Gordon Institute
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The influence of big data analytics capabilities on the performance of manufacturing firms

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Abstract

Rapid advances in technologies and complementary improvements in the Industrial Internet of Things have contributed to the exponential growth in data availability. This has resulted in a new level of dynamism and complexities manufacturing organisations must overcome to maintain performance levels, competitiveness and create value. Big data research has been primarily positioned as a conduit through which manufacturing organisations can improve performance through higher-order analytical techniques, which contribute to improved data-driven decision-making. Despite all the benefits that big data can have for manufacturing organisational performance, research on how big data should be implemented in these dynamic, continuously evolving environments is limited.

This research is theoretically positioned within the organisation's resource base view and dynamic capabilities. Organisational information technology capabilities (management, infrastructure and expert skills) are the foundational cornerstone of big data analytics capabilities influence performance in manufacturing organisations. This research has a particular focus on the impact process-orientated dynamic capabilities have on organisational performance. This is of significant importance to manufacturing organisations which consists of many distinct interrelated concurrent processes. Research into this construct is limited, and the findings could prove beneficial to organisations in overcoming current and future challenges that may impact the performance of the broader organisation.

This study analysed 165 online survey responses from South African manufacturing sector respondents. The research employed a higher-order formative-reflective PLS-SEM model. The findings of all three research hypothesis questions found that big data analytics capabilities positively influenced manufacturing organisations' performance and process-orientated dynamic capabilities. The study highlighted notable insights for manufacturing and academia through dynamic and process-orientated capabilities to extract value.

Keywords

Manufacturing, Big Data Analytics, Big Data Analytics Capabilities, Process orientated dynamic capabilities, 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.

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Chapter 1: Introduction

1.1 Primer on this research

Data generated from sensors monitoring equipment have been an ever-present feature on the factory floors of manufacturing organisations over the last few decades. Initially, sensors were only able to generate one-dimensional insights from the equipment the sensor was allocated to. Advances in technology, supported by the increase in the significance of the Internet, have allowed manufacturing operations to collate vast volumes of operational and commercial data to aid decision-making by the organisation (Tao et al., 2018b). Kitchin (2014) shares that big data analytics (BDA) represents a fundamental change in the manner which organisation will make decisions.

The increasing use of big data in organisations has been transformational on business models and influences both internal and external relationships (Rachinger et al., 2018). As the role and significance of BDA intensifies, manufacturing organisations are facing the challenge of establishing the best configuration of infrastructure, skills, and management to be leveraged in order to generate meaningful insights through which competitive advantages can be sustained in dynamic, continuously evolving business environments (Belhadi et al., 2019; Dubey et al., 2019a). BDA is recognised for its significant potential to identify opportunities of value and improve performance; however, many organisations need to clarify their big data strategy to achieve these objectives (Comuzzi & Patel, 2016).

There has been a concentrated effort into understanding the notion of big data analytics capabilities (BDAC) and its untapped value creation potential from a theoretical viewpoint, but organisations are still discovering how to identify, analyse and derive value from the underlying data (Belhadi et al., 2019; Dubey et al., 2019a; Garmaki et al., 2016). Kim et al. (2011) posit that to understand BDAC, organisations need to go beyond the data generated and focus on the organisation's core information technology (IT) capabilities from management, infrastructure and skills that can support in unleashing untapped opportunities that only big data analytics can discover.

Seminal research by Wamba et al. (2017) and Akter et al. (2016) highlight that organisations must fully understand the mechanisms underpinning BDA and, therefore, can learn how to fully extract value. This research intends to build on the information system research, which has established that an organisation's internal IT capability can improve organisational performance (Mikalef & Pateli, 2017). The influence of big data on daily life is irrefutable, as was illustrated during the COVID-19 pandemic when manufacturing companies relied on data to ensure that essential medical and consumer goods could reach consumers.

Rodrik (2018) shares that the rapid advances in technology will undoubtedly minimise the competitive positions of manufacturing organisations and the growth potential of developing economies such as South Africa. This research study will explore big data as a latent strategic resource which requires the mobilisation of internal organisation capabilities. The study will be an exploration of the association between the IT capabilities of manufacturing organisations and their performance within a data-determined ecosystem.

1.2 Research problem

The accelerated development of all technology-related segments and unprecedented growth in the Industrial Internet of Things (IIoT) has created a restrictive global network through which suppliers and all manufacturers compete for market share (Belhadi et al., 2019). The new status quo has resulted in organisations developing innovative technology-driven strategic solutions to overcome the new competitive complexities (Gupta & George, 2016; Dubey et al., 2019a; Belhadi et al., 2019). Manufacturing organisations have no choice but to transcend their established production management processes or face the threat of not being competitive (Cheng et al., 2018).

Manufacturing organisations have always embraced innovation as a means to improve organisational performance. Singh and Sharma (2020) have tracked the innovation path of manufacturing over the last four industrial development cycles and have clearly illustrated how manufacturing has continuously adapted to the evolving technological frontier. This industry’s adaptive capabilities and ability to accept change have resulted in the industry transitioning from the human and animal production system to sophisticated cyber-physical systems that can replicate physical environments digitally (Mohajan, 2019a; Sharma & Singh, 2020; Dogaru, 2020; ElMaraghy et al., 2021).

The advances in technology, specifically monitoring and sensor equipment, have resulted in organisations being able to collect significant volumes of data or big data. Manufacturing organisations' challenge is generating value-adding insights from the data under management (Belhadi et al., 2019; Comuzzi & Patel, 2016; Dubey et al., 2019a; Wamba et al., 2017). Manufacturing organisations can employ big data effectively, characterised by high capital expenditures and stringent time constraints on production targets. The intensity and stringent adherence to time-monitored processes in order to be the low-cost competitive leader highlights the need for BDA techniques. Despite the data being available for decision-making, manufacturing organisations have not fully defined how to integrate BDA into the manufacturing processes (Wamba et al., 2015; Belhadi et al., 2019; Kwon et al., 2014).

Big data relates to the volume of data collected from numerous resources and stored for further analysis (Gupta & George., 2016; Acharya et al., 2018; Mikalef et al., 2020). Kwon et al. (2014) describe BDA as a combination of organisational IT capabilities and analytical procedures that are applicable to large data sets which identify insights and opportunities to improve the competitive position of the organisation. BDA is the transmission mechanism that allows manufacturing organisations to transition from established processes to technology-enabled intelligent processes, which supports organisations in overcoming the complexities in the form of big data and the operating environment (Li et al., 2022).

Given the rapid changes in the business landscape, manufacturing organisations need to be aware of how technology is changing, employing an adaptive approach and incrementally evolving big data strategy across all business spheres to ensure no value is lost (ElMaraghy et al., 2021). Manufacturing organisations rely on many simultaneous processes that all require constant monitoring. It is these distinctive process orientation characteristics that differentiate manufacturing organisations apart from other organisations and where the most significant challenge lies as most companies do not know how to utilise BDA to improve distinctive processes that need to have high-performance levels to safeguard organisational competitiveness in this dynamic environment (Belhadi et al., 2019; Wamba et al., 2017; Kim et al., 2011; Kwon et al., 2014).

The challenge of the research is to identify the resources and dynamic capabilities manufacturing requires to ensure that the BDA strategy is effective at generating value and improving individual processes and organisational performance. This research investigates BDAC and its influence on the performance of manufacturing organisations from the lens of IT capabilities, focusing on managing the IT capabilities, organisational infrastructure and the skill levels of employees. The above three constructs combined constitute BDAC, and from this perspective, the research will attempt to understand how firm performance (FPer) and process-orientated capabilities are impacted.

1.3 Objective of this study

The objective of this research is to develop a framework to understand how BDAC influences strategic decision-making regarding processes-orientated dynamic capabilities (PODC) and ultimately influences FPer. Research into how manufacturing organisations develop organisation-wide big data strategies to build value is limited (Dubey et al.,2019a; Belhadi et al., 2019; Belhadi et al., 2019). Through research rigour, the objective of the study is to identify the key IT capabilities manufacturing organisations require to implement BDA strategies that improve FPer competitiveness and generate value in an active, evolving global business environment.

This research is focused on how manufacturing organisations can create strategies that best utilise IT resource capabilities, and as such, the following research objectives are derived.

1. Identify what are the key IT capabilities that underpin BDAC in manufacturing organisations,
2. Establish the optimal mix of capabilities that can work in harmony and be fully leveraged by the organisation to improve FPer,
3. Identify how the capabilities can best be used in specifically identified processes to improve the performance of that process and the broader organisation.

This research is bound to establish a base from which BDAC and PODC influence the performance of manufacturing organisations through a reflective evaluation of the dynamism of organisational IT capabilities.

1.4 Theoretical reasoning for this research

Over the past few years, a significant volume of research has concentrated on the connection between big data, IT capabilities and FPer (Wamba et al., 2015; Comuzzi & Patel, 2016; Mikalef & Pateli, 2017). It is a natural association for big data to be linked with organisational IT capabilities, and these relationships have been evaluated using the resource base and dynamic capabilities theoretical frameworks (Kim et al., 2011; Akter et al., 2016; Dubey et al., 2019a; Lin & Wu, 2014). Research exploring how to consolidate big data dynamic capabilities successfully so that organisations can improve FPer is still in the early stages of the research curve (Kim et al., 2011; Wamba et al.,2017; Akter et al., 2016).

The research has expanded the baseline understanding of how BDAC can improve FPer with a continuously evolving ecosystem. While attempts have been made to explore dynamic capabilities from an organisational context, there is no prescribed guiding framework with a manufacturing viewpoint (Belhadi et al., 2019). The research undertaken by Wamba et al. (2017), Akter et al. (2016) and even Gupta and George (2016), although similar, did not evaluate the relationship from a designated process-orientated industry point of view, and it is at this point that research differentiated itself. The justification for focusing on the manufacturing organisations is grounded in the view that manufacturing organisations must continuously adapt to survive (Sharma & Singh, 2020; ElMaraghy et al., 2020). In addition, the manufacturing organisations are process-orientated, and testing big data strategies on smaller processes within the organisation would allow the company to develop a big data strategy that can support the entire organisation. Understanding how BDAC influences the manufacturing process needs to be better developed (Wamba et al., 2017; Kim et al., 2011; Belhadi et al., 2019). This is where the research is bound to make an academic contribution.

1.5 Relevance to manufacturing organisations

The significance of big data and its potential influence on organisational performance and competitiveness has been discussed at length over the past few years (Wamba et al., 2015; Dubey et al., 2019a). Literature on big data positions the topic as the next seismic shift that will determine all aspects of organisational strategy, management and operations

(Comuzzi & Patel, 2016; Belhadi et al., 2019; Wamba et al., 2015). Big data can support organisations in achieving higher investment returns using big data to improve decision-making by employing higher-order analytical methods of analysis (Wamba et al., 2015; McAfee et al., 2012).

Notwithstanding all factors favouring the use of big data in organisations. Organisations face many challenges in obtaining the expected benefits associated with big data because organisational management structures need to gain experience and knowledge on utilising big data resources and capabilities (Vassakis et al., 2018). Raut et al. (2021) reinforces this perspective by identifying senior management structures in manufacturing organisations as needing to be more supportive of big data projects regarding leadership and finances and understanding how big data can positively impact organisations. Big data's significance needs to be interwoven into all organisational structures to succeed.

This research is positioned in the manufacturing industry to support the sector in overcoming internal operational challenges in the present but also use the learning to overcome future obstacles. The research aims to identify the critical management, infrastructure, and expert IT capabilities required to ensure that manufacturing companies can capitalise on vast data resources under management. In addition, this study aims to understand how effectively BDAC influences PODC. This is of significant value to manufacturing organisations because a single bottleneck in an integrated manufacturing process can significantly influence performance and competitiveness.

From a manufacturing perspective, big data should anticipate expected production outages based on past trends. Data generated from singular processes should be integrated into a larger data set that can provide value chain-wide insight that is of commercial benefit to the organisation.

1.6 Report structure

This research is developed in the following sequence:

Chapter 1: Discusses the research topic and provides context for selecting the area of research and chosen boundary parameters, the research challenge, the research objective, academic justification and business relevance.

Chapter 2: Begins with a review of the evolution of the manufacturing industry and highlights factors that could influence its future. The chapter reviews the underlying theories that support the research construct. The chapter concludes by evaluating the salient topics relating to dynamic capabilities, PODC, BDAC and the performance of manufacturing firms.

Chapter 3: Describes the hypothesis questions developed from the literature review chapter.

Chapter 4: Outlines the method by which this research was undertaken. The chapter highlights the research design, justifies the sample population, the level of aggregation of the sample population, discusses the survey instrument, the data collection process and an overview of the statistical method used to analyse the data.

Chapter 5: Pertains to the demographic analysis and hypothesis test results. The hypothesis tests were undertaken using the partial least squares method, which entails testing the outer and inner structural models and evaluating each hypothesis question.

Chapter 6: Discusses the results from analysis provided in Chapter 5. Highlighting critical inferences from the sample survey and in-depth review of each research question.

