The firm performance construct reported the highest reliability scores (0.94 – Cronbach Alpha and 0.95 Composite Reliability) whilst the Sensing construct reported the lowest within the study (0.82 – Cronbach Alpha and 0.87 Composite Reliability).

5.3.2 PCA Analysis

As discussed in Chapter 4, the researcher conducted a PCA analysis to test the construct applicability in the current research context and test the construct validity. The results of the PCA analysis by each construct is summarised in Table 14.

Table 14: Summary of PCA analysis

Validity					
Construct	**Number of items**	**KMO**	**Adequacy of the correlations**	**Bartlett's test for Sphericity**	**No. of components extracted**
Sensing	5	0.84	Meritorious	0.00	1
Seizing	4	0.78	Middling	0.00	1
Transforming	5	0.86	Meritorious	0.00	1
Decision Making Performance	5	0.85	Meritorious	0.00	1
Business Process Performance	4	0.83	Meritorious	0.00	1
Firm Performance	6	0.89	Meritorious	0.00	1

The KMO measure of sampling adequacy for the research constructs were reported as adequate based on the minimum 0.50 score as described in Chapter 4. With the exception of the Seizing construct all research constructs reported a KMO score > than 0.80 and were classified as “Meritorious” (Kaiser, 1974), whilst the seizing construct was classified with a “Middling” categorisation (0.70 < KMO < 0.8). All research constructs reported a Bartlett’s test p value = 0.00, indicating that the research was factorisable (Zikmund et al. 2009). All constructs reported only one extraction.

5.4. PLS outer model evaluation

As discussed in Chapter 4 the PLS outer model was evaluated for validity (reliability was reported in Section 5.3.1).

5.4.1 Validity testing

The researcher verified the convergent and discriminant validity. Convergent validity was verified by analysing two AVE scores (Chin (2010) and Hair et al. (2017)), Table 15. The AVE values for all latent constructs ranged between 0.58 – 0.76, well above the 0.5 threshold recommended by Chin (2010).

Table 15: Summary of validity scores

Convergent Validity scores	
Construct	**Average Variance Extracted (AVE)**
Sensing	0.58
Seizing	0.70
Transforming	0.67
Decision Making Performance	0.64
Business Process	0.66

Performance	
Firm Performance	0.76

Discriminant validity was confirmed by evaluating the Fornell-Larker criterion as recommended by Chin (2010) and Henseler (2015) as discussed in Chapter 4. The results are summarised in Table 16.

Table 16: Summary of Fornell-Larker criterion

Fornell-Larker criterion						
	Business Process Performance	Decision Making Performance	Firm Performance	Seizing	Sensing	Transforming
Business Process Performance	0.81					
Decision Making Performance	0.77	0.80				
Firm Performance	0.67	0.68	0.87			
Seizing	0.68	0.73	0.62	0.83		
Sensing	0.66	0.64	0.55	0.74	0.76	
Transforming	0.72	0.80	0.62	0.72	0.66	0.82

There were no correlations exceeding 0.9 as per recommendation Henseler et al. (2015). Based on these results, the researcher confirmed that there were no convergent and discriminant validity issues in the research outer model.

5.5. PLS inner model assessment

The researcher evaluated the research inner model through the assessment of the collinearity.

5.5.1 Assessment of collinearity

To assess for collinearity issues on the structural model, the VIF score was interpreted as discussed in Chapter 4. Collinearity was not an issue with the research model as the VIF scores, Table 17, fell below the maximum score adopted by the researcher (VIF < 5) (Hair et al., 2017).

Table 17: Summary of VIF results

Indicator	VIF
BPP1	1.91
BPP2	1.74
BPP3	1.86

BPP7	1.86
DMP2	1.86
DMP3	2.31
DMP4	2.08
DMP5	1.93
DMP7	1.72
FPer1	2.79
FPer2	3.72
FPer3	3.91
FPer4	3.56
FPer5	4.43
FPer6	2.39
Seizing1	1.50
Seizing1	2.07
Seizing3	2.69
Seizing3	2.93
Seizing4	3.19
Seizing5	2.20
Sensing1	2.58
Sensing2	2.11
Sensing4	1.57
Sensing5	1.56
Sensing8	1.78
Transf1	1.99
Transf2	2.82
Transf3	2.33
Transf4	2.41
Transf5	1.69

5.5.2 Structural model descriptive statistics

Table 18, provides descriptive analysis of the overall research constructs.

Table 18: Descriptive statistics for the research constructs

Descriptive Statistics							
Indicator	N	Mean	Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
Sensing1	173	2.44	1.06	0.62	0.18	-0.50	0.37
Sensing2	173	2.29	0.98	0.89	0.18	0.09	0.37
Sensing4	173	2.14	0.97	1.00	0.18	0.52	0.37
Sensing5	173	2.28	1.01	0.81	0.18	0.14	0.37
Sensing8	173	2.23	0.98	0.90	0.18	0.24	0.37
Seizing1	173	2.58	1.13	0.41	0.18	-0.92	0.37
Seizing3	173	2.35	0.84	0.62	0.18	-0.19	0.37
Seizing4	173	2.37	0.87	0.70	0.18	-0.04	0.37
Seizing5	173	2.39	0.94	0.70	0.18	-0.19	0.37
Transf1	173	2.20	1.05	0.98	0.18	0.33	0.37
Transf2	173	2.56	1.07	0.30	0.18	-0.90	0.37
Transf3	173	2.53	0.98	0.49	0.18	-0.59	0.37
Transf4	173	2.87	1.06	0.09	0.18	-0.77	0.37
Transf5	173	2.76	1.04	0.33	0.18	-0.66	0.37
DMP2	173	2.23	0.94	0.89	0.18	0.64	0.37
DMP3	173	2.42	0.98	0.52	0.18	-0.39	0.37
DMP4	173	2.83	1.07	0.14	0.18	-0.91	0.37
DMP5	173	2.61	0.99	0.40	0.18	-0.63	0.37
DMP7	173	2.63	1.06	0.58	0.18	-0.52	0.37
BPP1	173	2.49	1.05	0.71	0.18	-0.36	0.37
BPP2	173	2.33	0.90	0.88	0.18	0.25	0.37
BPP3	173	2.47	0.97	0.85	0.18	0.10	0.37
BPP4	173	2.31	0.89	0.76	0.18	0.52	0.37
BPP5	173	2.13	0.81	0.83	0.18	0.92	0.37
BPP7	173	2.25	0.90	0.68	0.18	0.21	0.37
FPer1	173	2.54	0.88	0.06	0.18	-0.19	0.37
FPer2	173	2.66	0.87	0.07	0.18	-0.29	0.37
FPer3	173	2.56	0.86	0.21	0.18	-0.17	0.37
FPer4	173	2.61	0.92	0.38	0.18	-0.23	0.37
FPer5	173	2.59	0.93	0.26	0.18	-0.39	0.37
FPer6	173	2.76	0.94	0.28	0.18	-0.12	0.37
Sensing	173	2.28	0.72	0.48	0.18	-0.17	0.37
Seizing	173	2.60	0.67	0.58	0.18	-0.25	0.37
Transforming	173	2.58	0.85	0.34	0.18	-0.51	0.37
DMP	173	2.49	0.77	0.41	0.18	-0.07	0.37

BPP	173	2.33	0.68	0.51	0.18	0.20	0.37
FPer	173	2.62	0.78	0.22	0.18	-0.12	0.37

Table 19: Summary of normality testing results

Tests of Normality						
	Kolmogorov-Smirnov[a]			**Shapiro-Wilk**		
Variable	**Statistic**	**df**	**Sig.**	**Statistic**	**df**	**Sig.**
Sensing	0.12	173	0.00	0.97	173	0.00
Seizing	0.13	173	0.00	0.96	173	0.00
Transforming	0.11	173	0.00	0.97	173	0.00
DMP	0.09	173	0.00	0.98	173	0.01
BPP	0.13	173	0.00	0.97	173	0.00
Firm Performance	0.10	173	0.00	0.98	173	0.01

The data was found to be not normally distributed, Table 19, as the significance was less than 0.05. However, as discussed in Chapter 4, this presented no issue for the PLS model.

5.5.3 Relationship assessment

The research model presented in Chapter 3 was assessed using the PLS algorithm in SmartPLS 3.0. In addition, the PLS bootstrapping algorithm was used to validate statistical significance of the structural model results. The results, Table 20, are summarised below:

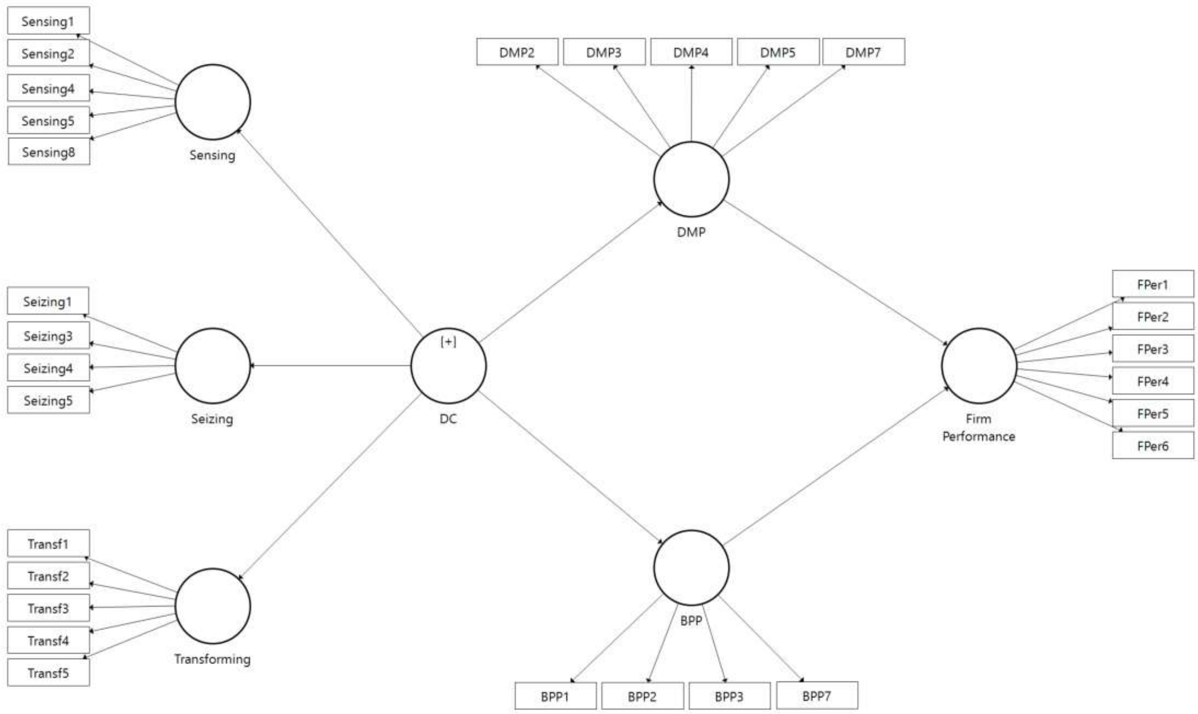

Figure 4: Revised research model applied in this study

Table 20: Summary of relationship results

Relationship	Path Co-efficient	P Values
DC -> Firm Performance	0.67	0.00
DC -> BPP	0.77	0.00
DC -> DMP	0.82	0.00
BPP -> Firm Performance	0.39	0.00
DMP -> Firm Performance	0.42	0.00