Chapter 7: Closes the research report with an overview of the findings for each of the three hypothesis questions, in addition to proposing new avenues of research, implications for organisations, contributing to the growth in the current knowledge base and expanding of factors restricting this research.

Chapter 2: Literature Review

2.1 Introduction

The literature underpinning this research is focused on understanding BDAC's influence on manufacturing firm performance. Big data has been described as the mechanism to improve firm FPer. The execution of how big data can enhance FPer remains vague as organisational complexities take precedence over developing dynamic capabilities due to the emergence of global value chains. Organisational competitiveness is now measured worldwide as such, priorities shift and developing dynamic capabilities become secondary. This research develops a combination of hypothesised perspectives on how data-driven ecosystems can improve the performance of manufacturing firms.

The chapter presents an overview of the current, emerging, seminal and theoretical literature pertaining to the research objectives and, as such, will be segmented into two broad themes. The first theme will focus on the origin and evolution of manufacturing. Most research on BDAC is mainly focused on a specific challenge rather than an industry. In contrast, there is no prescribed definition of manufacturing activities. This theme will focus on the evolution of manufacturing through the critical Industrial Revolution (IR) cycles and how they have influenced manufacturing systems and society. The final components of this theme will explore the future of manufacturing and expected challenges. This serves as the bridge in which this chapter can focus on the second literature theme relating to BDAC and how it can improve organisational performance. The section will begin with a review of the theories underpinning BDAC and subsequently progress to a review of research constructs. Illustrating how BDAC influences constructs on developing dynamic capabilities, which affects business processes and, ultimately, FPer. The purpose of the literature review is to validate that manufacturing is as vital today as it was during the Industrial Revolution and why BDAC is a crucial mechanism to improve organisational performance in an environmentally conscious world.

2.2 Evolution of manufacturing through the IR cycles

Manufacturing has long been regarded as a key driver of a country’s economic and social development (Haraguchi et al., 2017; Kelly et al., 2023). This section of the literature review explores the influence of manufacturing across the socioeconomic spectrum through global IR cycles. Sharma and Singh (2020) classify IR cycles into four distinct periods. These periods will form sub-sections through which the evolution of manufacturing will be reviewed.

2.2.1 The First IR

The first IR occurred during the eighteenth century in England. This period represents a significant turning point in the way humanity lived. Before this period, people worldwide mostly lived a rural subsistence way of life. The IR represented a considerable shift from human and animal-powered production to coal-powered machinery (Mohajan, 2019a). The coal powered steam engine and weaving loom machine were both invented during this period (Mohajan, 2019a; Sharma & Singh, 2020). These two inventions were significant machinery that allowed for a dynamic shift in how the world operated (Kelly et al.,2023). These two pieces of machinery transformed organised labour and significantly improved production (Mohajan, 2019a; Kelly et al., 2023).

The steam engine influenced many industries, but the most significant change occurred in the British textile industry. The spinning looms powered by coal fired steam engines significantly increased textile production. This resulted in the creation of factories that required artisanal labour. This resulted in a labour migration from rural to urban areas as workers transitioned from rural earners to waged employees (Mohajan, 2019a; Sharma & Singh, 2020; Kelly et al., 2023). This migration also contributed to the significant development in infrastructure with factories, cities and formalised service institutions (Mohajan a, 2019; Sharma & Singh, 2020; Kelly et al., 2023).

Shifts in the socioeconomic paradigm were not the only changes during the IR. There was now a need to manage and organise workplace practices to ensure that production output and FPer were sustained (Sharma & Singh, 2020). The factory system represented a significant change to manual production methods. The factory system resulted in a clustering of related activities, which influenced the allocation of investment, labour, machinery and innovation that supported the production of finished products (Geraghty, 2007). Trace elements of early manufacturing systems can still be prevalent in present manufacturing operations.

2.2.2 The Second IR

The first IR originated in England, but its influence spanned the globe. The second IR is considered the American IR. The first IR was coal-powered, and the second IR was powered by electricity (Mohajan, 2019b; Sharma & Singh, 2020). The second IR is significant because of the many innovations it generated during the nineteenth century, which contributed to the rapid growth of the manufacturing industry (Agarwal & Agarwal, 2017; Sharma & Singh, 2020).

The electrification of manufacturing operations brought forth opportunities to improve overall productivity through continuous innovation (Atkeson & Kehoe, 2001; Sharma & Singh, 2020). Technological innovations during this period were identifiable across industries, with growth in the petroleum, chemical, and automobile industry (Mohajan, 2019b). Innovations in steel manufacturing contributed to the expansion of railway infrastructure, which meant that products could reach customers faster. Adoption of mass production and the introduction of production lines were implemented as producers sought to increase productivity (Atkeson & Kehoe, 2001; Mohajan, 2019b; Sharma & Singh, 2020). According to Sharma and Singh (2020), mass production created research and development departments and interchangeable components on manufacturing lines because factories had to be operational due to increased competition.

The second IR also resulted in a transformation of financial institutions as banks now accepted deposits from workers for savings (Agarwal & Agarwal, 2017). With America being the epicentre of this IR, many workers migrated to America from all corners of the world. Manufacturing improvements also enhanced living standards as infrastructure improved, and many households had access to running water and indoor plumbing. This innovation spillover also contributed to an improvement in medicine and medical technology, which increased the living age (Mohajan, 2019b).

2.2.3 The Third IR

The preceding two sections on the first and second IR illustrate how manufacturing evolved from human and animal to steam and electricity. These innovations resulted in the formation of the factory system, standardised production lines, and improved infrastructure for factories and adjacent towns and cities, which were serviced through mass production (Mohajan, 2021). The third IR, which started in the 1950s, represents a period in which mechanical, electronic and digital innovations converge to support improvements in manufacturing efficiency (Troxler, 2013; Taalbi, 2019; Sharma & Singh, 2020; Mohajan, 2021).

The third industrial revolution occurred at a point in history when the world was undergoing significant change. The oil crisis during 1970s, combined with the growth in consumerism, necessitated that manufacturers automate a significant proportion of production lines to reduce costs and improve efficiencies (Taalbi, 2019; Sharma & Singh, 2020; Mohajan, 2021). Innovations in electronic devices, such as transistors and circuit boards, improved the efficiency and accuracy of machinery. The advances and integration of electronics in manufacturing systems prompted many producers to cut costs and move manufacturing operations to developing countries with lower labour rates (Sharma & Singh, 2020; Mohajan, 2021). Manufacturers now could automate a significant proportion of production and utilise semi-skilled labour for tasks that could not be automated at a lower labour rate. As manufacturing operations became more dispersed across the world, there was a need to develop supply chain management practices (Sharma & Singh, 2020). The dispersion of manufacturing operations to different locations was only possible due to the significant advances in digital communications through the creation of the internet, which led to emails, mobile phones, cloud computing and data accumulation, allowing faster decision making.

The third industrial revolution significantly impacted global economic growth and development as countries now traded more easily through improved logistics infrastructure and more efficient modes of transport. Living standards, life expectancy and entrepreneurship increased worldwide (Mohajan, 2021).

2.2.4 The Fourth IR

The ongoing fourth IR further develops advancements made during the third IR. The critical distinction between the two IR cycles is that the current cycle accelerated advances in digital technologies have become deeply embedded in all aspects of manufacturing administrative and operational systems (Sorooshian & Panigrahi, 2020; Sharma & Singh, 2020; Rymarczyk, 2020; Dogaru, 2020). Advances in information communication and technology (ICT) are the main instruments through which new digital technologies are introduced in manufacturing operations (Sharma & Singh, 2020; Dogaru, 2020).

During this period, there have been significant advancements in software and sensor technologies. Connecting to the internet allows factories to operate smartly and efficiently. (Sharma & Singh, 2020; Rymarczyk, 2020). Intuitively, the fourth IR operates on the premise that the operational performance of machines is monitored through sensors connected to the internet. The type of monitoring is called the IoT (Sharma & Singh, 2020). Manufacturing competitiveness relies on more than just the monitoring of machines. A consequence of globalisation implies that manufacturing companies need lean supply chains, and the IIoT provides a real-time link between vendors, creditors and operations. These information flows generate data that enable organisations to become more intelligent and remain competitive (Sharma & Singh, 2020; Rymarczyk, 2020).

Dogaru (2020) presents the view that the fourth IR will raise living standards through the spillover of technologies. New technologies' accelerated growth and sophistication have presented a skills challenge to organisations (Ellitan, 2020). Prior IRs have always contributed to a positive impact on economic development. The influence of digital technologies on economic development during this IR still needs to be clarified, as employment levels can be reduced due to increased automation because of the skills deficit (Sutherland, 2020). Organisations, too, are at risk of becoming uncompetitive and limiting potential revenues due to the skills shortage.

2.2.5 Summary of IR cycles

In summary, IR have made a significant contribution to the quality of human life through technological innovation. IR has evolved as technology has developed, starting with the steam engine, which created factories and the need for infrastructure development (Mohajan, 2019a). Each cycle of IR has required manufacturing firms to continuously innovate to improve performance and remain competitive. A compelling case exists for using data strategically due to globalisation and the rapid integration of ICT into manufacturing. The literature review will now explore the future of manufacturing post the fourth IR.

2.3 Future of manufacturing

The previous section illustrated the evolution of manufacturing systems from animal power to highly integrated digital platforms that relay information instantaneously through the IoT. The fourth IR is viewed as a period in which industry built on and enhanced the innovations of the third IR (Sharma & Singh, 2020; ElMaraghy et al., 2021). Manufacturing of the future is expected to be complex as organisations can no longer rely on any form of competitive advantage, as in past IR. Manufacturing organisations now face numerous ecosystem challenges due to increased digital interconnectedness and complex global value chains.

Manufacturing systems continuously evolve, and the organisational ecosystem no longer follows the traditional buy-make-sell model. The traditional approach of purchasing raw materials and converting the materials via manufacturing processes into finished products to sell is no longer applicable. Manufacturing ecosystems of the future resemble the characteristics outlined in Figure 2.1. Manufacturing organisations of the future must be aware of the trends, drivers, and enabling attributes that influence technology adoption, product development, manufacturing processes, and business strategies (ElMaraghy et al., 2021).

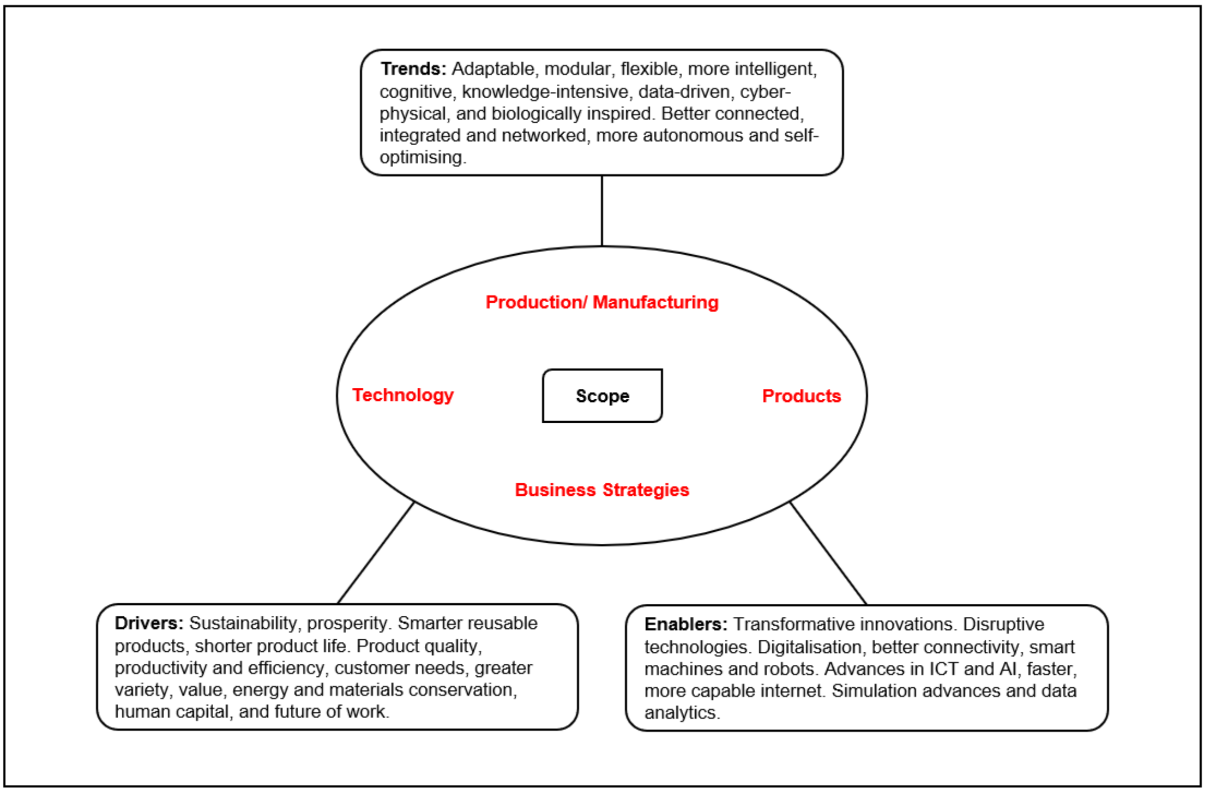

Figure 2.1: Manufacturing systems evolution trends and scope

Adapted from “ElMaraghy, Hoda, Laszlo Monostori, Guenther Schuh, and Waguih ElMaraghy. "Evolution and future of manufacturing systems." CIRP Annals 70, no. 2 (2021): 635-658.

This literature review section examines how issues around sustainable manufacturing, technology disruptors, and the influence of global value chains impact organisational performance. The purpose of the section is twofold: firstly, review recent literature on emerging issues that could impact future manufacturing. The second component of this section demonstrates the significant role BDAC will have in overcoming these future challenges.

2.3.1 Disruptive technologies

The fourth IR was broad in scope, focusing on a range of technological innovations designed to increase levels of ICT within organisations, which resulted in the creation of a globally interconnected cyber-physical ecosystem. The new wave of disruptive technologies is expected to revolutionise manufacturing organisations' operations and significantly influence value chains from sourcing materials, logistics and consumer preferences (Choi et al., 2022; Hughes et al., 2022). This proposition contrasts past IR, where there was always a positive external spillover that benefited the human condition

(Choi et al., 2022). This section intends to review the recent literature on the leading disruptive technologies and evaluate how these big data-powered technologies influence organisational performance and society. Choi et al. (2022) outline the main archetypes of disruptive technologies that will impact manufacturing organisations and society in future in Figure 2.2.

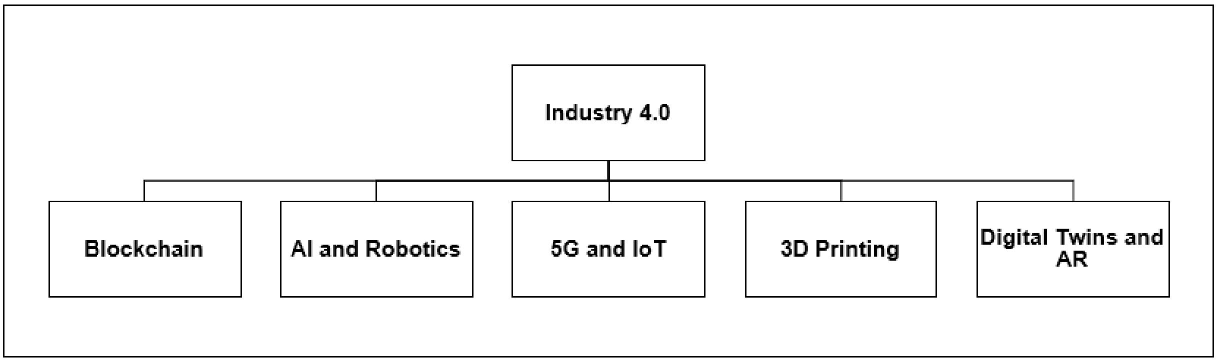

Figure 2.2: Main disruptive technologies.
Choi, Kumar, Yue, and Chan: “Disruptive Technologies and Operations Management in the Industry 4.0 Era and Beyond”. *Production and Operations Management* 31(1), pp. 9–31.

2.3.1.1 Blockchain

Blockchain technology refers to a distributed digital ledger connected to a highly secure network of computers (Abeyratne & Monfared, 2016; Leng et al., 2020; Lohmer & Lasch, 2020; Kurpjuweit et al., 2021; Choi et al., 2022). Blockchain technology was initially used in the financial industry as the foundation for cryptocurrency. The high degree of security in the technology has expanded its applications to include aspects of design, manufacturing operations management and supply chains (Abeyratne & Monfared, 2016). Trusted partners can securely analyse BDAC generated from IoT to manage risk, quality and FPer (Lohmer & Lasch, 2020; Kurpjuweit et al., 2021). There are numerous positives to employing blockchain technologies, such as accelerating sustainable manufacturing practices and overcoming global value chain obstacles. Caveats to consider when implementing blockchain technology are limited regulation. Governance protocols need to be developed. There is no prescribed method to distribute the cost across the network, and sharing information may reduce the organisation's comparative advantage (Choi et al., 2022).

2.3.1.2 Artificial intelligence (AI) and robotics

Integrating big data, AI, and robotics can create a robust ecosystem. This ecosystem is where human cognitive abilities, powered by big data along with AI machine learning algorithms, can efficiently harness the power of robotics. As a result, it can increase output and improve FPer cost-effectively. AI-based applications can analyse trends and patterns in big data that traditional approaches do not identify (Arinez et al., 2020). There are many AI and AI-powered robotics applications, like collecting data from IoT sensors to analyse production levels, historical breakdown patterns and automated maintenance founded on AI data (Arinez et al., 2020; Choi et al., 2022). AI can also improve logistics, inventory control, production management and business intelligence, thereby improving decision-making (Arinez et al., 2020; Chien et al., 2020; Choi et al., 2022). By all accounts, AI can positively improve manufacturing FPer, but with all innovations, there is always a significant upfront investment cost. AI-powered robots also present a legal liability for organisations should an accident occur (Choi et al., 2022). While AI presents a tremendous opportunity for cost reduction, conversely, there is also potential for significant reductions in staff, which will meet opposition in most countries.

2.3.1.3 Five G (5G) and IoT

Wireless network infrastructure is an integral component in ensuring manufacturing firms maintain levels of competitive FPer (Cheng et al., 2018a; Choi et al., 2022). Five G is an integral component in ensuring that organisations can capitalise on the full potential of big data transmitted from the IoT (Cheng et al., 2018b). Five G enables greater automation across the value chain, improving FPer and cost efficiency. Like AI, the initial investment is significant, and staff reductions are possible.

2.3.1.4 Three D (3D) printing

Three-D printing allows designers to customise and innovate complex new products with minimal waste and reduced cost (Ngo et al., 2018; Choi et al., 2022). This process entails printing levels of materials successively above of each other (Ngo et al., 2018). Advances in printing technologies now allow printing across various materials, ranging from alloys to metals and polymers. The wide range of source materials allows for printing complex designs across industries and applications. This flexibility lowers the cost of prototyping and can even be used in cases where speciality parts are required to mitigate supply chain risk (Choi et al., 2022). While this technology has many benefits, it has yet to be ready for mass production as the cost is too high. BDAC can analyse data for material and design defects and expedite the product life cycle, thus allowing for a greater degree of personalisation in future.

2.3.1.5 Digital twinning and augmented reality (AR)

Throughout the fourth IR, physical and cyber manufacturing systems were integrated into one digital ecosystem (Kritzinger et al., 2018; Choi et al.,2022). Kritzinger et al. (2018) explain digital twins as cyber replications of physical systems generated from data collected from the physical system through the IIoT. Both systems are linked with digital twin learning using big data AI machine learning models to improve decision-making (Tao et al., 2018a; Helu,2020; Choi et al.,2022). Digital twinning is an effective tool for manufacturing organisations to improve FPer. From an operational perspective, data is analysed to optimise processes, monitor equipment, and prevent breakdowns. New plant designs and simulated operational throughput can reduce fixed-cost investments. Real-time monitoring would improve customer value and ensure no repeated supply chain disruptions. This technology, while beneficial, still cannot fully replicate real-world outcomes.

2.3.2 Sustainable manufacturing systems

In recent decades, the swift advancement of technology has contributed to the significant and continuous expansion of manufacturing operations as companies strive to enhance their output to meet the public's desire for goods that better their lives (McLean et al., 2017; Swarnakar et al., 2021). Manufacturing organisations incur significant sustainability-related challenges across their value chains from operational bi-products, supply chain and customer consumption behaviour (Ahmad et al., 2018). The global adoption of the United Nations Sustainable Development Goals has segmented social, economic and environmental sustainability challenges that all organisations have to support in overcoming. Manufacturing activities are harmful to the environment. Manufacturers must develop sustainable strategies to remain competitive and maintain organisational performance across their value chains (Ren et al.,2019; Leng et al., 2020).

Sustainable development strategies must be identifiable across the value chain and product life cycles for an organisation to improve organisational performance and competitiveness (Dubey et al., 2016; Ren et al., 2019). The shift towards cyber-physical systems has enabled manufacturing organisations to accumulate vast amounts of big data through the IIoT to access smart manufacturing platforms and reduce their environmental impact across a spectrum of activities relating to material sourcing, process optimisation, supply chain inefficiencies and new product development aimed at a growing sustainably consumer base (Majeed et al., 2021). Three-D printing and additive manufacturing allow for faster complex prototyping at lower costs. In contrast, insights attained from big data allow organisations to adopt sustainable sourcing channels, improve operational processes, reducing waste and negative externalities from the production process (Ren et., 2019; Raut et al.,2019; Leng et al., 2020; Majeed et al., 2021). The current global environment, which has an environmental, social and governance (ESG) centric focus, strongly advocates for faster integration of BDAC to empower smart manufacturing applications and holistic decision-making.

2.3.3 Influence of disruptive technologies on global value chains (GVC)

Improvements in ICT and modality that happened during the third IR allowed multinational corporations (MNC) to segment production processes across geographical regions, therefore creating value by reducing costs and improving FPer (Hernández & Pedersen, 2017; Taalbi, 2019; Sharma & Singh, 2020; Mohajan, 2021; Antràs & Chor, 2022). Timmer et al. (2014) present an intuitive, simplistic description of a global value chain (GVC) as a process where the last step in the manufacturing process occurs before reaching the final consumer. There are many approaches to configuring GVC, which are based on the nature of the product. Aspects like proximity to raw materials, labour cost based on the manufacturing stage, cost of manufacturing, marketing and support services are all considered when segmenting a GVC (Hernández & Pedersen, 2017).

The accelerated sophistication with which disruptive technologies have emerged is bound to significantly change the structure of GVC (Strange & Zucchella, 2017). Implementing

IIoT and blockchain applications will improve an organisation's overall performance with access to reliable real-time data from sensors on machines and enterprise resource software to improve decision-making across regions (Strange & Zucchella, 2017; Egwuonwu et al., 2022). MNCs have traditionally used emerging economies for labour-intensive activities; improvement in robotics will signal a shift in the value chain as MNCs look to control costs and performance with reliable and sustainable robotics. AI, additive manufacturing and digital twinning will become integral tools that ensure organisations maintain competitive performance in the GVC with an increasing number of sustainable, aware customers (Strange & Zucchella, 2017; Ahmad et al., 2018; Leng et al., 2020; Majeed et al., 2021).

2.3.4 Consolidating views on the future of manufacturing

Manufacturing activities have come a long way since the coal-powered steam-powered steam of the eighteenth century. Technological innovations have improved living standards, infrastructure and multiple reliable modes of transport (Mohajan, 2019 a; Mohajan, 2019 b; Sharma & Singh, 2020). Advances in ICT led to the first phase of digital integration into manufacturing activities during the third IR (Sharma & Singh, 2020; Dogaru, 2020). This integration intensified during the fourth IR with the introduction of cyber-physical systems. Manufacturing of the future is powered by the IoT, which has transformed how MNCs operate and compete on a global scale (Choi et al., 2022; Hughes et al., 2022)

There has been much research on BDAC in recent years, with many organisations believing that insights obtained from big data will improve FPer. The first section in this chapter chronicled the evolution of manufacturing and how technological innovation improved performance and competitiveness. The following sections review the underlying framework of BDAC and its influence on an organisation's performance. The remaining literature is segmented because research on the use of BDA in manufacturing is underdeveloped (Ren et al.,2019; Belhadi et al., 2019).

2.4 Understanding Data, Big data, BDA, BDAC: a manufacturing perspective

The previous section of the literature review demonstrated how technological advancements have enhanced the productivity of manufacturing companies. The capability to obtain and use data in decision-making purposes is now considered a fundamental tool for improving business performance and competitiveness. As data is a significant topic across various disciplines, it is important to clarify key terms to prevent confusion regarding their meaning (Mikalef et al., 2018).

2.4.1 Data

Data is the accumulation of digital information from structured and unstructured activities that occur within and outside of an organisation (Grover et al., 2018; Baig et al.,2019). This indicates that data can originate from a spectrum of sources ranging from documents, sensors, enterprise resource system, video and audio to name a few (Baig et al.;2019; Sorooshian & Panigrahi, 2020; Sharma & Singh, 2020; Rymarczyk, 2020; Dogaru, 2020). With a variety of tools and applications to collect data, there has been an acceleration in the volume of data available for data driven decision making (DDDM) (Sharma & Singh, 2020; Rymarczyk, 2020). The expansion in the volume of data is now termed big data.