5.5.3.1 Research question one

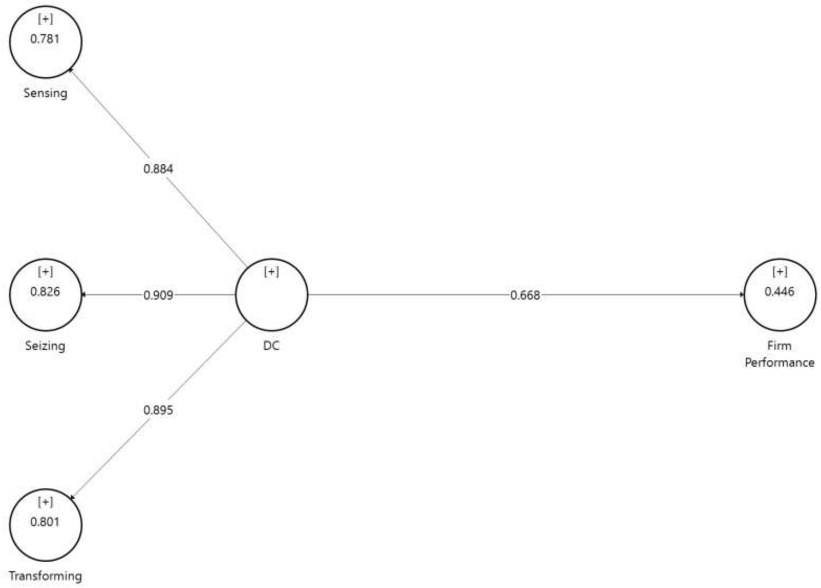

Figure 5: PLS Algorithm output for RQ1

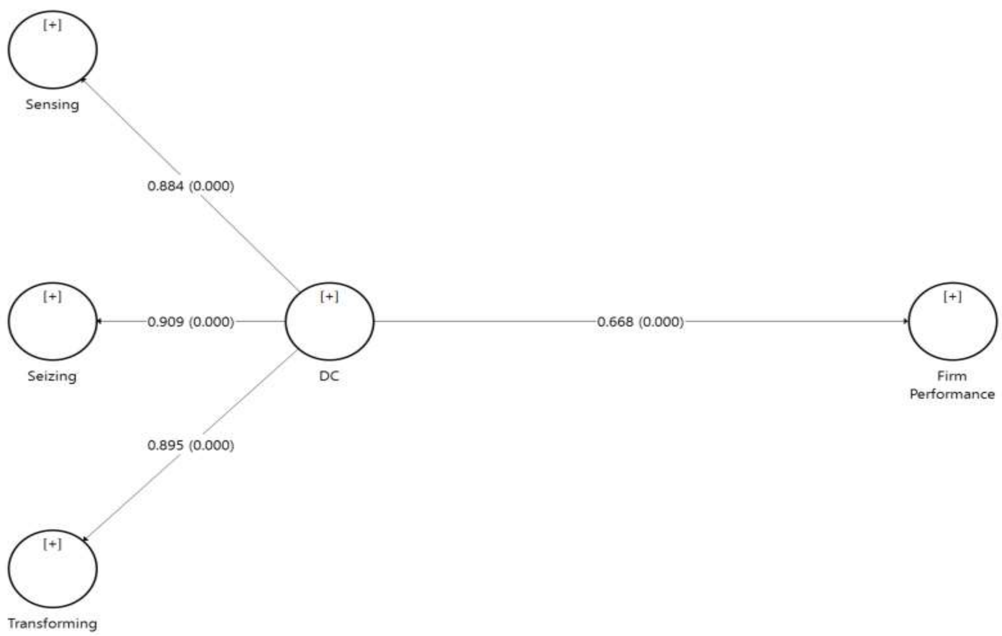

Figure 6: Bootstrap output for RQ1

Research question one sought to establish if there was a significant and positive relationship between Dynamic Capabilities and Firm Performance. As illustrated in Table 20, Dynamic

Capabilities has a positive and significant path coefficient of 0.67 ($p<0.05$). Thus, the researcher rejected the null-hypothesis and confirmed H_1. This result also confirms previous research by Kump et al., (2019), who also reported a positive relationship between Dynamic Capabilities and Firm Performance.

5.5.3.2 Research question two

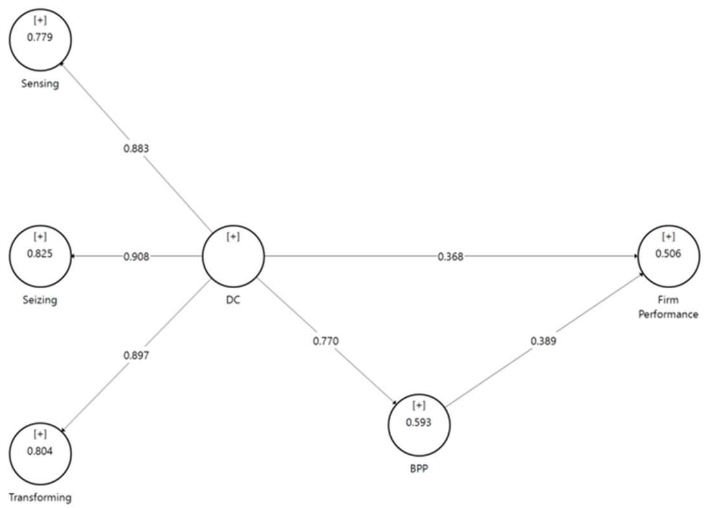

Figure 7: PLS Algorithm output RQ2

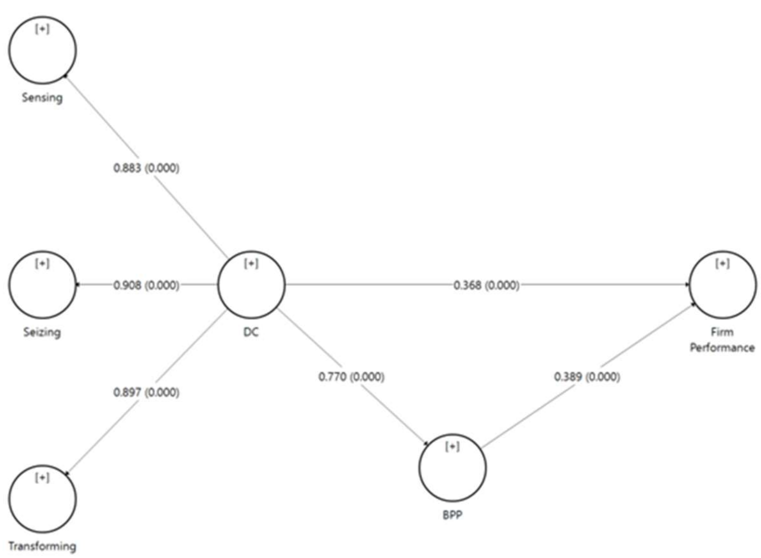

Figure 8: Bootstrap output RQ2

Research question two sought to establish if there was a significant and positive relationship between Dynamic Capabilities and Business Process Performance. As illustrated in Table

20, Dynamic Capabilities has a positive and significant path coefficient of 0.77 ($p<0.05$). Thus, the researcher rejected the null-hypothesis and confirmed H2. This result also confirms previous research by Aydiner, Tatoglu, Bayraktar, Zaim, et al., (2019), who also reported a positive relationship between Dynamic Capabilities and Business Process Performance.

5.5.3.3 Research question three

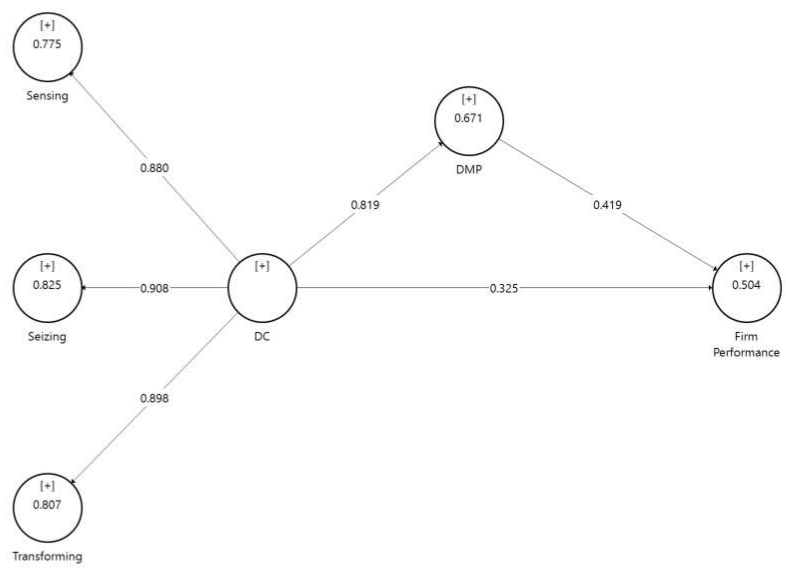

Figure 9: PLS Algorithm output RQ3

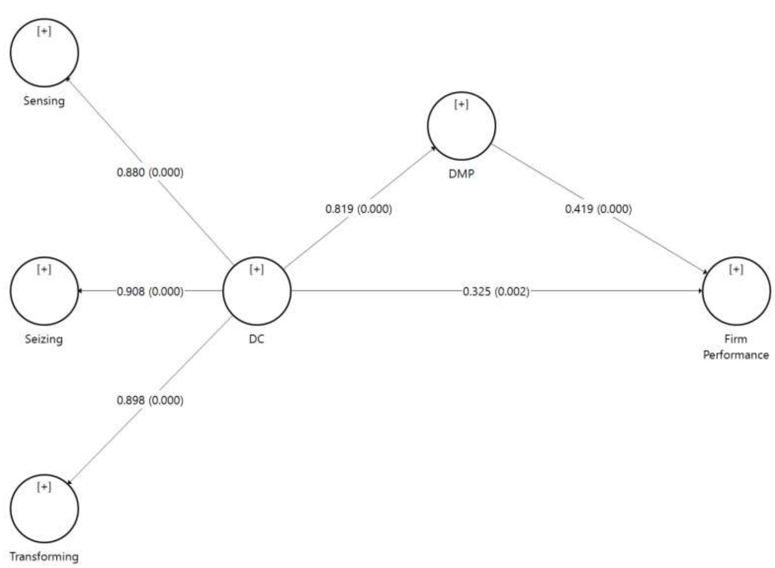

Figure 10: Bootstrap output RQ3

Research question three sought to establish if there was a significant and positive relationship between Dynamic Capabilities and Decision-Making Performance. As illustrated in Table 20, DMP has a positive and significant path coefficient of 0.82 ($p<0.05$). Thus, the researcher rejected the null-hypothesis and confirmed H_3. This result also confirms previous research by Aydiner, Tatoglu, Bayraktar, and Zaim (2019a), who also reported a positive relationship between Dynamic Capabilities and Decision-Making Performance.