2.4.2 Big data

Big data is described as large, real-time, intricate data which requires astute management and relevant situational analytical techniques to develop value-adding management insights (Acharya et al., 2018; Mikalef et al., 2018; Dubey et al., 2019a; Mikalef et al., 2020). Schroeck et al. (2012) define big data as combining four Vs: volume, velocity, veracity, and variety. 'Volume' describes the quantity of data that can be managed and warehoused, 'Velocity' is the pace with which data can be collected, 'Veracity' refers to the integrity of the information and 'Variety' infers the number of different sources that the data collected from (Mikalef et al., 2018; Grover et al., 2018). This definition helps organisations to create opportunities that give them a competitive advantage in a global marketplace. BDA is data that is modified through analytical data techniques, with the findings visualised in a way that identifies and creates opportunities for organisations to attain material value (Gantz & Reinsel, 2012; Wamba et al., 2017). To benefit from BDA and achieve a competitive advantage, organizations must continuously develop BDAC.

2.4.3 BDAC

Mikalef et al., 2020 believe that firms use human capital to manage and analyse data, creating valuable insights. BDAC are essential skills through which organisational strategies are identified, developed and achieved, ensuring that financial and competitive performance is realised. More than just allocating financial resources is required to build the required BDAC. Organisations must have a holistic strategy that is innovative in identifying resources and merging capabilities to grow BDAC and improve organisational performance and competitiveness (Gupta & George., 2016; Mikalef et al., 2018). This approach is in adherence to the RBV, which guides organisations on identifying and allocating resources so that the resources under management can improve FPer and sustain competitiveness.

2.5 Resource based view (RBV)

RBV operates around the proposition that organisations can realise competitive positions by producing strategic resource capabilities (Barney, 1991; Dubey et al., 2019a; Mikalef et al., 2020). Gupta and George (2016) present the view that dynamic capabilities are developed within RBV as a distinctive combination of resources (tangible and intangible) that are identified and combined to assist the firm in improving overall FPer. The resource-based model outlined in Peteraf (1993) posits that an organisation's long-term profitability cannot exclusively be attributable to market fluctuations. In the context of manufacturing organisations, long-term profitability depends on how resources within organisations are managed to improve FPer (Ashrafi et al., 2019; Kristoffersen et al., 2021). Resources need to be scarce, unique, immobile and most importantly, in demand to avoid the product being replicated (Peteraf, 1993; Ashrafi et al., 2019; Kristoffersen et al., 2021). Intangible assets refer to organisational culture, human capital and management expertise (Gupta & George, 2016; Kristoffersen et al., 2021).

RBV is the platform most suited to this research because manufacturing organisations operate globally. Organisations must first understand the resources under management and how best to utilise them to capitalise on decision making underpinned by data (Gupta & George, 2016).

Research suggests that RBV improves organisational performance (Lin & Wu, 2014), but having the assets alone is insufficient to improve economic returns. Tangible, intangible and human capital resources must continuously be strategically developed to ensure that FPer continuously improves (Gupta & George., 2016; Acharya et al., 2018; Mikalef et al., 2018; Dubey et al., 2019a; Mikalef et al., 2020; Kristoffersen et al., 2021). RBV research postulates that organisational capabilities are elevated variables that require strategically consolidating resources (Mikalef et al., 2018; Dubey et al., 2019a). An overview of the RBV structure in Figure 2.3 will be explained in the next paragraph.

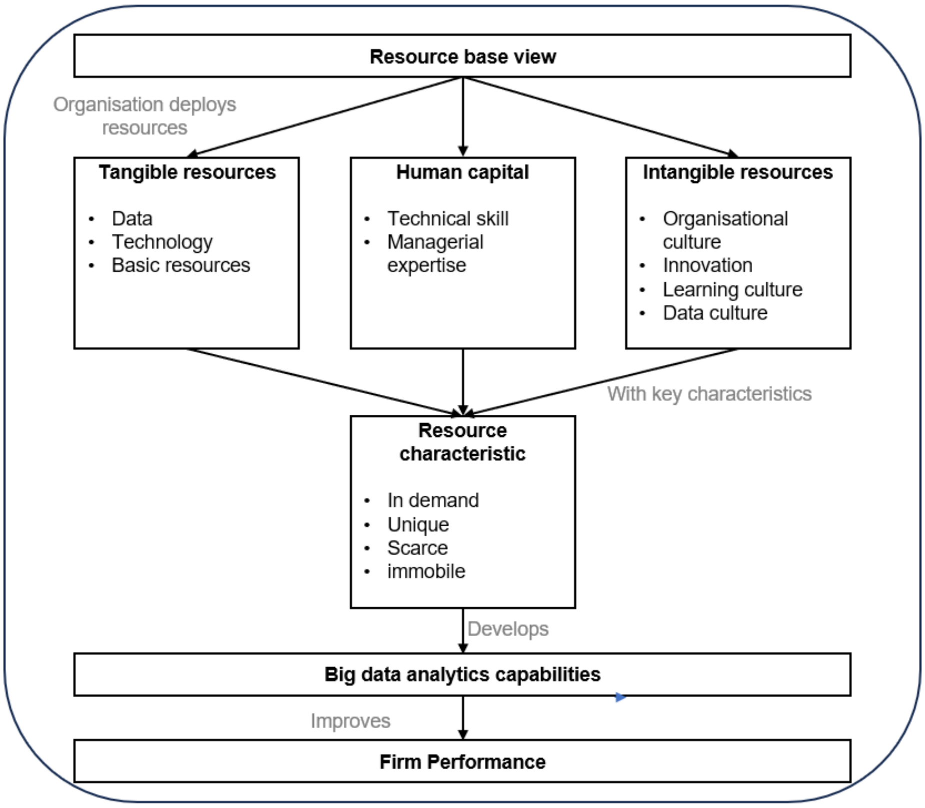

Figure 2.3: RBV framework

Adapted from “Gupta, M., & George, J. F. (2016). Toward the development of a big data analytics capability. Information & Management, 53(8), 1049-1064”.

Tangible resources

Tangible resources can be freely acquired, disposed, and identified in an organisation’s financial statements. These resources are available to comparable organisations and do not yield any form of competitive advantage individually but are required to create resource capabilities (Gupta & George., 2016). Data differentiation can create competition over competitors (Mikalef et al., 2020) and support firms in reducing costs (Dubey et al., 2016). It has been previously mentioned that it can originate from various sources (Baig et al., 2019; Sorooshian & Panigrahi, 2020; Sharma & Singh, 2020; Rymarczyk, 2020; Dogaru, 2020). For BDAC tools to support manufacturing activities in the future, a significant financial investment is required to procure and set up the technology ecosystems (Sharma & Singh, 2020; Dubey et al., 2019a). While these platforms may not be one of a kind, they empower DDDM when amalgamated with other resources (Gupta & George., 2016; Dubey et al., 2019a).

Human capital

In the big data world, technical skills that support the implementation of BDAC are required to improve FPer and competitiveness (Dubey., 2019a; Kristoffersen et al., 2021). In this model, skills are segmented into technical and managerial. Technical skills include managing data storage and statistically building models to forecast and develop quality insights that empower DDDM with organisations' available digital platforms (Dubey et al., 2019a).

The skills necessary to manage organisational processes are normalised and accepted practices (Gupta & George., 2016). Mikalef et al. (2018) pointed out that there are instances when management does not trust the insights generated from BDAC. This presents a challenge for practitioners of BDA as uninformed responses limit the development validity of the BDA discipline. Kushwaha et al. (2021) state that the manufacturing industry has IoT, and cloud computing driven by BDA. However, they express caution when management challenges arise and opt to objectively question results based on experience instead of an emotional reaction.

Intangible resources

In order to remain competitive, the manufacturing industry has always been the first adopter of technological innovations, as illustrated in the first section. This view, as illustrated by the global growth in manufacturing, aligns with the organisational culture is essential to ensure that cross-functional teams can share knowledge successfully (Gupta & George., 2016)

2.6 Dynamic capabilities manufacturing organisation perspective

The rationale behind the Dynamic Capability Theory (DCT) was first introduced by Teece et al. (1994), and the concepts were further clarified in a follow-up paper by Teece et al. (1997). The central theme was coherence, which postulated that FPer improves when organisational activities are aligned regarding strategy, business process and organisational cultures (Teece et al.,1994). Organisations with a high degree of coherence are the first in line adopters of new technologies, which have allowed new technology-driven organisations to gain a competitive advantage over competitors (Teece et al.,1994; Teece et al.,1997). This quest for achieving competitive advantage requires that organisational resources are combined in a way that allows for dynamic capabilities to develop (Lin & Wu, 2014).

DCT complements RBV in that organisational resources must be intentionally evolving through modification or expansion (Ambrosini et al., 2009; Helfat & Peteraf, 2003). The principle that underscores DCT is the view that organisation and accumulation of endogenous resources, expertise and capabilities determine FPer and competitiveness (Barney et al., 2001). While organisations are an amalgamation of resources, there is a differentiation in the resources grouping and competencies between organisations, which influences the organisation's competitive state. Barney (1991) states that for an organisation to sustain a competitive position, resources and capabilities characteristics need to be valuable, rare, inimitable and not substitutable (VRIN). The perspective aligns with the view presented in Figure 2.3 by Gupta and George (2016). In order for an organisation to achieve a competitive advantage, both types of resources tangible and intangible must be differentiated. Rugman et al. (2011) refer to this differentiation as the Firm Specific Advantage (FSA), which could be for licenced technology, skilled workers, brand awareness and geographical positioning, allowing organisations to leverage their unique capabilities into competitive market positions.

The traditional perspective on DCT has evolved as the world has become more digitally integrated. Transposing the DCT principle to manufacturing organisations is relatively straightforward, given the chronological overview provided earlier in the chapter on the evolution of manufacturing. Manufacturing, in its simplest form, is a series of processes that allow for the transformation of primary materials into final goods. The management of this distinct process is knowledge accumulated over the years by management, and this knowledge must be coded, digitalised and communicated to ensure that the competitive advantage is sustained (Cepeda & Vera, 2007; Macher & Mowery., 2009). Knowledge management is essential to ensure manufacturing organisation can maintain their FSA, as described in (Rugman et al., 2011). This codification of knowledge relating to business processes is the first foray of manufacturing organisations' transition into digital technologies, which need to be stored and managed in order to maintain the organisation's competitive position (Cepeda & Vera, 2007; Macher & Mowery., 2009). For manufacturing organisations to be competitive in a global marketplace with increased competition and complexity, organisations must adapt faster to changing customer preferences by using digital technology to support manufacturing systems (Tracey et al., 1999).

Dynamic capabilities are positioned as applications for steady-state environments where standardised workflow processes can be incrementally improved, contributing to increased competitiveness (Zollo & Winter, 2002; Ambrosini et al., 2009). In the case of manufacturing, market outlooks and consumer preferences are continuously changing, this market dynamism requires that organisations integrate both ordinary and dynamic capabilities and leverage both to bring about improved FPer in dynamic environments (Eisenhardt & Martin, 2000; Schriber & Löwstedt, 2020). While these perspectives may appear to contrast each other, they do imply that realising a competitive advantage is possible by strategically leveraging and enhancing both dynamic and ordinary capabilities. This alignment of viewpoints highlights the significance of BDA as a determinant of this study. Manufacturing organisations have long been proponents of developing tangible and intangible resource capabilities to achieve competitive firm performance (Sharma & Singh, 2020; Rymarczyk, 2020).

2.7 Synthesising BDAC and IT process capabilities within manufacturing organisations

The influence of IT capabilities within organisations is well-researched in academia (Mikalef & Pateli, 2017; Dubey et al.,2019a). The RBV and DCT are the foundational cornerstones of IT capabilities. They present the view that although resources between organisations may be similar, organisations with unique capabilities are not copied, reducing the risk of the organisation losing its competitive position. Research undertaken by Kim et al. (2012), Gupta and George (2016), and Dubey et al. (2019) support this view. Much research asserts that organisations with dynamic IT capabilities can improve Fper directly and indirectly (Mikalef & Pateli, 2017; Brynjolfsson & McElheran, 2016; Dubey et al.,2019a).

Despite the growth in interest in BDA, key IT capabilities concerning manufacturing have yet to be established (Belhadi et al., 2019). Most organisations, not only manufacturing, want to embrace big data in their operational and commercial processes but need to learn how to exploit big data to generate value fully (Wamba et al., 2017; Belhadi et al., 2019). Attempts to fully explain the linkages between BDA and manufacturing process have lacked substance and did not provide a holistic view of how value can be attained from a complex and dynamic system with many interrelated and integrated processes (Belhadi et al., 2019; Dubey et al., 2019a).

Belhadi et al. (2019) propose a conceptual framework for BDAC and the manufacturing process in Figure 2.4. This framework has three layers to analyse the BDAC's influence in manufacturing.