5.5.3.4 Research question four

Research question four sought to establish if there was a significant mediation effect of Business Process Performance on the relationship between Dynamic Capabilities and Firm Performance. As discussed in Chapter 4, the researcher adopted the mediation analysis guidelines as specified by Hair et al., (2017). This required the verification of significance on the direct relationship between DC and Firm Performance, DC and BPP and BPP and Firm Performance. The first two requirements were met through the results of Research questions 1 and 2. As summarised in Table 20 and Figure 8, the path co-efficient between BPP and Firm Performance was 0.39 and significant at the 95% significance level. Therefore, the conditions to test for mediation were present. As summarised in Table 21, it was confirmed that BPP partially mediates the relationship between DC and Firm Performance. The indirect effect was calculated as the product between the path coefficients between DC – BPP (0.77) and that of BPP – Firm Performance (0.39), which was 0.30. For one standard deviation increase in DC, the results predict a 0.30 increase in Firm Performance through BPP. In addition, the total effect was calculated at 0.67. BPP was also shown to have a complementary partial mediation between DC and Firm Performance, therefore the researcher rejected the null hypothesis.

Table 21: Summary of results RQ4

Relationship	Direct effect	Indirect effect	Total effect	Mediation type
DC - BPP - Firm Performance	0.37	0.30	0.67	Complementary partial mediation

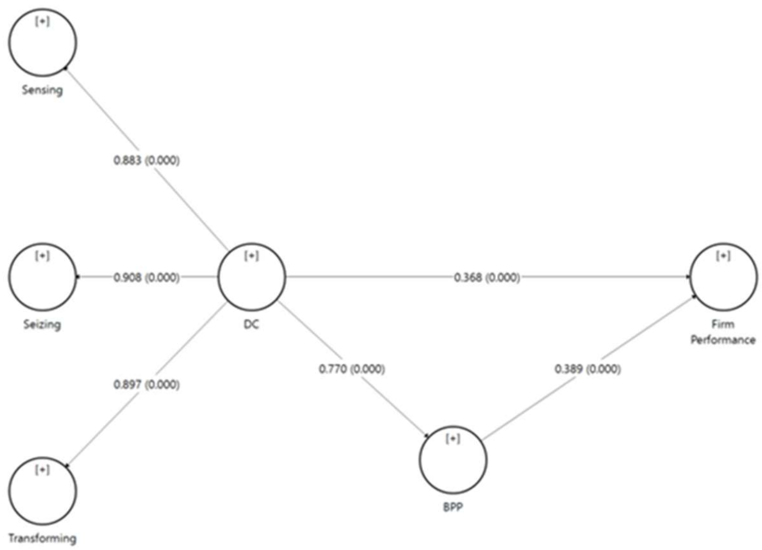

Figure 11: Bootstrap output RQ4

5.5.3.5 Research question five

Research question Five sought to establish if there was a significant mediation effect of Decision-Making Performance on the relationship between Dynamic Capabilities and Firm Performance. As discussed in Chapter 4, the researcher adopted the mediation analysis guidelines as specified by Hair et al., (2017). This required the verification of significance on the direct relationship between DC and Firm Performance, DC and DMP and DMP and Firm Performance. The first two requirements were met through the results of research questions 1 and 3. As summarised in Table 20 and Figure 10, the path co-efficient between DMP and Firm Performance was 0.42 and significant at the 95% significance level. Therefore, the conditions to test for mediation were present. As summarised in Table 22, it was confirmed that DMP partially mediates the relationship between DC and Firm Performance. The indirect effect was calculated as the product between the path coefficients between DC – DMP (0.82) and that of DMP – Firm Performance (0.42), which was 0.34. For one standard deviation increase in DC, the results predict a 0.34 increase in Firm Performance through DMP. In addition, the total effect was calculated at 0.67. DMP was also shown to have a complementary partial mediation between DC and Firm Performance, therefore the researcher rejected the null hypothesis.

Table 22: Summary of results RQ5

Relationship	Direct effect	Indirect effect	Total effect	Mediation type
DC - DMP - Firm Performance	0.33	0.34	0.67	Complementary partial mediation

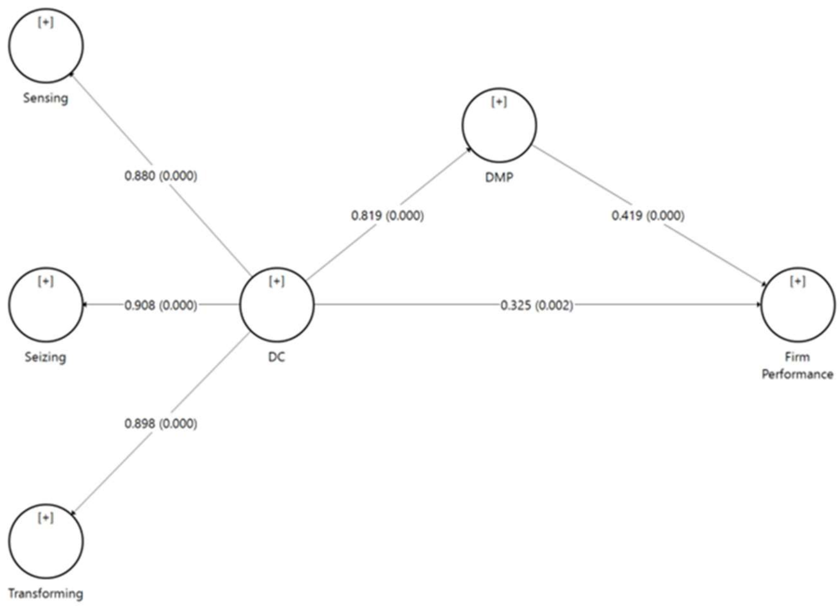

Figure 12: Bootstrap output RQ5

5.5.3.6 Research question six

Research question six sought to establish if there was a significant multiple mediation effect of Decision-making Performance and Business Process Performance on the relationship between Dynamic Capabilities and Firm Performance. As discussed in Chapter 4, the researcher adopted the mediation analysis guidelines as specified by Hair et al., (2017). As presented in Chapter 5 the conditions to test for mediation were present for the multiple mediation effect. As summarised in Table 23, it was confirmed that DMP and BPP fully mediates the relationship between DC and Firm Performance. In addition, the total effect was calculated at 0.66. DMP and BPP was also shown to have a full indirect mediation as the direct relationship between DC and Firm Performance was not significant at the 95% confidence level in the multiple mediation model, therefore the researcher rejected the null hypothesis.

Table 23: Summary of results RQ6

Relationship	Direct effect	Indirect effect	Total effect	Mediation type
DC - BPP - Firm Performance	0.20	0.22	0.66	Indirect only (Full mediation)
DC - DMP - Firm Performance	0.20	0.24		

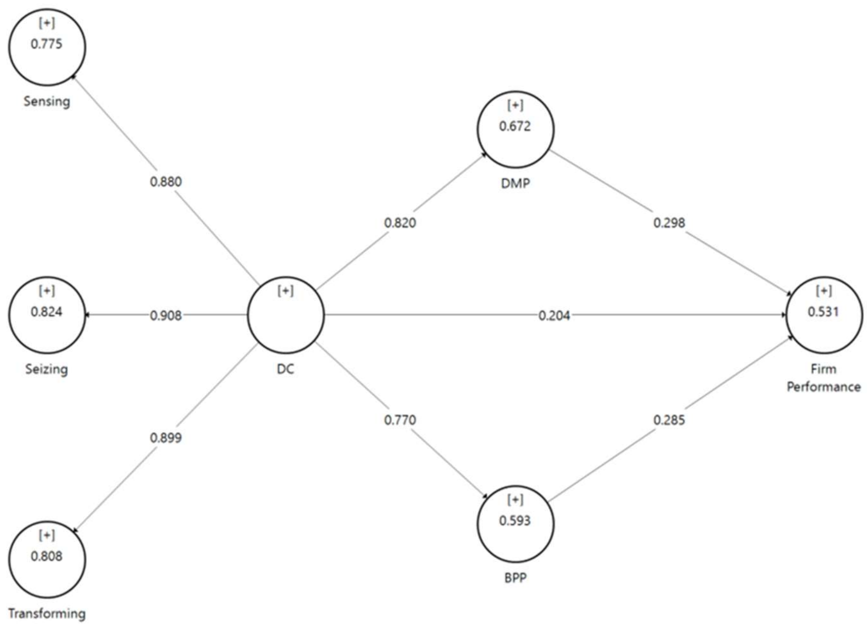

Figure 13: PLS Algorithm output RQ6

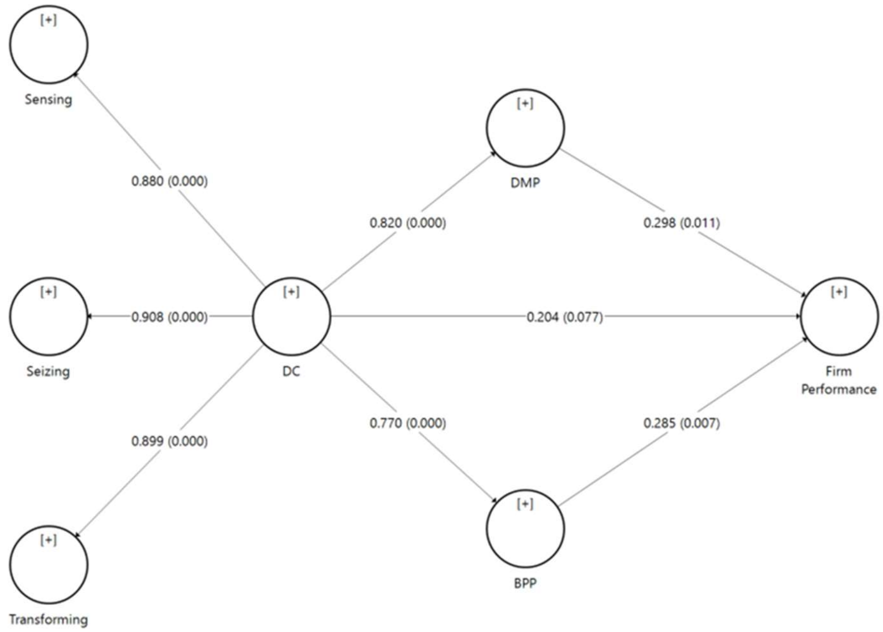

Figure 14: Bootstrap output RQ6

5.5.4 Structural model fit assessment

The results of the bootstrap test for the adjusted R^2 is summarised on Table 24. All the R^2 values of the constructs in the model were greater than 0.1 as recommended by Falk and Miller (1992).

Table 24: Results of the bootstrap test for the significance of the adjusted R^2

Construct	Adj R^2 value	P Values
Business Process Performance	0.59	0.00
Decision Making Performance	0.67	0.00
Firm Performance	0.51	0.00
Seizing	0.82	0.00
Sensing	0.77	0.00
Transforming	0.81	0.00

Table 25 summarises the effect size (f^2) for the independent variables in the structural model. As expected the effect size for Decision making Performance on Dynamic Capabilities, was much higher and was characterised as large effects over those of Business Process Performance and that of Seizing was the highest of the first order constructs (4.69) followed by Transforming (4.19) and then Sensing (3.46).