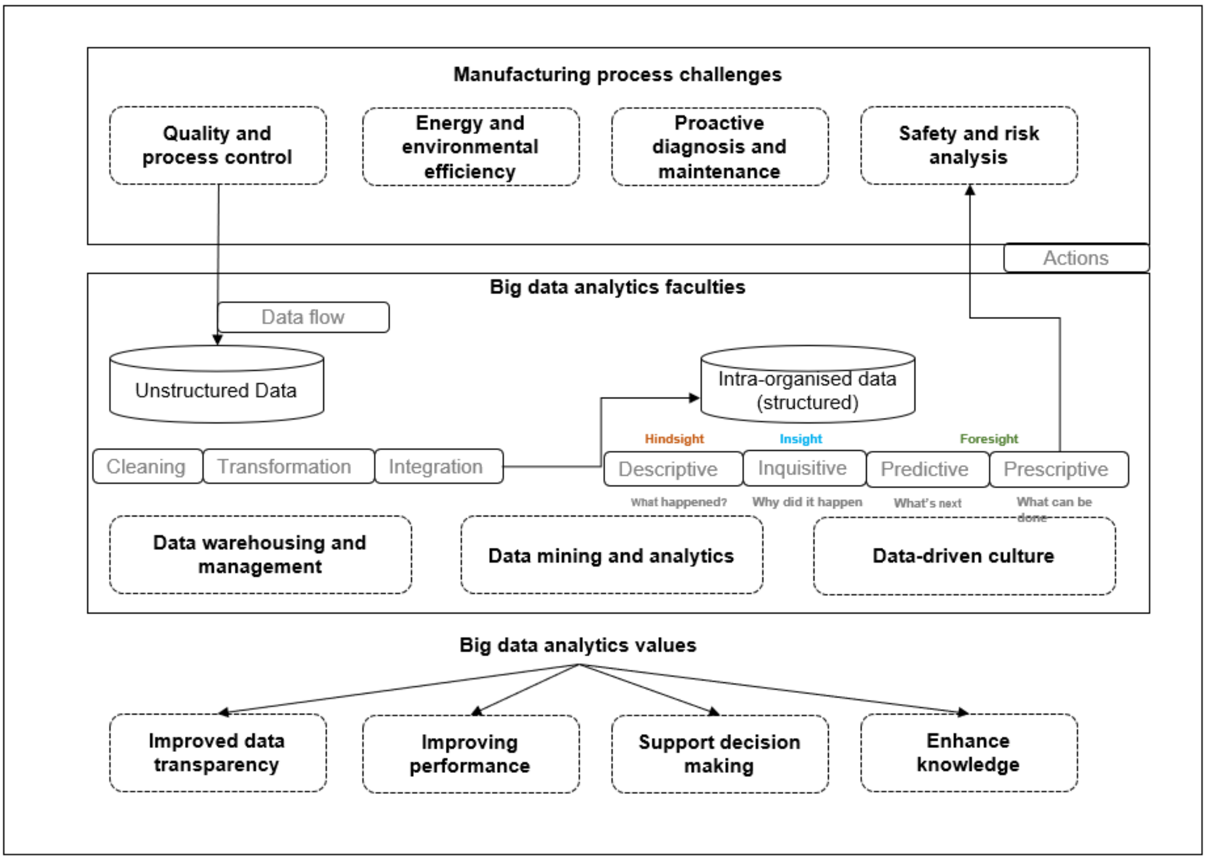

Figure 2.4: Framework BDAC in manufacturing organisations.

Adapted from “Belhadi, A., Zkik, K., Cherrafi, A., & Sha'ri, M. Y. (2019). Understanding big data analytics for manufacturing processes: insights from literature review and multiple case studies. Computers & Industrial Engineering, 137, 106099”.

Manufacturing process challenges

Level one of this framework relates to connecting sensors that monitor equipment at operational sites which submit large amounts of data through the IIoT (Sorooshian & Panigrahi, 2020; Sharma & Singh, 2020; Rymarczyk, 2020; Dogaru, 2020). This real-time data allows for effective quality monitoring and predicts process deviations ahead of competitors through advanced analytics techniques (Belhadi et al., 2019). BDAC allows the introduction of the next generation of statistical process control (SPC) methods which focus on identifying abnormalities in processes to prevent unplanned shutdowns in production (He & Wang et al., 2018; Belhadi et al., 2019).

Growing concerns about reducing natural and mounting environmental concerns have prompted manufacturing organisations to use BDA to manage and mitigate environmental risks (Zhang et al., 2018; Belhadi et al., 2019; Ren et al.,2019; Leng et al., 2020). BDAC capabilities allow organisations to understand the emission discharges from their operational processes, optimise the process, and mitigate the environmental impact (Chiang et al., 2017; Belhadi et al., 2019).

A critical competitive advantage for organisations developing BDAC is for early detection and maintenance of equipment to avoid unplanned shutdowns (Krumeich et al., 2014; Chiang et al., 2017). Advances in sensor technology and IIoT allow for abnormalities patterns in equipment to be easily identifiable before critical breakdown (Belhadi et al., 2019; Sharma & Singh, 2020; Rymarczyk, 2020; Dogaru, 2020).

As the manufacturing process becomes sophisticated, analysing patterns of behaviour relating to health and safety becomes more critical (Choi et al., 2018). BDAC can provide insights into harmful behaviours and allow the establishment of more robust safety-related policies and procedures, better-protecting workers, equipment and the environment (Belhadi et al., 2019).

Big data analytical faculties

Ensuring high-quality data is a significant challenge for effective BDAC. Technological applications require data to be in a prescribed format and quality (Belhadi et al., 2019; Cui et al., 2020). Figure 2.4 shows the BDA ecosystem, including technological support systems (faculties) that can improve manufacturing competitiveness.

Data generated as a result of the manufacturing process can originate from defined or undefined sources (Grover et al., 2018; Baig et al.,2019; Belhadi et al., 2019). Warehousing and managing data are essential in manufacturing, especially considering that most data is sourced from disaggregated sources (Baig et al.,2019). Cleaning, transforming, and integrating data into a structured format allows for practical big data mining, significantly improving organisations' ability to process real-time data (Cheng et al., 2018).

Data mining and analytical methods allow the organisation to generate insights and deeper levels of insight trends from the large volume of data accumulated from the manufacturing process (Cheng et al., 2018). Creating a closed-looped system where data mining algorithms are integrated into process monitoring and decision support systems identifies compromised processes and corrects them before escalating (Zhang et al., 2017).

Fostering a data-driven culture within an organisation allows for continuous monitoring and refinement of operational processes (Mikalef et al., 2017; Belhadi et al., 2019). Historically, operational data is used for monitoring operational processes with BDA embedded in the process, now creates a platform to improve the process (Sadati et al., 2018; Belhadi et al., 2019).

Big data analytics values

Applying BDA techniques in manufacturing processes creates many opportunities for an organisation to expand its competitive position by leveraging the insights gathered from the data process (Rugman et al., 2011; Lee et al., 2018; Belhadi et al., 2019).

The most significant value an organisation can obtain from using BDA is improved transparency of all data within the ecosystem, irrespective of whether the source is internal or external (Chongwatpol, 2015; Dubey et al., 2019b; Belhadi et al., 2019). Research has shown that using BDA in manufacturing does improve Fper across manufacturing processes (Chiang et al., 2017; Belhadi et al., 2019). Isaksson et al. (2018) share the view that BDA develops new perspectives and expands the body of knowledge on the manufacturing process, which lends to an improvement in decision making. Sophisticated statistical and analytical techniques can be employed using the data, and this unearths a new level of patterns and trends that were previously unknown (He & Wang et al., 2018; Zhang et al., 2018; Belhadi et al., 2019). BDA improves more than just the technical value aspects of the manufacturing process. Li (2016) states that BDA creates opportunities for workers to expand their skills and knowledge through skills training from online platforms that simulate processes and generate new insights.

This chapter started with a historical overview of manufacturing through the various IRs. The purpose of this was to illustrate that technical innovation has been a critical determinant in the growth of innovation. Figure 2.4 from Belhadi et al. (2019) contextualises how significant BDAC's influence on manufacturing in the future as organisations have to grapple with sustainability and value chain challenges to be competitive and improve FPer.

2.8 BDAC influence on manufacturing FPer

The interest in BDA as an enabling mechanism to improve Fper has gathered much momentum in recent years as many organisations have invested in BDA, but the research on how value is created is not well structured and defined in academic literature (Maroufkhani et al., 2019, Popovič et al., 2018). Understanding the linkages between BDA and FPer requires a structured approach, the first section will provide context to this relationship guided by the underlying theoretical constructs and the second and third sections will examine the direct and indirect influence from a manufacturing point of view.

Organisations that perform better than competitors have a combination of resources that are of value, unique, and scarce (Barney, 1991). Sustaining a competitive advantage requires organisational resources to be flexible (Barney, 1991; Wamba et al., 2017). The confirmed connection between the RBV and DCT allows for the organisation to grow the dynamic capabilities required by the organisation to realise a competitive advantage and improve Fper (Ambrosini et al., 2009; Helfat & Peteraf, 2003; Rugman et al., 2011; Wamba et al., 2017; Popovič et al., 2018). Both Wamba et al. (2017) and Chen et al. (2014) share the view that developing an organisations internal IT capabilities will positively impact FPer, as the higher order constructs BDAC and FPer. BDAC allows organisations via DDDM to achieve competitive advantages over competitors as a result of higher-order dynamic IT capabilities (Gupta & George, 2016)

Data ecosystems are in a state of continuous change, implying that the organisation's BDA insights must be strategically and timeously implemented to sustain the organisations competitiveness. Lin and Wu (2014) share the view that organisations with distinctive capabilities must continuously and strategically ensure that resources and capabilities evolve to improve FPer. Organisations need to prioritise leveraging dynamic capabilities as mechanisms with which to remain competitive in dynamic, changing business environments (Mikalef and Pateli, 2017; Akter et al., 2016; Wamba et al., 2017).

BDAC directly enables manufacturing organisations to generate insights from operations that impact a cross-section of organisational activities and improve competitiveness and performance (Belhadi et al., 2019). According to Wamba et al. (2017) who clarify that BDAC capabilities allow organisations to observe live processes, which in turn allows for the improved management of operational assets and capital expenditure. A feature of the fourth IR has been the integration of sensor technology with IIoT, which monitors process patterns and allows for the early detection and correction of abnormalities in operational processes (Belhadi et al., 2019; Sorooshian & Panigrahi, 2020; Sharma & Singh, 2020; Rymarczyk, 2020; Dogaru, 2020). The nature and pace of manufacturing imply that any disruption could impact competitiveness and Fper. BDAC improves the overall visibility of the entire value chain and can protectively identify potential deviations and mitigate them without impacting FPer (Wamba et al., 2017; Belhadi et al., 2019; Ren et al.,2019; Leng et al., 2020). Popovič et al. (2018) state that leveraging BDAC capabilities in manufacturing creates external spillovers which bring about societal and economic changes. Earlier in this chapter, the idea of a sustainable manufacturing approach was introduced, which delved into why manufacturing organisations need to utilise technology for environmental risk across the value chain (Ren et al.,2019; Leng et al., 2020; Majeed et al., 2021). BDAC allows organisations to monitor their process emissions and mitigate potential risks (Chiang et al., 2017; Belhadi et al., 2019).

An indirect link created by developing BDAC in manufacturing organisations is that there are now new insights into customer behaviour and preferences (Rachinger et al., 2018) as customer preferences change in favour of more sustainable and circular products. Organisations can strategically position themselves using the BDAC to understand the changing customer patterns and thereby establish a competitive advantage to improve Fper (Strange & Zucchella, 2017; Ahmad et al., 2018; Leng et al., 2020; Majeed et al., 2021). Generic manufacturing strategies like just-in-time (JIT), total quality management (TQM) and enterprise resource planning (ERP) have been largely ineffective at combating dynamism in the market (Gunasekaran et al., 2018). Belhadi et al. (2019) highlight BDA values that combine this dynamism and create a platform for evolving strategies to dynamically restructure resources to develop capabilities to adjust to the changing environment of business (Omar et al., 2019).

BDAC positively influences FPer by developing dynamic capabilities (Ambrosini et al., 2009; Popovič et al., 2018; Wamba et al., 2017). BDAC directly influences manufacturing FPer and competitiveness by using a spectrum of technologies that monitor and control operational processes Belhadi et al. (2019), and this allows for better management of costs, improving competitiveness and profitability. Omar et al. (2019) presents the view that organisations are dynamic in resource allocation can develop capabilities that allow flexible strategy changes due to changes in consumer preferences and maintain market share and FPer as an indirect consequence of BDAC.

2.9 Conclusion

This literature was structured to demonstrate the symbiotic relationship between BDA and competitive FPer within a manufacturing context. To better understand this relationship, a recollection of the evolution of manufacturing was included to demonstrate how influential technology has been in manufacturing (Sharma & Singh, 2020). The review progressed to understanding the concepts of data, its progression to BDAC and the link to its role in manufacturing. The complementary theoretical constructs RBV and DCT that underpinned this research contextualised that manufacturing organisation resources must continuously evolve to grow the dynamic capabilities needed in a competitive manufacturing environment (Ambrosini et al., 2009; Helfat & Peteraf, 2003; Dubey et al., 2019).

The latter part of this chapter explored the link between BDAC IT capabilities in manufacturing settings using the framework developed by (Belhadi et al., 2019). This framework demonstrates why BDAC is needed across the entire manufacturing organisation to maintain efficiency and competitiveness in the dynamic manufacturing space that is highly technological and globally integrated. This literature review sets the foundations for the research objectives of understanding the connection between BDAC and the performance of manufacturing organisations in South Africa.