Table 25: Summary of effect size (f^2) analysis

Dependent variable	Independent variable	Effect size (f^2)
Sensing		3.46
Seizing		4.69
Transforming	Dynamic Capabilities	4.19
Business Process Performance		1.46
Decision Making Performance		2.04

The Stone-Geisser's Q^2 value, Table 26, is an indicator of the structural model's predictive relevance. The Q^2 value obtained for all constructs indicated a large predictive relevance (>0.35) (Hair et al., 2017).

Table 26: Blindfolding procedure analysis - Q^2

Dependent variable	Q^2
Business Process Performance	0.37
Decision Making Performance	0.40
Firm Performance	0.37
Sensing	0.42
Seizing	0.53
Transforming	0.51

An SRMR value less than 0.10 was adopted by the researcher as the model fit index (Hair et al., 2017). The SRMR value reported was 0.09 ($p \leq 0.05$) indicating that the research model met the goodness of fit criteria.

Chapter 6: Discussion of results

6.1. Introduction

The aim of this study was to understand and gain further insight into the value that can be leveraged by an organisation through the development and application of dynamic capabilities, within the maintenance management domain. This value was intended to be analysed by evaluating the relationships through path linkages between dynamic capabilities, business process performance, decision-making performance, and their respective involvement in improving firm performance. Theoretical positions in Chapter 2 shaped a foundation for creating and model Figure 1, that was tested through research questions identified in Chapter 3. A methodology for conducting the research analysis was presented in Chapter 4 and the results of the analysis was presented in Chapter 5. The purpose of this chapter is to discuss the findings that were determined in Chapter 5.

6.2. Discussion of Dynamic Capabilities

It has been observed that successful organisations have enabled their inherent dynamic capabilities to create new value and sustain a competitive advantage (Kump et al., 2019). Further to this, Teece (2018), postulated that the higher order capabilities of sensing, seizing and transforming need to be developed and applied at all levels in order for an organisation to create a competitive advantage and sustain it over the long term. This is no exception for the maintenance management domains of organisations. Continuous improvement initiatives are required for creating a dynamic capability (Anand et al., 2009), within the organisations maintenance management activities, that will potentially lead to improved firm performance.

The proposed model, Figure 1, considered the first order constructs for DC. The PLS-SEM technique found that there were positive and significant relationships between the constructs of sensing, seizing, and transforming, to the second order construct of DC. The result produced reported high connection strengths, with the seizing construct path coefficient of 0.91, followed by the transforming construct with a path coefficient of 0.83, and lastly sensing with a path coefficient of 0.88, which infers that these three constructs are strong predictors of DC within an organisation. This infers that these constructs must improve together, in order to improve DC. Similarly, as these capabilities erode, so will the DC in the organisation. This emerges clearly in support of views that increases in sensing, seizing and transforming, will result in increased DC, within an organisation (Kump et al., 2019; Teece, 2018; Teece et al., 2009; Wilden et al., 2013). In research conducted by Kump et al. (2019), the model presented path coefficients that also represented high connection strengths with the seizing construct path coefficient of 0.96, followed by the transforming construct with a path coefficient of 0.83 and lastly, the sensing construct with a path coefficient of 0.63. In both, this study and the study conducted by Kump et al. (2019), the seizing constructs has been observed to have the strongest path coefficient and the transforming being a close second. This could be due to the seizing and transforming capabilities, being strongly linked to strategy (Kump et al., 2019), and possibly requiring large amounts of investments to capitalise on the opportunity or follow a "do nothing approach" that has been identified utilising the sensing capability. As a result of the decisions taken, this could have either positive or negative impacts on the competitive advantage of the organisation, especially in the competitive production operating environment, due to their strong connection strengths.

6.3. Discussion of Research Question 1

The first research question focused on the relationship between DC and its effect on FPer. The hypothesis of research question was articulated as:

H_1: Dynamic Capabilities has a significant positive relationship with Firm Performance

The dynamic capability theory consists of three constructs which are sensing, seizing and transforming (Teece, 2014), where it is posited that to derive a competitive advantage, opportunities need to be sensed, then seized, then the organisation needs to transform its operations to sustain the competitive advantage (Wilden et al., 2013). Jamkhaneh et al. (2018), further postulates that capabilities and exceptional resources are required in the maintenance management domain, which could lead to a sustained competitive advantage to derive improved firm performance. In alignment with these positions, the positive effect that DC has on Fper has been studied extensively, and have been proven in studies conducted by Birkinshaw et al. (2016), Kump et al. (2019); Mikalef and Pateli (2017), Teece et al. (2009), Wilden et al. (2013), and Teece and Leih (2016).

Using the PLS-SEM technique, this study found that there were positive and significant relationships between the second order construct of DC and Fper. Dynamic Capabilities has a positive and significant path coefficient of 0.67 to Fper. Additionally, DC explained a substantial amount, approximately 45% of the variance in Fper. This infers that DC increases firm performance which emerges clearly in support of views by Birkinshaw et al. (2016), Kump et al. (2019); Mikalef & Pateli (2017), Teece et al. (2009), Wilden et al. (2013) and Teece & Leih (2016). Based on these findings, the converse also holds true as neglecting to develop and apply DC within the organisation could negatively impact the organisation's ability to sustaining competitive advantage, and in turn, erode firm performance. The results also infer that the seizing construct is the biggest predictor of firm performance. This is conceivable as seizing is related to strategy of an organisation and is the capability used for investment decisions for capitalising on opportunities that are in alignment with a firms organisational strengths (Kump et al., 2019).

6.4. Discussion of Research Question 2

The second research question focused on the relationship between DC and its effect on BPP. The hypothesis of research question was articulated as:

H_2: There is a positive relationship between Dynamic Capabilities and Business Process Performance in the maintenance management domain of an organisation

A firm exhibits dynamic capabilities in its ability to transform, improve and integrate its business processes, which will lead to improved firm performance (Kim et al., 2011). Further to this, it is posited that full adherence to business processes in maintenance management will lead to improved organisational performance (Abreu et al., 2013). In alignment with these views, the positive effect that DC has on BPP was confirmed in studies conducted by Aydiner, Tatoglu, Bayraktar, Zaim, et al. (2019) and Kim et al. (2011).

Using the PLS-SEM technique, this study found that there were positive and significant relationships between the second order construct of DC and BPP. Dynamic Capabilities has a positive and significant path coefficient of 0.77 to BPP. Additionally, DC explained a substantial amount, approximately 59% of the variance in BPP. This infers that DC increases BPP which emerges clearly in support of views by Aydiner, Tatoglu, Bayraktar, Zaim, et al. (2019) and Kim et al. (2011). Based on these findings, the converse also holds true as neglecting to develop and apply DC within the organisation could negatively impact the organisation's ability to sustaining competitive advantage, and in turn, erode BPP. The results also infer that the seizing construct is the biggest predictor of BPP. This is probably due to improvements and changes to BPP such as factors of investment, alignment, sequencing and efficiency within and between business processes, being decided on in the seizing construct based on strategy (Kim et al., 2011), where consequences have the strongest ability to increase or erode BPP within an organisation.

6.5. Discussion of Research Question 3

The third research question focused on the relationship between DC and its effect on DMP. The hypothesis of research question was articulated as:

H_3: There is a positive relationship between Dynamic Capabilities and Decision-Making Performance in the maintenance management domain of an organisation

There exists a relationship between the analytical capabilities and decision making performance in an organisation, through the availability of data, domain knowledge and analytical skills (Ghasemaghaei et al., 2018). It is also posited that organisations derive competitiveness through data analytics and strategic decision making in the maintenance domain (Jamkhaneh et al., 2018). In alignment with these views, the positive effect that DC has on DMP, was confirmed in studies conducted by Aydiner, Tatoglu, Bayraktar, & Zaim (2019a).

Using the PLS-SEM technique, this study found that there were positive and significant relationships between the second order construct of DC and DMP. Dynamic Capabilities has a positive and significant path coefficient of 0.82 to DMP. Additionally, DC explained a substantial amount, approximately 67% of the variance in DMP. This infers that DC increases DMP which emerges clearly in support of views by Aydiner, Tatoglu, Bayraktar, & Zaim (2019a). Based on these findings, the converse also holds true as neglecting to develop and apply DC within the organisation could negatively impact the organisation's ability to sustaining competitive advantage, and in turn, erode DMP. The results also infer that the seizing construct is the biggest predictor of DMP. This is probably due to improvements and changes to DMP such as factors of effectiveness and efficiency within the decision making process, being decided on in the seizing construct, where consequences have the strongest ability to increase or erode DMP within an organisation (Ghasemaghaei et al., 2018).

6.6. Discussion of Research Question 4

The fourth research question focused on the mediating role of BPP between DC and Fper. The hypothesis of research question was articulated as:

H_4: Business Process Performance mediates the relationship between Dynamic Capabilities and Firm Performance in the maintenance management domain of an organisation

Aydiner, Tatoglu, Bayraktar, Zaim, et al. (2019), posited a mediation effect of BPP between business analytics and firm performance. This mediation effect was also posited by Wamba et al. (2017). The mediating effect that BPP has between the relationship of DC and Fper, was confirmed in studies conducted by Aydiner, Tatoglu, Bayraktar, Zaim, et al. (2019) and Wamba et al. (2017). Aydiner, Tatoglu, Bayraktar, Zaim, et al. (2019), confirmed a full mediation role of BPP between DC and Fper, while a partial mediation role was confirmed by Wamba et al. (2017).

Using the PLS-SEM technique, this study found that BPP played a positive and significant partial mediation role between the second order construct of DC and Fper. The mediation role that BPP presented had positive and significant path coefficient of 0.39 between DC and Fper. The direct effect reported was 0.37 and the indirect effect was 0.30. This shows that the direct effect of DC to Fper, was higher than the mediation effect. Wamba et al. (2017) reported a direct effect of 0.56 and an indirect effect of 0.24. This infers that both DC and BPP will have to increase, in order to improve Fper. This view emerges clearly in support of views by Wamba et al. (2017). Based on these findings, the converse also holds true as neglecting to develop and improve either DC or BPP within the organisation could negatively impact the organisation's ability to sustaining competitive advantage, and in turn, erode Fper.

6.7. Discussion of Research Question 5

The fifth research question focused on the mediating role of DMP between DC and Fper. The hypothesis of research question was articulated as:

H_5: Decision-Making Performance mediates the relationship between Dynamic Capabilities and Firm Performance in the maintenance management domain of an organisation

Baum & Wally (2003), posited a meditation effect of strategic decision making between organisational factors such as dynamism and its relationship with firm performance. This view was also adopted by Aydiner, Tatoglu, Bayraktar, & Zaim (2019a), who posited a mediating effect of decision making performance between dynamic capabilities and firm performance. The mediating effect that DMP has between the relationship of DC and Fper, was confirmed to be positive in studies conducted by Baum & Wally (2003).

Using the PLS-SEM technique, this study found that DMP played a positive and significant partial mediation role between the second order construct of DC and Fper. The mediation role that DMP presented had positive and significant path coefficient of 0.42 between DC and Fper. The direct effect reported was 0.33 and the indirect effect was 0.34. Baum and Wally (2003) reported a direct effect of 0.27 and an indirect effect of 0.08. They concluded a partial mediating role for DMP between DC and Fper. This infers that both DC and DMP will have to increase, in order to improve Fper. This view emerges clearly in support of views by (Baum & Wally, 2003). Based on these findings, the converse also holds true as neglecting to develop and improve either DC or DMP within the organisation could negatively impact the organisation's ability to sustaining competitive advantage, and in turn, erode Fper. Further to this, DMP presented a slightly higher path coefficient in the partial mediation role, as compared to BPP. This could possibly be due to the targeted population, employees involved in maintenance management, being predominantly focused on making decisions that are experience based (Ylipää et al., 2017), which is primarily informal in nature.

6.8. Discussion of Research Question 6

The sixth research question focused on the mediating role of DMP between DC and Fper. The hypothesis of research question was articulated as:

H_6: Decision-Making Performance and Business Process Performance combined, mediates the relationship between Dynamic Capabilities and Firm Performance

According to research conducted by Baum & Wally (2003), it was concluded that strategic decision making speed presented to have a mediating relationship effect between organisational factors such as dynamism and firm performance. In research conducted by Aydiner, Tatoglu, Bayraktar, Zaim, et al. (2019), it was concluded that business process performance plays a mediating role between dynamic capabilities and firm performance. Both these conclusions led Aydiner, Tatoglu, Bayraktar, & Zaim (2019a), to develop and test a full model consisting of both business process performance and decision making performance playing mediating roles between dynamic capabilities and firm performance in the information technology domain. However, the full model results offered no support to each mediation but instead found a significant serial mediation role of decision-making performance and business process performance, between dynamic capabilities and firm performance (DC→DMP→BPP→Fper).

Using the PLS-SEM technique, the study on the full model found that both BPP and DMP combined, play a full mediation role between DC and FPer. Both indirect effects, proved to be higher than the direct effects, therefore this results in a full multiple mediation. The combined effect is also much higher than the relationship between DC and Fper, as well as both individual mediations, as discussed in research question 1, research question 4 and research question 5. This infers that both the mediations must be present, and both will have to increase together, in order to improve Fper. Based on these findings, the converse also holds true as neglecting to develop and improve either mediators, or having none of these mediators within the organisation could negatively impact the organisation's ability to sustaining competitive advantage, and in turn, erode Fper.

6.9. Summary of findings

Based on the findings presented, the objectives of this study have been met. The results have been found to support theoretical positions in literature that conclude a direct positive relationship between dynamic capabilities and firm performance, as well as two indirect relationships where business process performance and decision making performance, which were found to play mediating roles between dynamic capabilities and firm performance. Table 27, illustrates the summary of the findings from this study.

Table 27: Summary of overall findings

Research Hypotheses	Result	Theoretical Confirmation
H_1: Dynamic Capabilities has a significant positive relationship with Firm Performance.	Supported	Kump et al. (2019)
H_2: Dynamic Capabilities has a significant positive relationship with Business Process Performance.	Supported	Aydiner, Tatoglu, Bayraktar, Zaim, et al. (2019) and Kim et al. (2011)
H_3: Dynamic Capabilities has a significant positive relationship with Decision Making Performance.	Supported	Aydiner, Tatoglu, Bayraktar, & Zaim (2019a)
H_4: Business Process Performance mediates the relationship between Dynamic Capabilities and Firm Performance	Supported (partial mediation)	Wamba et al. (2017)
H_5: Decision-Making Performance mediates the relationship between Dynamic Capabilities and Firm Performance	Supported (partial mediation)	Baum & Wally (2003)
H_6: Decision-Making Performance and Business Process Performance combined, mediates the relationship between Dynamic Capabilities and Firm Performance	Supported (Full indirect mediation)	Wamba et al. (2017) and Baum & Wally (2003)

Chapter 7: Conclusion

7.1. Introduction

In consideration of the research problem presented, the aim of this chapter is to conceptualise the findings of this study and relate the contribution that this study holds for both business and theory. Literature highlights the need for computerised maintenance management systems (CMMS) information to be used effectively in decision making to improve performance (Rastegari & Mobin, 2016), and that further research is needed to identify the capabilities needed in maintenance organisations to improve competitive advantage and performance through analytics (Bokrantz et al., 2017). However, it is not only an analytics capability that is required for developing a competitive advantage, but entangled with it, a higher order dynamic capability is required within the organisation (Teece, 2018). Therefore, the purpose of this study was to explore the relationship between dynamic capabilities and firm performance within the maintenance management environment, and whether business process performance and decision making performance have a role to play between the dynamic capabilities and firm performance, within the organisation.

7.2. Key findings

The first objective of this study was to explore the relationship between dynamic capabilities and firm performance. The study found that there exists a strong positive and direct relationship between dynamic capabilities and firm performance which means that improvements to increase dynamic capabilities in maintenance management, will result in a competitive advantage and improved firm performance. However, the converse also holds true that any decrease in the dynamic capabilities will result in a reduced competitive advantage and with it, a reduced firm performance.

The second objective was to explore the relationship between dynamic capabilities and business process performance and the third objective was to explore the relationship between dynamic capabilities and decision-making performance. It was also revealed that dynamic capabilities have strong positive and direct relationships with both business process performance as well as decision-making performance. Moreover, it was found that the seizing capability was the biggest predictor of firm performance, business process performance and decision-making performance.

The fourth objective of this study was to explore whether business process performance played a mediating role between dynamic capabilities and firm performance while the fifth objective of this study was to explore whether decision making performance played a mediating role between dynamic capabilities and firm performance. Both mediating roles were confirmed to be significant but partially supported which means that each of these mediators play a complementary role with dynamic capabilities, in order to obtain improved performance.

Further to this, the sixth objective was to establish whether decision making performance and business process performance had a multiple mediating effect between dynamic capabilities and firm performance. It was found that enabling the combined mediating relationships to act together in the model, resulted in a full indirect mediation role and a higher variance in firm performance than compared to the other direct and indirect relationships in this study.

7.3. Implications for business

According to Bokrantz et al. (2017), the world is facing the fourth industrial revolution, where a radical increase in the reshaping of companies and competition within the asset intensive industries is being observed. Organisations in these industries are being forced to rethink traditional ways of working and gearing the workforce with higher and more diversified competency profiles (Bokrantz et al., 2017). This suggests that the traditional way of executing maintenance management, being predominantly reactive (Gulati, 2013) and the lack of data driven decision making (Baglee & Marttonen, 2015), is certainly inadequate for a sustainable competitive advantage. An improved way of managing maintenance should be through developing and applying dynamic capabilities within the maintenance organisation. This will therefore enable the organisation to position itself to adapt to changing environments and sustaining a competitive advantage (Birkinshaw et al., 2016;

Teece & Leih, 2016).

The findings in this study affords some guidance in how businesses could better manage and further develop on the existing capabilities of their organisations in the asset intensive industries. The results of this study support and contribute to theoretical positions of previous studies conducted in the dynamic capabilities and related fields by Birkinshaw et al. (2016), Kump et al. (2019); Mikalef and Pateli (2017), Teece et al. (2009), Teece & Leih (2016), Aydiner, Tatoglu, Bayraktar, Zaim, et al. (2019), Kim et al. (2011), Aydiner, Tatoglu, Bayraktar, & Zaim (2019a), Wamba et al. (2017) and Baum and Wally (2003).

Based on the key findings of this study, the researcher posits that organisations in the asset intensive industries should invest in dynamic capability (DC) training, reinforced by continuous improvement tools in Table 1, to improve maintenance domain knowledge and develop analytical capabilities of CMMS data for employees in the maintenance management domain to be able to sense, seize and transform opportunities within the organisation relating to improved performance, reducing cost and reducing risk to the business. These training initiatives should ensure that employees understand and can derive insights from the maintenance and related data. This should be managed through continuous improvement initiatives within the organisation, bearing in mind that these training programmes will have to further the knowledge of the employee in executing their current roles as been in the operational, tactical or strategic level of the organisation.

Due to the seizing capability being found to be the biggest predictor of improved business process performance (BPP), decision-making performance (DMP) and firm performance (Fper), the researcher posits that further focus should also be drawn on training initiatives for maintenance managers in financial decision making and strategy for maintenance improvement projects.

This study found that both BPP and DMP play partial mediation roles between DC and Fper, which means that they are both complementary to DC in its relationship with Fper. However, when these mediation roles are combined, the multiple mediation roles of both business process performance (BPP) and decision-making performance (DMP) are found to have a full mediation effect, which mimics reality, as they are expected to be integrated, and these mediators have been statistically proven to have a behavioural integration that further improves firm performance. The researcher posits that managers need to be cognisant that these two constructs must be integrated and not act individually within the maintenance management domain, thus positioning a better prospect for competitive advantage and an improved firm performance to materialise.

7.4. Recommendations for future research

This study was intended to explore the direct and indirect effects between dynamic capabilities and firm performance, in the maintenance management context. The scope encompassed mediating factors such as business process performance and decision-making performance. Further research should explore other possible mediating factors that may have a significant positive effect between dynamic capabilities and firm performance.

Leadership and organisational culture are key artefacts of change management within organisations. Future research should focus on these artefacts to determine the right types of leaderships and culture that will enable a data driven ethos, and how these artefacts act as moderating factors in the relationship between dynamic capabilities and firm performance.

Given that this study adopted a cross-sectional research design due to time constraints, the researcher recommends a longitudinal study to be conducted to understand the long-term effects on maintenance management maturity, by applying the model presented in this study.

Due to the full mediation effect observed in this study, where the mediation effects of BPP and DMP combined have been proven to further improve firm performance, future research should be positioned to unpack the entanglement and intricacies, that give rise to a new component which takes into account the combined dynamic relationships that BPP and DMP have. The researcher posits that BPP and DMP are 1st order constructs of a new higher order construct that could be further explored.

7.5. Research limitations

Considering all research studies in academia, this study has been conducted with theoretical and methodological limitations observed. Firstly, a theoretical limitation was observed due to the scope of this study. The scope of this study considered the direct and indirect relationships between dynamic capabilities (DC) and firm performance (Fper), with mediating roles of business process performance (BPP) and decision-making performance (DMP). The full model that considered the combined full mediation effect of BPP and DMP, explained a 53% variance in Fper. The consequence of this limitation is that there are other variables in literature that could theoretically interact with this model that may possibly lead to an improved explained variance.

Secondly, various methodological limitations have been discussed in Section 4.10 which highlighted sampling biases due to non-probability sampling methods adopted. Further to this, the researcher highlighted a limitation on cross-sectional study adopted due to time constraints, as a longitudinal study would be better suited to assess the effect of the application of the full research model, in the maintenance context of an organisation, over time.