3.1 Overview of chapter

Prior chapters have established the primary research objectives which is to understand the importance of BDAC in developing dynamic capabilities in terms of direct manufacturing processes and indirectly in terms of skills development and improved environmental and supply chain sustainability from theoretical and industry perspectives. Utilising recent literature on BDA and dynamic capabilities within the context of continuously changing environments, the research proposes the hypothesised model in Figure 3.1. Guided by prior research on the manufacturing industry, this research was informed by the theory of dynamic capabilities. BDA is identified as the core driver of the dynamic capabilities viewpoint suggested for this research. The core ambition of this research was to attain a more profound understanding of how manufacturing organisations could improve real DDDM by exploiting BDAC to influence FPer in a continuously progressing environment.

3.2 Proposed hypothesis questions

To achieve the main research objective, the following research questions were formulated as three individual hypotheses, which is explained in the following sub-sections.

3.2.1 Hypothesis 1

Does BDAC have positive influence on the on manufacturing FPer?

This research question aims to establish if there is an influential relationship between BDAC and the performance of manufacturing organisations. Early studies attempting to understand why some organisations have competitive advantages over contemporaries was explained through varying dynamic capabilities states (Mikalef & Pateli, 2017).

Literature supports the view that there is a positive association between IT capabilities, BDAC and manufacturing organisational performance (Brynjolfsson & McElheran, 2016; Mikalef & Pateli, 2017; Dubey et al.,2019a; Chen et al., 2014; Wamba et al., 2017).

H_1: BDAC is positively related to manufacturing FPer.

3.2.2 Hypothesis 2

Do process-orientated dynamic capabilities (PODC) and manufacturing FPer have a positive relationship?

Question 2 concentrated on the relationship between PODC and manufacturing FPer. Belhadi et al. (2019) developed a structure for BDAC relevant for manufacturing organisations, starting with operational processes. Building of a Dynamic Capability Theoretical Base Belhadi et al. (2019) identify how developing dynamic capabilities can support manufacturing organisations in mitigating manufacturing process challenges regarding the operational process, environmental sustainability, proactive maintenance diagnosis and safety and risk. Wamba et al. (2017) backs this view by suggesting that BDA enables the effective monitoring of operational assets.

H_2: PODC has a positive relationship with manufacturing FPer

3.2.3 Hypothesis 3

Is there a positive association between BDAC and PODC in manufacturing organisations?

The third research question aims to understand how BDAC influences PODC of manufacturing organisations. Belhadi et al. (2019) state that manufacturing organisations have numerous process-related challenges that big data can resolve. This relationship is also tested by Wamba et al. (2017) from an IT managers perspective. This construct is differentiated in this research by selecting respondents who are employees in the manufacturing sector and use any form of BDA.

H_3: BDAC are positively linked and influential on PODC

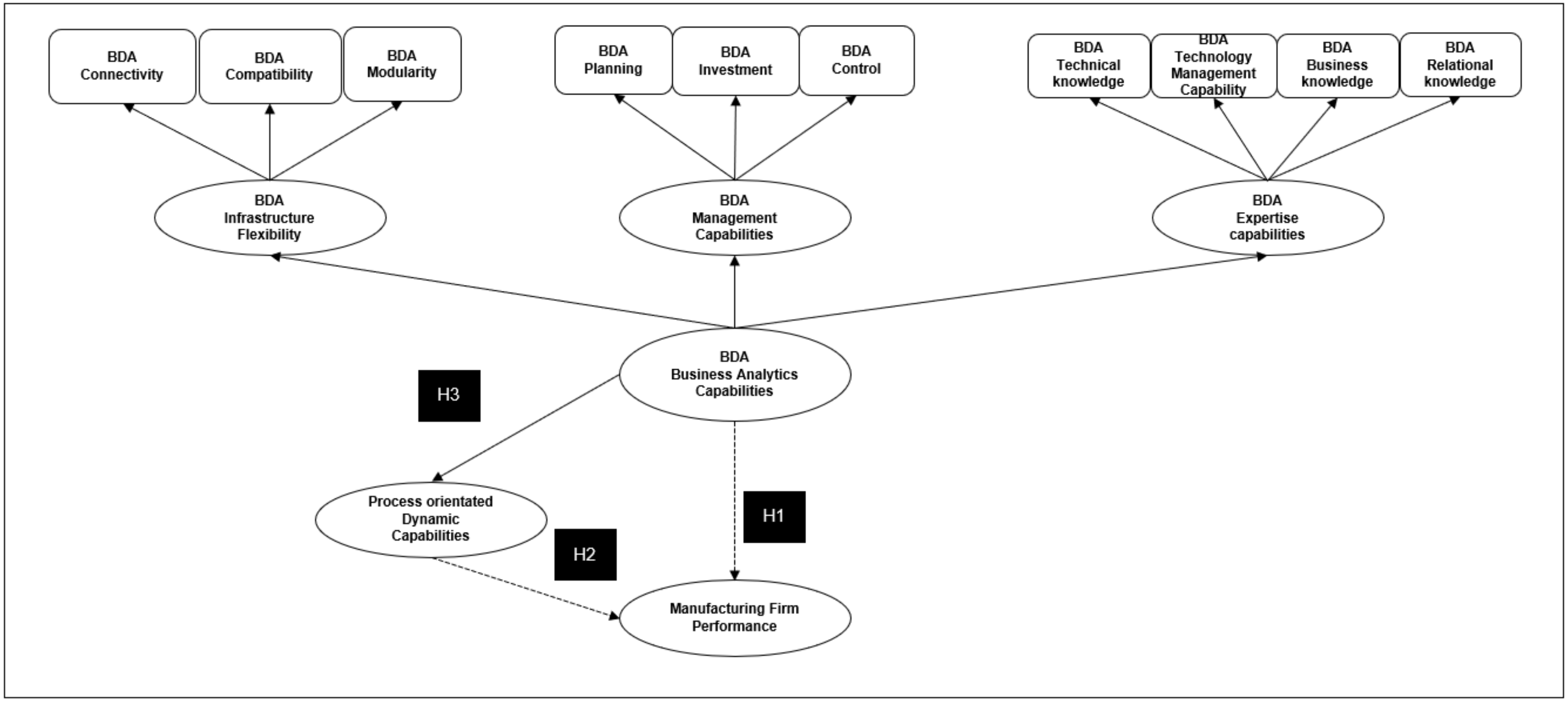

Figure 3.1: Conceptualised research model

Modified from "Big data analytics and firm performance: Effects of dynamic capabilities, by Wamba et al., 2017, Journal of Business Research, 70, p. 363".

Chapter 4: Research methods framework

4.1 Overview

The purpose of this chapter is to outline a comprehensive methodology for answering this study's hypothesis questions. The goal of the research project is to add to the existing literature around how big data generated from manufacturing organisation systems and processes can improve organisational performance and competitiveness guided by Wamba et al. (2017) hypothesised model on the effect of BDA and organisational performance. The literature review in Chapter 2 outlines the position of technology in the evolution of manufacturing through the four industrial revolution periods and positions the role of technology and data in manufacturing of the future. Guided by the overarching theory of dynamic capabilities and Belhadi et al. (2019) framework for BDAC in manufacturing. The remainder of Chapter 2 explored how big data dynamic capabilities can improve the performance and competitive position of manufacturing organisations. The hypothesis questions described in the third chapter were derived from the research model in Wamba et al. (2017) and the proposed BDAC strategic framework by Belhadi et al. (2019). Expanding on the insight and knowledge obtained from the preceding chapters, this chapter will explain the research method used to achieve this study's research objectives.

The chapter will clarify the research design, population sample composition and expand on the reason behind selecting this specified unit of analysis. Thereafter, discuss the survey as the primary means to collect data, followed by data collection, preparing and analysing the data methodologies.

4.2 Research design

Pandey and Pandey (2021) describe the research design as the process used to accumulate and analyse the data most efficiently, yielding reliable, informative results. The object of this research is to assess the influence of BDAC and PODC on manufacturing FPer. Chapter 2 reviewed the theoretical framework and recent research on this subject from the perspective of the manufacturing industry. The hypothesis questions presented in the third chapter were designed from the relationships identified in the literature review.

The research intends to empirically evaluate the identified variables related to BDAC and manufacturing FPer.

The research will be exploratory as it aims to identify the causal associations between variables (Zikmund et al., 2019; Rahi, 2017). Aligning with Wamba et al. (2017), Ghasemaghaei et al. (2017) and Gupta & George (2016), this research utilises the survey method to collect data from the identified population. Chapter 2 provided the foundation of the research constructs, and a non-experimental survey strategy was used on the survey population (Zikmund et al., 2013). Surveys are recommended for explanatory research because they can accurately establish the norm, quickly identify outliers and analyse relationships between variables (Gable, 1994; Wamba et al., 2017). Surveys are recommended for explanatory research because the generalised results offer greater surety (Straub et al., 2004). The explanatory research method is used because of the research objective to establish if there are significant and influential linkages between BDAC, PODC and manufacturing FPer.

This research is explanatory in nature, and a positivist philosophy underpins this. This philosophy ensures that results are generated using techniques that reflect any form of bias or ambiguity (Saunders & Lewis, 2018). Positivists use scientific methods to acquire knowledge (Rahi, 2017). The standard philosophical approach used in studies exploring the impact of BDAC and IT capabilities of FPer is positivism (Wamba et al., 2017; Upadhyay & Kumar, 2020; Gupta & George, 2016). The research aims to understand how BDAC can improve FPer in manufacturing. This is a common purpose shared by all manufacturing organisations and is closely related to Nyein et al. (2020) view that a positivist philosophy is developed from the perspective that there is a need to understand the cause and effect of an outcome from a shared population.

This research adheres to a deductive method which aims to describe the causal linkages between the research constructs (Saunders & Lewis, 2018). This aligns to the positivist philosophy which uses scientific method to develop an understanding of the relationships (Rahi, 2017). This method solidified from the viewpoint of Saunders & Lewis (2018) who assert that a deductive approach is employed when testing a theoretical construct via a hypothesis using a quantitative method.

This study uses a mono-quantitative method where surveys are used the collect quantitative data. The survey for this research will be an adaptation of surveys undertaken by Dubey et al. (2016) and Wamba et al. (2017), as they are similar to this study's research questions. Surveys are generally associated with a deductive approach (Saunders et al., 2012). Measurement instruments such as surveys enable researchers to collect quantitative data for descriptive and inferential statistics (Mercer et al., 2017). Surveys allow researchers to collect standardised data to analyse the causal relationships among variables (Pinsonneault & Kraemer, 1993). In addition, surveys can obtain information from a targeted population and analyse the research constructs, knowing that the information is not biased by emotions (Rahi, 2017).

The data required for this research was accumulated during a cross-sectional time frame. Cross-sectional time frames imply that data is gathered over short periods and specified locations (Zikmund et al.,2013; Zikmund et al., 2013). Wamba et al. (2017) concentrated their survey deployment in the region with an intense concentration of retail-focused internet-based companies.

4.3 Justification of the research population

Within a research context, a population is described as a complete and specified group of observations sharing similar attributes and features (Pandey & Pandey, 2021). Rapid technological advancements in ICT and the IIoT have resulted in the volume of data being generated increasing exponentially. This has contributed to manufacturing organisations using big data to derive insights and intelligence to support real-time decision-making (He & Wang, 2018). As access to data improves, so has the appetite for all manufacturing organisations to use big data in one form or another. According to Kuo and Kusiak (2019) and Dubey et al. (2019a), there has been significant interest from the manufacturing industry on how to exploit big data and increase performance in manufacturing organisations. Accounting for the growth in consuming BDA, establishing the actual population would require a significant allocation of resources. Aligning to the research objectives of understanding the nature of the relationship between BDAC and PODC on manufacturing FPer, the population for this research is characterised as manufacturing organisations that use a form of BDA to support DDDM to improve FPer ultimately.

No restrictions were placed on the scale and type of manufacturing activities on the population. In addition, there was no restriction on the type of data being collected, analytical methods used, and volume of data stored. The thought process behind this decision was that BDA has been utilised in a spectrum of activities and functions from operational processes, supply chain, new product development, strategic intelligence and marketing (Wamba et al., 2017; Belhadi et al., 2019; Kuo & Kusiak, 2019). Past research limited the population by focusing on specific designations of employees like IT managers and professionals in Wamba et al. (2017) and Ghasemaghaei et al. (2017). Meanwhile, Belhadi et al. (2019) share that much research has concentrated on specific processes and regional industries.

This research does not restrict the designation of manufacturing employees because a feature of the fourth IR and future manufacturing is based on pairing technologies with people capabilities (Sharma & Singh, 2020; Ghasemaghaei et al., 2017). On the premise of the aforementioned, this research does not place any restrictions on the population-relating characteristics, employee designation and manufacturing classification type. The underlying rationale for limited restrictions is a safeguard that the findings of this hypothesis questions on BDAC and PODC influence on the performance of manufacturing organisations are robust and generalisable.

4.4 About the unit of analysis

Kumar (2018) describes the unit of analysis in business research as the collection of data from whom or what organism is being researched at the prescribed level of aggregation. The identified unit of analysis for this study is manufacturing organisations that use big data. To answer the hypothesis questions posed in the preceding chapter, which relate to how manufacturing organisations use big data. The data in this research is collected from an employee's viewpoint. In business research, data is primarily collected per individual, as this research pertains to a perception of the organisation or population under review (Kumar, 2018).

This objective of this study is to empirically understand the relationship between the research constructs of BDAC and PODC and manufacturing FPer, which were developed from existing research on BDA and dynamic capabilities from an IT perspective. The unit of analysis is aligned to the research population to generate robust generalisable results applicable to the manufacturing industry as a collective.

4.5 Method to obtaining the sample population

Taherdoost (2016) advises that the first action in the sampling processes is defining the research population clearly, followed by establishing the sampling frame, which identifies all of the attributes of the sample population. The sample frame's characteristics were outlined in this chapter's population section. Taherdoost (2016) and Rahi (2017) share that probability, and non-probability are only two probability sampling techniques. Probability sampling is when each unit or item tested, while non-probability does not disclose which unit of the sample will be selected (Rahi, 2017). The researcher does not have a list of all employees in manufacturing organisations using big data. Hence the non-probability sampling method is used in this research.

A mixture of purposive and snowball sampling was deployed in this research. Rahi (2017) describes purposive sampling as using defined criteria and characteristics when selecting respondents, while snowball sampling uses initial respondents as leverage to get supplementary respondents (Zikmund et al., 2019). Snowball sampling uses the initial respondents to encourage new respondents to participate, resulting in an increase in the sample size (Taherdoost, 2016). The purposive component of the sample size was attained from the researcher's network, while the remainder of the sample population was generated from the sampling method.

4.6 Defining the sample size

Survey research aims to obtain data that adequately represents the sample to generalise findings in line with the population (Kotrlik et al., 2001). Ahmad and Halim (2017) state that there has been an increase in demand for organisational management research, and this requires a scientific method to determine a research sample. Selecting the appropriate sample size is essential because statistical outcomes are strongly influenced by the sample size (Rahi, 2017).

There is a significant degree of variability and differentiation between manufacturing organisations. The size of the research for this study was determined based on the statistical tests required from the proposed model in in Figure 3.1. Kim et al. (2011), Ghasemaghaei et al. (2017) and Wamba et al. (2017) used a similar research method in past studies.

The sample size is crucial when undertaking structural equation modelling (SEM). There are many techniques that can be employed to calculate the respondents required in SEM. Hair et al. (2021) suggest a general guideline stating that the smallest allowable sample should be approximately ten times (10X) the highest number of links directed to any dependent variable in the model. Kock and Hadaya (2018) state that the size of the sample does not only rely on the number of connections to the dependent variables, but the magnitude of R-squared value needs to be considered as well.

The following minimum sample sizes were calculated using the ten times rule suggested by Hair et al. (2021) and the minimum R-squared and inverse root square method outlined by Kock and Hadaya (2018) in Table 4.1. The research has 165 responses, deemed sufficient based on the guiding criteria.

Table 4.1: *Sample size guideline*

Article reference	Calculation method	Prescribed sample size
Hair et al. (2021)	10 times rule	20
Kock and Hadaya (2018)	Minimum R-squared (3 arrows, *0.10 r-squared*)	110
Kock and Hadaya (2018)	Inverse root square method	159

4.7 Characteristics of the survey

Prior research on BDA, IT capabilities and FPer utilised a survey strategy to understand the researched phenomena (Kim et al., 2011; Wamba et al., 2017; Ghasemaghaei et al., 2017). The survey questions were divided into two sections. The survey consists of two sub-sections, the first being demographic questions and the latter section consisting of questions relating to the three research constructs. The demographic questions provide descriptive insights into the sample population and characteristics of the type of respondents who work in manufacturing organisations. The second part of the survey comprises of twelve questions associated with the study parameters BDAC, PODC and manufacturing FPer. The questions in the survey were slighted modified from Kim et al. (2011), and these questions were re-used by Wamba et al. (2017). This research adopted the same approach to ensure that the research could be reproduced objectively. The survey question assesses the perception of big data capabilities in organisations.

4.7.1 Qualifying questions

The survey had one pre-qualifying question that allowed participation since the research focused on understanding BDAC's influence amongst manufacturing organisations. This was implemented to ensure that the target population participated and respondents who did not qualify did not participate. There was also an option for "other" should the respondent not feel that their classification of manufacturing was not included.

4.7.2 Demographic information

The demographic information required pertained to gender, age, education level, field of specialisation, level within the organisation, years of employment, intensity of use relating to big data in the organisation and the basis for the respondents using big data. The demographic questions went into some depth because this is the baseline in which insights can be attained from the character of manufacturing sector respondents.

4.7.3 Questions relating to the research constructs

The survey contains twelve questions relating to the IT capabilities of a manufacturing organisation. The literature review determined that IT capabilities of an organisation seamlessly transform into big data as a result of advances in technology (Sharma & Singh, 2020; Dubey et al., 2019a). The twelve questions of the survey relating to the research construct are as follows. The twelve questions are divided into five sections relating to manufacturing FPer, process-orientated dynamic capabilities, BDA infrastructure flexibility, BDA management capabilities and BDA expertise capabilities. The latter three sections reflect on ten questions (independent variables) relating to three sub-sections reflecting BDAC.

4.7.4 Survey pilot test

Following on from the ethical clearance process and prior to the official data gathering process, a trial test was performed. Collins (2003) states that pre-testing is necessary to ensure that there is no misrepresentation or misunderstanding in the hypothesis questions, which could bias the findings of this study. The pilot test was deployed to ensure that Qualtrics was collecting the data correctly.

While there is no definitive guideline on the number of surveys that can be distributed to respondents for a pilot survey, the number of surveys sent out during the pilot phase was guided by Perneger et al. (2015), who state that 10-15 surveys should be distributed in a pilot and Hill (2008) who state that a pilot survey size should not be less than 10 surveys. For this pilot, 15 surveys were distributed to respondents from the Toyota Wessels Institute of Manufacturing class. Respondents were sent a Qualtrics survey link via email and WhatsApp. The pilot survey respondents were requested to identify anomalies of vagueness or grammatical errors in the questions.

The pilot survey was implemented for two weeks, and all 15 respondents completed it. Most of the suggested improvements related to grammatical errors and formatting were corrected. Three respondents said the survey needed to be shorter. Comments regarding the length of the survey were acknowledged. A further four respondents suggested explaining the technical term in more detail. This prompted an adjustment to clarify specific questions in the survey. These were the only changes made to the survey to make certain that the survey design remained consistent with past research.

4.8 Data collection method

An anonymous survey link was generated using Qualtrics. The researcher emailed and WhatsApped this link to their manufacturing network and requested assistance in soliciting new respondents. The anonymous link was posted on LinkedIn within the researcher's network with a note asking that those employed in manufacturing and using a computer to perform work-related tasks, participate in the research.

The survey link was posted on manufacturing and data forums on LinkedIn. The researcher connected with more than 600 new connections on LinkedIn who were identified by the organisation they were employed at or their job title, which included keywords such as manufacturing, operation, strategy, and intelligence. A hybrid selection of organisations and job titles expanded the researcher's network. Once the connection request was received, the researcher sent the link and requested participation in the research. Two additional reminders to participation requests were conveyed to each respondent. The survey was created on 7 November 2023 and closed on 11 February 2024. There were 259 survey responses attempted during the specified dates mentioned. The raw data was extracted to a Microsoft Excel document for further investigation.

4.9 Data analysis process

The survey data was exported from Qualtrics and needed to be transformed to statistically analyse and uncover insights on the research constructs. The data transformation process was guided by the four step process outlined in Zikmund et al. (2013). The process outlined to transform the raw data entails editing, coding and creating the data file for analysis.

4.9.1 Data editing

Editing assesses the data for abnormalities through missing data and inaccuracies (Zikmund et al., 2013). Researchers have developed many alternative techniques to overcome the challenge of missing data. Recent or rather modern techniques to address missing data entail using multiple imputation and or maximum likelihood calculations to resolve instances where data is missing (Baraldi & Ender, 2010). The single imputation and deletion method is the more common approach to address the challenge of missing data (Baraldi & Ender, 2010). Newman (2014) describes the single imputation technique as a best guess estimation for the missing data made by the researcher. Newman (2014) and Baraldi and Ender (2010) suggest that these methods are bias analysis estimates because an average value would be selected for the missing value.

The survey's conception, design, and implementation in Qualtrics negated the need to compute missing values. The initial screening question requesting respondents to identify which manufacturing sector they belong to allowed for participants not part of the manufacturing sector to be removed from the final data. Allowing for the unit of analysis to align with the research goals. In addition, through Qualtrics, respondents had to complete each question before progressing to the next question. This created the room to omit incomplete surveys and avoid the missing completely at random (MCAR) challenge identified by Newman (2014).

4.9.2 Data coding

The survey questions relating to the research constructs needed to be coded because the results were generated using a seven point Likert scale. South et al. (2022) shares that Likert scales allow for researchers to gather quantitative data through subject inquiry, generating empirical estimates that can be analysed and evaluated. The Likert scale code used in the research is shown in Table 4.2.

Table 4.2: *Likert scale coding*

Likert Scale	Value
Strongly Disagree	1
Disagree	2
Somewhat disagree	3
Neither agree nor disagree	4
Somewhat agree	5
Agree	6
Strongly agree	7

4.9.3 Preparing the data file and storage

Zikmund et al. (2013) describe the data file as the instrument containing all the research information once it has been coded and edited. In line with established practices, all versions of data and report transcripts about this research are stored in a Google Drive folder for seven years in addition to a universal memory device that only contains information related to this research.

4.9.4 Overview of the statistical analysis process

This part of the report will describe the structure and detail the analytical techniques used to analyse the data collected. This research required the imputation of different analytical techniques. The first process in the data analysis was examining the descriptive statistics computed using Microsoft Excel and the Statistical Package for the Social Sciences (SPSS). The next component of the analysis relates to the inferential statistics.

The inferential statistics component of the analysis can have a few sub-elements. The first part of analysis process was to explain the construct validity and reliability of the research constructs in the measurement model using SmartPLS-4. The second part of the statistical analysis was to derive the structural Partial Least Square (PLS)-SEM after validating the measurement model. SmartPLS was the software package selected for this step of the analysis because of its suitability for PLS-SEM analysis Hair et al. (2021), and according to Ammad et al. (2021) it simplifies the analysis of complex data sets.

4.9.4.1 Descriptive Statistics

A descriptive analysis was conducted to understand the features of the sample population. Cooksey and Cooksey (2020) describe descriptive statistics as the process whereby a general description and summation of the sample data characteristics and behaviours. In this section of the survey, the researcher formulated insights on the gender, age, and level of education of the respondents in the survey population. In addition, descriptive statistics were generated on respondents' occupation (field of specialisation), level within the organisation, years of employment in the organisation, organisation's use of BDA, and the respondents' basis for using big data. Descriptive statistics were employed for the final sample of 165 respondents. The researcher used a blend of means, frequencies and graphical visualisations to describe the demographic data in the sample population.

4.9.4.2 Exploratory statistical analysis

This research has more than three variables, and as such, Zikmund et al. (2013), suggests that in order to test the reliability, validity and each hypothesis a Multivariate Statistical Analysis (MSA) should be used. Zikmund et al. (2013) further adds that multivariate techniques can consider the influence of many variables at once. The researcher established that SEM was the most applicable MSA approach, as this technique is used to assess complex relationships involving the model variables.

4.9.4.2.1 Validity test

Bagozzi (2011) states that there are two types of construct validity tests, the first being divergent and the latter being convergent. This research is a reflective model assessing manufacturing organisations' various big data IT capabilities to understand how the big data generated can improve manufacturing FPer. Hair et al. (2021) advocates that reflective models test for convergent and discriminate validity. Becker et al. (2012) do caution that discriminate validity scores can be challenging to draw stable results and thus should be evaluated with caution for higher-order models with 2nd and 3rd level constructs similar to what is presented in this model.

Convergent validity is described as reflecting the magnitude of two variables measuring a common construct (Carlson & Herdman, 2012). Hair et al. (2021) assert that convergent validity is achieved when the standard factor loading is above 0.708, and values below 0.4 should be deleted. The second condition for convergent validity suggests that the average variance extracted (AVE) be greater than 0.5, implying that the dependent variable explains half of the variance in the observed variables.

Discriminate validity is evaluated using the Heterotrait–Monotrait (HTMT) ratio. This test assesses the correlations between the latent constructs. An indication of discriminate validity requires that HTMT values to be smaller than 0.85 or 0.9 (Hair et al., 2021; Rasoolimanesh, 2022).