References

Abreu, J., Martins, P. V., Fernandes, S., & Zacarias, M. (2013). Business Processes Improvement on Maintenance Management: A Case Study. *Procedia Technology*, *9*, 320–330. https://doi.org/10.1016/j.protcy.2013.12.036

Akhtar, P., Frynas, J. G., Mellahi, K., & Ullah, S. (2019). Big Data-Savvy Teams' Skills, Big Data-Driven Actions and Business Performance. *British Journal of Management*, *30*(2), 252–271. https://doi.org/10.1111/1467-8551.12333

Akter, S., Wamba, S. F., Gunasekaran, A., Dubey, R., & Childe, S. J. (2016). How to improve firm performance using big data analytics capability and business strategy alignment? *International Journal of Production Economics*, *182*, 113–131. https://doi.org/10.1016/j.ijpe.2016.08.018

Alsyouf, I. (2009). Maintenance practices in Swedish industries: Survey results. *International Journal of Production Economics*, *121*(1), 212–223. https://doi.org/10.1016/j.ijpe.2009.05.005

Anand, G., Ward, P. T., Tatikonda, M. V., & Schilling, D. A. (2009). Dynamic capabilities through continuous improvement infrastructure. *Journal of Operations Management*, *27*(6), 444–461. https://doi.org/10.1016/j.jom.2009.02.002

Ansari, F., Fathi, M., & Seidenberg, U. (2016). Problem-solving approaches in maintenance cost management: A literature review. *Journal of Quality in Maintenance Engineering*, *22*(4), 334–352. https://doi.org/10.1108/JQME-04-2015-0012

Aydiner, A. S., Tatoglu, E., Bayraktar, E., & Zaim, S. (2019a). Information system capabilities and firm performance: Opening the black box through decision-making performance and business-process performance. *International Journal of Information Management*, *47*, 168–182. https://doi.org/10.1016/j.ijinfomgt.2018.12.015

Aydiner, A. S., Tatoglu, E., Bayraktar, E., Zaim, S., & Delen, D. (2019). Business analytics and firm performance: The mediating role of business process performance. *Journal of Business Research*, *96*, 228–237. https://doi.org/10.1016/j.jbusres.2018.11.028

Baglee, D., & Marttonen, S. (2015). The need for Big Data collection and analyses to support the development of an advanced maintenance strategy. *Conference on Data Mining (DMIN)*, *July*. http://search.proquest.com/openview/eafd161dd06964464e13ac7a9af11d10/1?pq-origsite=gscholar

Barney, J. (1991). Firm Resources and Sustained Competitive Advantage. *Journal of Management*, *17*(1), 99–120. https://doi.org/10.1177/014920639101700108

Baum, J. R., & Wally, S. (2003). Strategic decision speed and firm performance. *Strategic Management Journal*, *24*(11), 1107–1129. https://doi.org/10.1002/smj.343

Bhandari, K. R., Rana, S., Paul, J., & Salo, J. (2020). Relative exploration and firm performance: Why resource-theory alone is not sufficient? *Journal of Business Research*, *118*(June), 363–377. https://doi.org/10.1016/j.jbusres.2020.07.001

Birkinshaw, J., Zimmermann, A., & Raisch, S. (2016). How do firms adapt to discontinuous change? Bridging the dynamic capabilities and ambidexterity perspectives. *California Management Review*, *58*(4), 36–58. https://doi.org/10.1525/cmr.2016.58.4.36

Bokrantz, J., Skoogh, A., Berlin, C., & Stahre, J. (2017). Maintenance in digitalised manufacturing: Delphi-based scenarios for 2030. *International Journal of Production Economics*, *191*(June), 154–169. https://doi.org/10.1016/j.ijpe.2017.06.010

Bokrantz, J., Skoogh, A., Berlin, C., Wuest, T., & Stahre, J. (2020). Smart Maintenance: an empirically grounded conceptualization. *International Journal of Production Economics*, *223*(August 2019), 107534. https://doi.org/10.1016/j.ijpe.2019.107534

Bokrantz, J., Skoogh, A., & Ylipaa, T. (2016). The use of engineering tools and methods in maintenance organisations. *49th CIRP Conference on Manufacturing Systems*, 556–561.

Bordens, K. S., & Abbott, B. B. (2010). *Research design and methods: A process approach (8th ed.)*. New York, NY: Mcgraw-Hill.

Bryman, A., & Bell, E. (2011). *Business Research Methods 3rd Edition.* New York: Oxford University Press Inc.

Brynjolfsson, E., Hitt, L., & Kim, H. (2011). Strength in numbers: How does data-driven decision making affect firm performance? *Social Science Research Network*, 1–28.

Brynjolfsson, E., & McElheran, K. (2016). The rapid adoption of data-driven decision-making. *American Economic Review*, *106*(5), 133–139. https://doi.org/10.1257/aer.p20161016

Carpenter, S. (2018). Ten steps in scale development and reporting: A guide for researchers. *Communication Methods and Measures*, 12(1), 25-44.

Checkland, P., & Holwell, S. (1998). *Information, Systems, and Information Systems: Making sense of the field.* Chichester, UK: John Wiley and Sons Ltd.

Chin, W. W. (2010). How to write up and report PLS analyses. In Handbook of partial least squares. *Springer Handbooks of Computational Statistics*, 655-690.

Contreras, D., & Salamo, M. (2020). Data-driven decision makin in critque based recommenders: from a critique to social media data. *Journal of Intelligent Information Systems*, 23-44. https://doi.org/10.1007/s10844-018-0520-9.

Eisenhardt, K. M., & Martin, J. A. (2000). Dynamic capabilities: What are they? *Strategic Management Journal*, *21*(10–11), 1105–1121. https://doi.org/10.1002/1097-0266(200010/11)21:10/11<1105::AID-SMJ133>3.0.CO;2-E

Falk, R. F., & Miller, N. B. (1992). *A primer for soft modeling*. The University of Akron Press.

Fraser, K., Hvolby, H. H., & Tseng, T. L. B. (2015). Reliability paper Maintenance management models: A study of the published literature to identify empirical evidence a greater practical focus is needed. *International Journal of Quality and Reliability Management*, *32*(6), 635–664. https://doi.org/10.1108/IJQRM-11-2013-0185

Fredriksson, C. (2018). Big data creating new knowledge as support in decision-making: practical examples of big data use and consequences of using big data as decision support. *Journal of Decision Systems*, *27*(1), 1–18. https://doi.org/10.1080/12460125.2018.1459068

Garrido, I. L., Kretschmer, C., de Vasconcellos, S. L., & Gonçalo, C. R. (2020). Dynamic capabilities: A measurement proposal and its relationship with performance. *Brazilian Business Review*, *17*(1), 46–65. https://doi.org/10.15728/BBR.2020.17.1.3

GFMAM. (2016). *The Maintenance Framework.* Global Forum for Maintenance and Asset Management.

Ghasemaghaei, M., Ebrahimi, S., & Hassanein, K. (2018). Data analytics competency for improving firm decision making performance. *Journal of Strategic Information Systems*, *27*(1), 101–113. https://doi.org/10.1016/j.jsis.2017.10.001

Gowen, C. R., McFadden, K. L., & Settaluri, S. (2012). Contrasting continuous quality improvement, Six Sigma, and lean management for enhanced outcomes in US hospitals. *American Journal of Business*, *27*(2), 133–153. https://doi.org/10.1108/19355181211274442

Gu, J. W., & Jung, H. W. (2013). The effects of IS resources, capabilities, and qualities on organizational performance: An integrated approach. *Information and Management*, *50*(2–3), 87–97. https://doi.org/10.1016/j.im.2013.02.001

Gulati, R. (2013). *Maintenance and Reliability Best Practices*. New York, NY: Industrial Press Inc. https://books.google.com/books?id=fwuDBgAAQBAJ&pgis=1

Gupta, M., & George, J. F. (2016). Toward the development of a big data analytics capability. *Information and Management*, *53*(8), 1049–1064. https://doi.org/10.1016/j.im.2016.07.004

Gutierrez-Gutierrez, L., & Antony, J. (2020). Continuous improvement initiatives for dynamic capabilities development: A systematic literature review. *International Journal of Lean Six Sigma*, *11*(1), 125–149. https://doi.org/10.1108/IJLSS-07-2018-0071

Hair, Joe F., Ringle, C. M., & Sarstedt, M. (2011). PLS-SEM: Indeed a silver bullet. *Journal of Marketing Theory and Practice*, *19*(2), 139–152. https://doi.org/10.2753/MTP1069-6679190202

Hair, Joseph F, Black, W. C., Babin, B. J., & Anderson, R. E. (2010). *Multivariate Data Analysis: A Global Perspective (7th ed.)*. New Jersey: Pearson Education. https://doi.org/10.4324/9781351269360

Hair, Joseph F, Black, W. C., Babin, B. J., & Anderson, R. E. (2019). *Multivariate Data Analysis: the data constructs (8th ed)*. Cengage Learning. https://doi.org/10.2307/2007941

Hair Jr, J., Hult, G. T., Ringle, C., & Sarstedt, M. (2017). *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM) (2nd ed.)*. Sage.

Hansen, D., & Møller, N. (2016). Conceptualizing Dynamic Capabilities in Lean Production: What are They and How Do They Develop? *EMJ - Engineering Management Journal*, *28*(4), 194–208. https://doi.org/10.1080/10429247.2016.1238727

Hasan, N., Miah, S. J., Bao, Y., & Hoque, M. R. (2019). Factors affecting post-implementation success of enterprise resource planning systems: a perspective of business process performance. *Enterprise Information Systems*, *13*(9), 1217–1244. https://doi.org/10.1080/17517575.2019.1612099

Helfat, C. E., & Peteraf, M. A. (2003). The dynamic resource-based view: Capability lifecycles. *Strategic Management Journal*, *24*(10 SPEC ISS.), 997–1010. https://doi.org/10.1002/smj.332

Helfat, C. E., & Peteraf, M. A. (2009). Understanding dynamic capabilities: progress along a developmental path. *Strategic Organisation*, 7(1), 91-102. doi:0.1177/1476127008100133.

Helfat, C. E., Finkelstein, S., Mitchell, W., Peteraf, M., Singh, H., Teece, D., & Winter, S. G. (2007). *Dynamic Capabilities: Understanding Strategic Change in Organizations.* Blackwell, London: John Wiley & Sons.

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, *43*(1), 115–135. https://doi.org/10.1007/s11747-014-0403-8

Jamkhaneh, H. B., Khazaei Pool, J., Khaksar, S. M. S., Arabzad, S. M., & Verij Kazemi, R. (2018). Impacts of computerized maintenance management system and relevant supportive organizational factors on total productive maintenance. *Benchmarking*, *25*(7), 2230–2247. https://doi.org/10.1108/BIJ-05-2016-0072

Kaiser, H. F. (1974). An index of factorial simplicity. *Psychometrika*, 39(1), 31-36.

Karim, R., Westerberg, J., Galar, D., & Kumar, U. (2016). Maintenance Analytics – The New Know in Maintenance. *IFAC-PapersOnLine*, *49*(28), 214–219. https://doi.org/10.1016/j.ifacol.2016.11.037

Kelly, A. (2006). Maintenance Systems and Documentation. http://onlinelibrary.wiley.com/doi/10.1002/cbdv.200490137/abstract

Kim, G., Shin, B., Kim, K. K., & Lee, H. G. (2011). IT capabilities, process-oriented dynamic capabilities, and firm financial performance. *Journal of the Association for Information Systems*, *12*(7), 487–517. https://doi.org/10.17705/1jais.00270

Kitchens, B., Dobolyi, D., Li, J., & Abbasi, J. (2018). Advanced customer analytics: Strategic value through integration of relationship-oriented big data. *Journal of Managmenet Information Systems*, 35(2), 540-574.

Kump, B., Engelmann, A., Kessler, A., & Schweiger, C. (2019). Toward a dynamic capabilities scale: Measuring organizational sensing, seizing, and transforming capacities. *Industrial and Corporate Change*, *28*(5), 1149–1172. https://doi.org/10.1093/icc/dty054

Lovallo, D. P., & Sibony, O. (2006). Distortion and Deceptions in strategic decisions. *McKinsey Quarterly*, (1), 18-29.

Ma, Z., Ren, Y., Xiang, X., & Turk, Z. (2020). Data-Driven decision making for equipment maintenance. *Automation in Construction*, 1-17. https://doi.org/10.1016/j.autcon.2020.103103.

Macchi, M., Roda, I., & Fumagalli, L. (2017). On the advancement of maintenance management towards Smart Maintenance in manufacturing. *IFIP International Conference on Advances in Production Management Systems* (pp. 383-390). Cham: Switzerland: Springer.

Mardiasmo, D., Tywoniak, S., Brown, K. A., & Burgess, J. (2008). Asset Management and Governance: Analysing Vehicle Fleets in Asset-intensive Organisations. *Contemporary Issues in Public Management: The Twelfth Annual Conference of the International Research Society for Public Management (IRSPM XII)*, *2008*, 1–20. http://eprints.qut.edu.au/15323/

Mazzei, M. J., & Noble, D. (2017). Big data dreams: A framework for corporate strategy. *Business Horizons*, *60*(3), 405–414. https://doi.org/10.1016/j.bushor.2017.01.010

Mcabee, S. T., Landis, R. S., & Burke, M. I. (2017). Inductive reasoning: The promise of big data. *Human Resource Management Review*, 27(2), 277-290. doi:https://doi.org/10.1016/j.hrmr.2016.08.005.

Mcafee, A., & Brynjolfsson, E. (2012). Spotlight on Big Data Big Data: The Management Revolution, 2012. Acedido em 15-03-2017. *Harvard Business Review*, *October*, 1–9. http://tarjomefa.com/wp-content/uploads/2017/04/6539-English-TarjomeFa-1.pdf

Mikalef, P., Krogstie, J., Pappas, I. O., & Pavlou, P. (2020). Exploring the relationship between big data analytics capability and competitive performance: The mediating roles of dynamic and operational capabilities. *Information and Management*, *57*(2), 103169. https://doi.org/10.1016/j.im.2019.05.004

Mikalef, P., & Pateli, A. (2017). Information technology-enabled dynamic capabilities and their indirect effect on competitive performance: Findings from PLS-SEM and fsQCA. *Journal of Business Research*, *70*, 1–16. https://doi.org/10.1016/j.jbusres.2016.09.004

Mitchell, J. S. (2015). *Operational Excellence: Journey to creating sustainable value*. New Jersey: John Wiley & Sons, Inc.

Moore, R. (2015). *Making common sense common practice (4 ed)*. Reliabilityweb.com.

Newbert, S. L. (2007). Empirical research on the resource-based view of the firm: An assessment and suggestions for future research. *Strategic Management Journal*, *28*(2), 121–146. https://doi.org/10.1002/smj.573

Pallant, J. (2007). *SPSS survival manual (3rd ed).* New York: McGrath Hill.

Perneger, T. V., Courvoisier, D. S., Hudelson, P. M., & Gayet-Ageron, A. (2015). Sample size for pre-tests of questionnaires. *Quality of Life Research*, *24*(1), 147–151. https://doi.org/10.1007/s11136-014-0752-2

Pinjala, S. K., Pintelon, L., & Vereecke, A. (2006). An empirical investigation on the relationship between business and maintenance strategies. *International Journal of Production Economics*, *104*(1), 214–229. https://doi.org/10.1016/j.ijpe.2004.12.024

Provost, F., & Fawcett, T. (2013, March). Data science and its relationship to big data and data-driven decision making. *Big Data*, pp. 1(1), 51-59. http://doi.org/10.1089/big.2013.1508.

Raghavan, M., Jain, K., & Jha, S. K. (2013). Technology and intellectual property strategy of a firm: A view through the commons theory lens. *IIMB Management Review*, *25*(4), 213–227. https://doi.org/10.1016/j.iimb.2013.07.003

Rastegari, A., & Mobin, M. (2016). Maintenance decision making, supported by computerized maintenance management system. *Proceedings - Annual Reliability and Maintainability Symposium*, *2016-April*. https://doi.org/10.1109/RAMS.2016.7448086

Roldán, J. L., & Sanchez-Franco, M. J. (2012). Variance-based structural equation modeling guidelines for using partial least squares in information systems research. *Research Methodologies, Innovations and Philosophies in Software Systems Engineering and Information Systems*, 193–221. https://doi.org/10.4018/97821246662017926.ch010)

Roy, R., Stark, R., Tracht, K., Takata, S., & Mori, M. (2016). Continuous maintenance and the future - Foundations and technological challenges. *CIRP Annals - Manufacturing Technology*, 65(2), 667-688. https://doi.org/10.1016/j.cirp.2016.06.006.

Rugman, A. M., Verbeke, A., & Nguyen, Q. T. (2011). Fifty years of international business theory and beyond. *Management International Review*, 51(6), 755-786. doi:https://doi.org/10.1007/s11575-011-0102-3.

Ruschel, E., Santos, E. A. P., & Loures, E. de F. R. (2017). Industrial maintenance decision-making: A systematic literature review. *Journal of Manufacturing Systems*, *45*, 180–194. https://doi.org/10.1016/j.jmsy.2017.09.003

Salonen, A., & Bengtsson, M. (2011). The potential in strategic maintenance development. *Journal of quality in Maintenance Engineering*.

Saunders, M., & Lewis, P. (2018). Doing research in business and management. An essential guide to planning your project. Harlow: Pearson.

Sena, V., Bhaumik, S., Sengupta, A., & Demirbag, M. (2019). Big Data and Performance: What Can Management Research Tell us? *British Journal of Management*, *30*(2), 219–228. https://doi.org/10.1111/1467-8551.12362

Sharma, R., Mithas, S., & Kankanhalli, A. (2014). Transforming decision-making processes: A research agenda for understanding the impact of business analytics on organisations. *European Journal of Information Systems*, *23*(4), 433–441. https://doi.org/10.1057/ejis.2014.17

Smith, R., & Mobley, R. K. (2011). *Rules of thumb for maintenance and reliability engineers.* Butterworth-Heinemann.

Teece, D. J. (2014). The foundations of enterprise performance: Dynamic and ordinary capabilities in an (economic) theory of firms. *Academy of Management Perspectives*, *28*(4), 328–352. https://doi.org/10.5465/amp.2013.0116

Teece, D. J. (2018). Business models and dynamic capabilities. *Long Range Planning*, *51*(1), 40–49. https://doi.org/10.1016/j.lrp.2017.06.007

Teece, D. J., & Leih, S. (2016). Uncertainty, innovation, and dynamic capabilities: An introduction. *California Management Review*, *58*(4), 5–12. https://doi.org/10.1525/cmr.2016.58.4.5

Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic Capabilities and strategic management. *Strategic Management Journal*, 18(7), 509-533.

Teece, D. J., Pisano, G., & Shuen, A. (2009). Dynamic capabilities and strategic management. *Knowledge and Strategy*, *18*(7), 77–116. https://doi.org/10.1142/9789812796929_0004

Torres, R., Sidorova, A., & Jones, M. C. (2018). Enabling firm performance through business intelligence and analytics: A dynamic capabilities perspective. *Information and Management*, *55*(7), 822–839. https://doi.org/10.1016/j.im.2018.03.010

Wade, M., & Hulland, J. (2004). The resource-based view and information systems research: Review, extension, and suggestions for future research. *MIS Quarterly*, *28*(1), 107–142. https://www.jstor.org/stable/pdf/25148626.pdf

Wamba, S. F., Gunasekaran, A., Akter, S., Ren, S. J. fan, Dubey, R., & Childe, S. J. (2017).

Big data analytics and firm performance: Effects of dynamic capabilities. *Journal of Business Research*, *70*, 356–365. https://doi.org/10.1016/j.jbusres.2016.08.009

Wegner, T. (2016). *Applied business Statistics: Methods and excel-based applications.* Cape Town: Juta & Company Ltd.

Wilden, R., Gudergan, S. P., Nielsen, B. B., & Lings, I. (2013). Dynamic Capabilities and Performance: Strategy, Structure and Environment. *Long Range Planning*, *46*(1–2), 72–96. https://doi.org/10.1016/j.lrp.2012.12.001

Williams, C. (2007). Research methods. *Journal of Business & Economic Research*, *5*(3), 65–72. https://doi.org/10.1017/9781108656184.003

Wojcik, P. (2015). Exploring links between dynamic capabilities perspective and resource-based view: A literature overview. *International Journal of Management and Economics*, 83-107.

Ylipää, T., Skoogh, A., Bokrantz, J., & Gopalakrishnan, M. (2017). Identification of maintenance improvement potential using OEE assessment. *International Journal of Productivity and Performance Management*, *66*(1), 126–143. https://doi.org/10.1108/IJPPM-01-2016-0028

Zikmund, W. G., Babib, B. J., Carr, J. C., & Griffin, M. (2009). *Business Research Methods (8th ed)*. CENGAGE Learning.

Appendix A

The effects of dynamic capabilities on organisational performance in asset-intensive industries

Dear Respondent

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

I am conducting research on the effects of dynamic capabilities on an organisation's performance, for organisations in the asset-intensive industries that should have maintenance management practices and strategies in place. To this end, you are asked to complete a survey questionnaire that will take approximately 10-12 minutes to complete and will aid in a better understanding of the role that dynamic capabilities in maintenance management play, in achieving firm-level performance. Your participation is voluntary, and you can withdraw at any time without penalty. In addition, your participation is anonymous, and only aggregated data will be reported. By completing the survey, you indicate that you voluntarily participate in this research.

If you have any concerns, please contact me or my research supervisor on the following details:

Researcher Name: Kuben Kullenda

Email: kubenk747@gmail.com

Phone: 0825490747

Research Supervisor: Rishal Balkissoon

Email: rishal.balkissoon@gmail.com

Section 1

This section of the questionnaire focuses on a few background questions relating to yourself as well as your organisation. Please answer the questions by selecting the relevant option that best describes yourself and your organisation.

* 1. Does your company make use of a computerised maintenance management system (CMMS) or a maintenance management module in an Enterprise Asset Management System?

◯ Yes

◯ No

* 2. What age group are you in?

◯ Under 18

◯ 18-24

◯ 25-34

◯ 35-44

◯ 45-54

◯ 55-64

◯ 65+

* 3. Which of the following best describes the principal industry of your organisation?

* 4. How long have you been associated with the field of maintenance management?

- ○ 0 - 2 years
- ○ 10 - 15 years
- ○ 3 - 5 years
- ○ 15+ years
- ○ 6 - 9 years

* 5. How long have you been associated with the field of data analytics?

- ○ 0 - 2 years
- ○ 10 - 15 years
- ○ 3 - 5 years
- ○ 15+ years
- ○ 6 - 9 years

* 6. How long has your organisation actively pursued or applied data analytics to its business?

- ○ 0 - 2 years
- ○ 10 - 15 years
- ○ 3 - 5 years
- ○ 15+ years
- ○ 6 - 9 years

* 7. What is your main association with the analytics capability?

- ○ User of analytics within business
- ○ Data analyst (Direct processor of data)
- ○ IT Systems or Infrastructure (Data Technology environment)
- ○ Big Data Management (Driving application of resources)
- ○ Other (please specify)

* 8. What is the approximate total number of employees within your organisation?

◯ 1 - 99
◯ 100 - 499
◯ 500 - 999
◯ 1000 or more
◯ I do not know

* 9. Which of the following best describes your current job level?

◯ Owner/Executive/C-Level
◯ Senior Management
◯ Middle Management
◯ Specialist (including maintenance planners, schedulers and technical coordinators)
◯ Junior/Entry Level
◯ Other (please specify)

* 10. In what country do you work?

Section 2

In this section, you are required to best describe your organisation with regard to the ability to identify opportunities for improvement, using data analytics. Please rate the extent to which you agree or disagree with the following statements.

* 11. Our data is configured in a way to make it easier for analysis

◯ Strongly agree
◯ Agree
◯ Neither agree or disagree
◯ Disagree
◯ Strongly disagree

* 12. Our analysts are able to present data in a suitable way for maintenance decision-makers

◯ Strongly agree
◯ Agree
◯ Neither agree nor disagree
◯ Disagree
◯ Strongly disagree

* 13. Multiple checks are done to make sure that our maintenance data is accurate and complete

◯ Strongly agree
◯ Agree
◯ Neither agree nor disagree
◯ Disagree
◯ Strongly disagree

* 14. We have relevant maintenance KPI's to identify and trigger an event when an intervention is needed

- Strongly agree
- Agree
- Neither agree nor disagree
- Disagree
- Strongly disagree

* 15. Our managers and other decision-makers have the analytical capability to understand and interpret the data presented

- Strongly agree
- Agree
- Neither agree nor disagree
- Disagree
- Strongly disagree

* 16. Our analysts and managers are knowledgeable in maintenance methodologies and processes

- Strongly agree
- Agree
- Neither agree nor disagree
- Disagree
- Strongly disagree

* 17. We have identified areas of improvement for our data analytics capability

- Strongly agree
- Agree
- Neither agree nor disagree
- Disagree
- Strongly disagree

* 18. Our data strategy for maintenance management is aligned to achieving the goals of our overall organisational strategy

- Strongly agree
- Agree
- Neither agree nor disagree
- Disagree
- Strongly disagree

Section 3

In this section, you are required to best describe your organisation with regard to the ability to capitalise on opportunities for improvement, through insights derived from data analytics. Please rate the extent to which you agree or disagree with the following statements.

* 19. We are able to aggregate data from multiple sources into one system for analysis

- ◯ Strongly agree
- ◯ Agree
- ◯ Neither agree nor disagree
- ◯ Disagree
- ◯ Strongly disagree

* 20. We have multi-disciplinary meetings where decisions can be made using the presented data

- ◯ Strongly agree
- ◯ Agree
- ◯ Neither agree nor disagree
- ◯ Disagree
- ◯ Strongly disagree

* 21. When an opportunity or threat is identified using data analytics, our managers can be decisive about the course of action

- ◯ Strongly agree
- ◯ Agree
- ◯ Neither agree nor disagree
- ◯ Disagree
- ◯ Strongly disagree

* 22. When an opportunity or threat is identified using data analytics, our managers can make effective decisions about which course of action to pursue quickly

- ◯ Strongly agree
- ◯ Agree
- ◯ Neither agree nor disagree
- ◯ Disagree
- ◯ Strongly disagree

* 23. When an opportunity is identified using data analytics, our managers and other decision-makers can create a strategy to capitalise on the situation

- ◯ Strongly agree
- ◯ Agree
- ◯ Neither agree nor disagree
- ◯ Disagree
- ◯ Strongly disagree

* 24. Legacy systems and manual activities in our organisation prevents us from realising a benefit from our data

- ◯ Strongly agree
- ◯ Agree
- ◯ Neither agree nor disagree
- ◯ Disagree
- ◯ Strongly disagree

Section 4

In this section, you are required to best describe your organisation with regard to the ability to reconfigure processes and resources to quickly take advantage of opportunities derived from data analytics insights. Please rate the extent to which you agree or disagree with the following statements.

* 25. We embrace and encourage an environment for innovation and creativity

- ◯ Strongly agree
- ◯ Agree
- ◯ Neither agree nor disagree
- ◯ Disagree
- ◯ Strongly disagree

* 26. We are able to reallocate resources quickly to add value and insights to enhance and align the strategy between business units

- ◯ Strongly agree
- ◯ Agree
- ◯ Neither agree nor disagree
- ◯ Disagree
- ◯ Strongly disagree

* 27. We are able to adapt our processes to positively respond to both the changing business environment and changing stakeholder needs in a manner that retains alignment of the various activities within the organisation

- ◯ Strongly agree
- ◯ Agree
- ◯ Neither agree nor disagree
- ◯ Disagree
- ◯ Strongly disagree

* 28. When responding to a competitor's innovation, we can easily reconfigure our internal processes to reduce the cost of operation

- ◯ Strongly agree
- ◯ Agree
- ◯ Neither agree nor disagree
- ◯ Disagree
- ◯ Strongly disagree

* 29. Our organisation has better communication and coordination abilities than our peers and/or competitors

- ◯ Strongly agree
- ◯ Agree
- ◯ Neither agree nor disagree
- ◯ Disagree
- ◯ Strongly disagree

Section 5

In this section, you are required to best describe your organisation with regard to the ability to make good decisions using data analytics insights. Please rate the extent to which you agree or disagree with the following statements.

* 30. Our company communicates the results of organisational level analysis to workgroup and/or functional level operations to enable effective support for decision-making

- ◯ Strongly agree
- ◯ Agree
- ◯ Neither agree nor disagree
- ◯ Disagree
- ◯ Strongly disagree

* 31. Our company has a culture to facilitate long term strategic planning

- ◯ Strongly agree
- ◯ Agree
- ◯ Neither agree nor disagree
- ◯ Disagree
- ◯ Strongly disagree

* 32. Our company makes strategic decisions effectively

- ◯ Strongly agree
- ◯ Agree
- ◯ Neither agree nor disagree
- ◯ Disagree
- ◯ Strongly disagree

* 33. Our company reduces the time required to make decisions

- ◯ Strongly agree
- ◯ Agree
- ◯ Neither agree nor disagree
- ◯ Disagree
- ◯ Strongly disagree

* 34. Our company's organisational intelligence is designed to reach accurate and comprehensive information in a timely manner

- ◯ Strongly agree
- ◯ Agree
- ◯ Neither agree nor disagree
- ◯ Disagree
- ◯ Strongly disagree

* 35. Decisions are less consistent between various departments in our company

- ◯ Strongly agree
- ◯ Agree
- ◯ Neither agree nor disagree
- ◯ Disagree
- ◯ Strongly disagree

* 36. Our organisation insists that when decisions are made, they need to be supported largely by insights from our data analytics

- ◯ Strongly agree
- ◯ Agree
- ◯ Neither agree nor disagree
- ◯ Disagree
- ◯ Strongly disagree

Section 6

In this section, you are required to best describe your organisation with regard to the extent to which the business processes, including maintenance management business processes, are aligned in support to achieving the organisation's strategic objectives. Please rate the extent to which you agree or disagree with the following statements.

* 37. All roles and responsibilities are aligned to our business processes and our people understand how their role can affect the desired outputs

◯ Strongly agree
◯ Agree
◯ Neither agree nor disagree
◯ Disagree
◯ Strongly disagree

* 38. Areas for improvement are identified for enhancement and better alignment of our business processes

◯ Strongly agree
◯ Agree
◯ Neither agree nor disagree
◯ Disagree
◯ Strongly disagree

* 39. The percentage utilisation of tools, equipment and labour has been improved

◯ Strongly agree
◯ Agree
◯ Neither agree nor disagree
◯ Disagree
◯ Strongly disagree

* 40. We consistently meet the required demand, quality, and delivery expectations of our customers

◯ Strongly agree
◯ Agree
◯ Neither agree nor disagree
◯ Disagree
◯ Strongly disagree

* 41. We are consistently improving our operations for environmental sustainability

◯ Strongly agree
◯ Agree
◯ Neither agree nor disagree
◯ Disagree
◯ Strongly disagree

* 42. We are consistently improving our operating environment to eliminate safety and property incidents

◯ Strongly agree
◯ Agree
◯ Neither agree nor disagree
◯ Disagree
◯ Strongly disagree

* 43. We have observed improved asset availability in our operating environment

- ◯ Strongly agree
- ◯ Agree
- ◯ Neither agree nor disagree
- ◯ Disagree
- ◯ Strongly disagree

Section 7

In this section, you are required to best describe your organisation with regard to the performance over the past 3 years. Please rate the extent to which you agree or disagree with the following statements.

* 44. Through exploring and taking advantage of insights derived from our data analytics, we have observed improved customer retention during the last 3 years relative to our peers and/or competitors

- ◯ Strongly agree
- ◯ Agree
- ◯ Neither agree nor disagree
- ◯ Disagree
- ◯ Strongly disagree

* 45. Through exploring and taking advantage of insights derived from our data analytics, we have observed improved Sales Growth during the last 3 years relative to our peers and/or competitors

- ◯ Strongly agree
- ◯ Agree
- ◯ Neither agree nor disagree
- ◯ Disagree
- ◯ Strongly disagree

* 46. Through exploring and taking advantage of insights derived from our data analytics, we have observed improved Profitability during the last 3 years relative to our peers and/or competitors

- ◯ Strongly agree
- ◯ Agree
- ◯ Neither agree nor disagree
- ◯ Disagree
- ◯ Strongly disagree

* 47. Through exploring and taking advantage of insights derived from our data analytics, we have observed improved Return on Investment (ROI) from our data analytics system, during the last 3 years

- ◯ Strongly agree
- ◯ Agree
- ◯ Neither agree nor disagree
- ◯ Disagree
- ◯ Strongly disagree

* 48. Through exploring and taking advantage of insights derived from our data analytics, we have observed improved overall financial performance during the last 3 years relative to our peers and/or competitors

- ◯ Strongly agree
- ◯ Agree
- ◯ Neither agree nor disagree
- ◯ Disagree
- ◯ Strongly disagree

* 49. Through exploring and taking advantage of insights derived from our data analytics, our market share has increased in comparison to our competitors

- ◯ Strongly agree
- ◯ Agree
- ◯ Neither agree nor disagree
- ◯ Disagree
- ◯ Strongly disagree