4.9.4.2.2 Reliability test

Testing the reliability of the research construct is crucial as it ensures that the measurement instruments are valid and accurate. In 1951, Lee Cronbach developed a measure of internal consistency between 0 and 1. Tavakol and Dennick (2011) define internal consistency as the degree with which all test variables measure the common research construct. According to Cronbach (1951), variables need to have similar attributed measures and be related to each other. The most common test used for measuring reliability is Cronbach’s coefficient alpha.

Cronbach’s has been proven to be sensitive with a tendency to underestimate the reliability of PLS models (Becker et al., 2012; Hair et al., 2014). The composite reliability test is more consistent with PLS models (Hair et al.,2021). Cronbach’s alpha assumes that latent variables and measured variables are equally related and substitutable, while the composite reliability factors in the different factor loadings are from the measured variables (Hair et al., 2021). Both tests produce scores between 0 and 1, with Hair et al. (2021) stating that variables achieving a score below 0.7 be deleted.

4.9.4.2.3 PLS-SEM model

As mentioned earlier, this research will use a PLS-Sem model to evaluate and analyse the data to extract insights into the connection between BDAC, PODC and manufacturing FPer. A PLS-SEM model consists of multiple stages, the first being specifying the inner model and thereafter calibrating the outer model from which the structural model is estimated and evaluated.

The SEM in the research was derived from past studies relating to big data and FPer. The research model used in this was an interpretation of similar models and theories about dynamic capabilities, BDAC and FPer. This research model is a variant of similar models used by Kim et al., (2011), Wamba et al. (2017), Gupta and George (2016) and Akter et al. (2016). This model, however, concentrated on manufacturing because the sectors are the first adopters of new technologies, and the increasingly complex business environment warrants developing BDAC to realise a competitive advantage and improve

FPer (Dubey et al., 2019a). Therefore, the unit of analysis focuses on big data from an IT capabilities viewpoint amongst manufacturing companies.

The modelling technique used in this research is described as a reflective-formative model. Reflective-formative models can be viewed as two components, the reflective component is essentially the measured variable reflecting on the dependent variable as the identifiable measured behaviour, the second component is the consolidation of the reflective dependent variables forming the next level dependent variable through which the research hypothesis is influenced and assessed (Esposito, 2010), as illustrated in Figure 4.1. This model contains three orders of latency. The first-order latent model is for manufacturing FPer, the second-order latent model is PODC, and the third-order latent model is for BDAC, which reflects manufacturing IT capabilities that generate large volumes of data which need to be filtered by analytical techniques (Belhadi et al., 2019). PLS-SEM method of analysis consists of two broad staged with sub-elements. The first the stage being the outer model evaluation and there after the structural model evaluation and assessment.

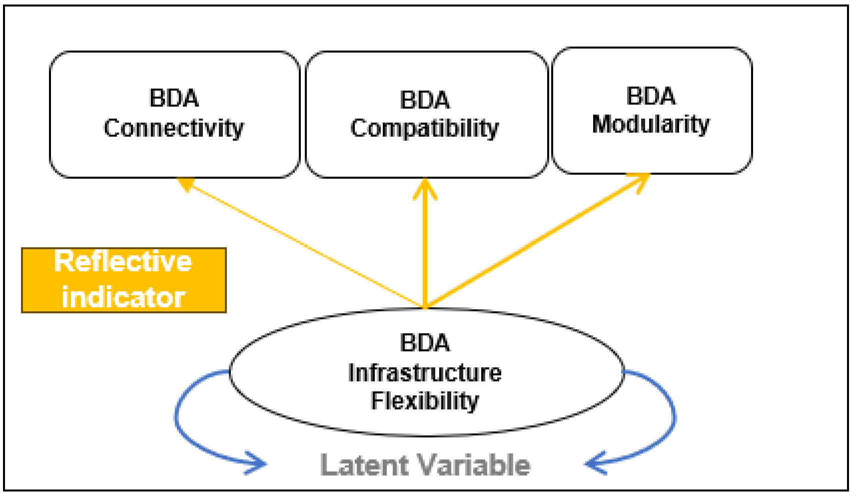

Figure 4.1: Reflective model illustration

The outer model describes the relationship between measured (observed/reflective) and the research construct (Esposito, 2010). Outer model evaluation tests the reliability and validity of the quantifiable variables (survey questions) (Esposito, 2010; Hair et al., 2014). The inner structural model can only be accurately run only when the outer model has been evaluated.

The structural model evaluation can only begin once the measurement model is specified, verified in addition to evaluated based on the selected reliability and validity criteria (Esposito, 2010; Hair et al., 2014). The inner model evaluation acts as surety that the theoretical model is appropriate (Esposito, 2010). Guided by Hair et al. (2021), the procedure outlined in Figure 4.2 will guide the assessment of the structural model.

The first stage in evaluating the PLS-SEM structural inner model is to test for collinearity. An Ordinary Least Squares (OLS) method generates the path weightings from the latent variables to the higher-order variables. Hair et al. (2021) state that a collinearity test must be undertaken to avoid the path coefficient estimates not being biased by the predicted variables and compromising the interpretation of the relationship constructs. Collinearity can influence the significance of the model even when there is a high R2. Values. Henseler et al. (2015), Hair et al. (2021), and Esposito (2010) advocate for using the Variance Inflation Factor (VIF). The VIF is viewed as the inverse tolerance, whereby the variance of the independent variables are Unrelated to each other (Hair et al., 2021).

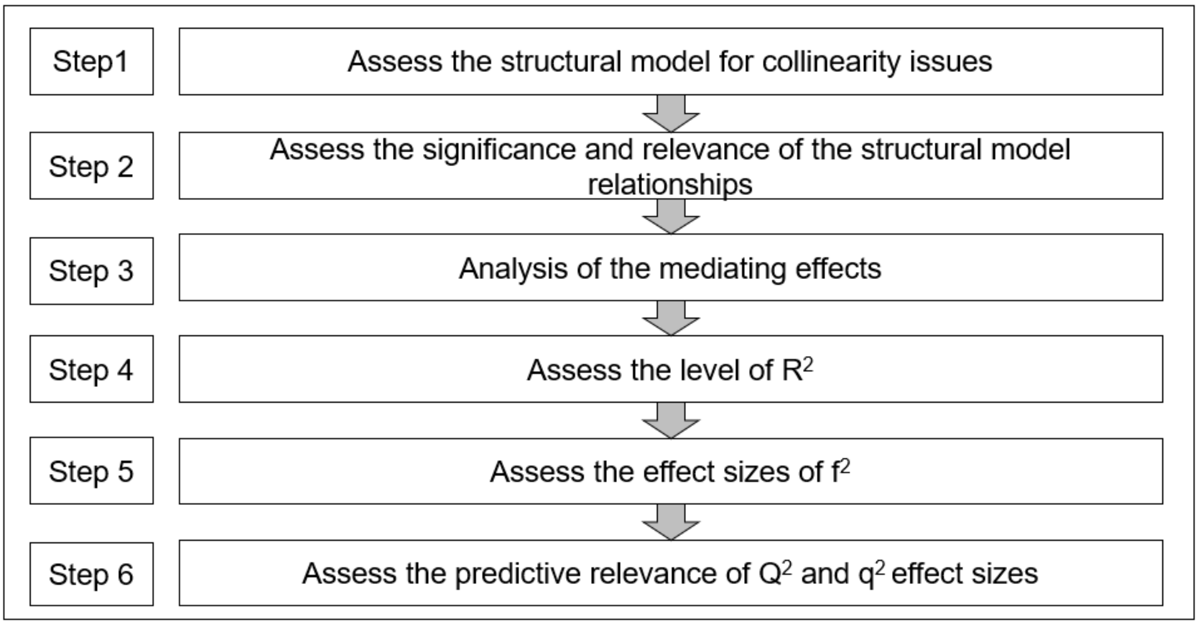

Figure 4.2: PLS inner model evaluation.

“Hair Jr, J., Hair Jr, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2021). A primer on partial least squares structural equation modeling (PLS-SEM). Sage publications.”

There are differing suggestions for the threshold limits. Hair et al. (2021) propose 5, while Henseler et al. (2015) propose 10. The researcher has aligned with Hair et al. (2021) limit of 5 to quantify the level of collinearity among the OLS estimates. This statistical technique was used by Wamba et al. (2017) and Akter et al. (2017). Measured variables with a VIF value greater than 5 would therefore be removed.

Path weightings in the research model identify the research interaction between the model variables. Path coefficients are standardised estimated values within band between 0 to 1 with the resulted closer to 1 implying that there is strong link amongst the variables (Hair et al., 2021). A bootstrap algorithm was used to assess the path coefficients and Hair et al. (2021) suggests that for a critical value to be significant at the 99% level the t-statistics must be 2.57.

A bootstrap procedure was performed on the structural model using SmartPLS-4 to test the linkages, between the various hypothesis questions identified in Chapter 3. The bootstrapping procedure was highlighted as helpful in testing for mediation in PLS-SEM models (Nitzl et al., 2016; Hair et al., 2021). The Coefficient of determination (R^2) demonstrates that the variance between the latent variable can be because of an independent variable and influences the explanatory capabilities of the model (Esposito, 2010). R^2 value band from 0 to 1, closer to 1 implying stronger explanatory power (Henseler et al., 2015; Hair et al., 2021). Cohen's f^2 assesses the degree of influence of the estimated variable on the latent construct. Hiar et al. (2021) classify values as weak at 0.02 and strong at 0.35. Stone-Geisser’s Q^2 evaluates the estimated significance of explanatory variables in the model (Esposito, 2010). A value greater than 0 is an indicator of strong predictive power in line with Hair et al. (2021) assessment of Cohen's $f^{2.}$

The Standardised Root Mean Square Residual (SRMR) test is used to assess the overall model fit of PLS-SEM (Hair et al., 2021; Henseler et al., 2015). The SMRS assess the mean deviations amongst the expected and observed relations as a determining factor in determining the congruence of the model. An SMSR value which is less than 0.08 implies that overall model is a good fit and appropriately specified (Hair et al., 2021).

4.10 Conclusion

This chapter concludes the overview the research method framework followed by this research to which aims to answer the hypothesis questions proposed in the preceding chapter. The upcoming chapter will discuss the finding from the undertaken analysis.

Chapter 5: Research analysis findings

5.1 Introduction

The research outcomes presented in this chapter are described in the sequence of the preceding chapter. The chapter begins with a review of the descriptive statistical analysis about the survey sample and demographic characteristics guided by the process identified. The inferential statistics is then discussed guided by steps in section 4.9.4.2. The inferential statistics will cover the research question from chapter 3.

5.2 Descriptive analysis about survey population

5.2.1 Survey population

The initial goal of this research was to collect 200 surveys from BDA practitioners employed by manufacturing organisations in South Africa. From the researcher's perspective, a BDA practitioner is any individual in a manufacturing company that uses a computer to analyse any variant of information that has been transformed into data that can be analysed to obtain new depths in insights and improve DDDM. Past studies by Wamba et al. (2017), Chen et al. (2014) and Mikalef and Pateli (2017) all aimed for a range of 200 to 300 responses.

Table 5.1 summarises the method used to attain the final sample data set. The raw survey sample size realised was 259 responses, of which 93 were removed because of being incomplete. One respondent was disqualified from the sample data based on the response from the qualifying survey question, "Are you employed in any of the following South African manufacturing sub-sectors?" see Appendix A. In which the response recorded was "Banking and Finance", this respondent was removed.

The final survey sample data comprises 165 respondents from the manufacturing sector, representing 64% of the raw sample data. This completion rate is encouraging, considering the online survey completion rate is 44% (Wu et al., 2022). Surveys must be sent to an identified population to influence the response rate, and more surveys do not have higher responses (Wu et al., 2022).

Table 5.1: *Overview of survey screening process*

Survey screening process	**sample size**	**% of the raw survey sample**
Raw survey sample data	259	100%
Respondents did not finish the survey	93	36%
Respondents were removed from the survey because of the qualifying criteria	1	0.4%
Final sample data set	**165**	**64%**

5.2.2 Features of respondent in the sample

This research used eight demographic questions to summarise the respondents' characteristics and provide an intuitive link to the potential insights that can be attained in the next step in the analysis process.

In Figure 5.1, there were 116 male respondents compared to 49 female respondents who completed the survey. The male respondents account for 70% of this survey sample insights, while 30% are gathered from a female point of view.

Figure 5.2 illustrates the age dispersion of the research sample. Age categories 42-55 accounted for the most significant proportion of the sample, with 59 or 36% of the sample responses. Categories 34-41 comprised 56 responses or 34% of the sample responses. These two categories combined constituted 115 or 70% of the total sample responses. The age category 26-33 provided 41 or 25% of the sample responses. The remaining 9 or 6% of the sample respondents were from the age category greater than 55 and 3 from the age category 18-25.

This sample of manufacturing employees is highly skilled, as 162 or 98% of all respondents have some form of tertiary qualifications. In Figure 5.3, the highest categories of education in the sample are equally shared among respondents who have a Master's/Ph.D. or a Post-graduate diploma, with each category consisting of 69 or 42% of all respondents. Eighteen respondents have an undergraduate degree, and 3 respondents had some form of secondary schooling.

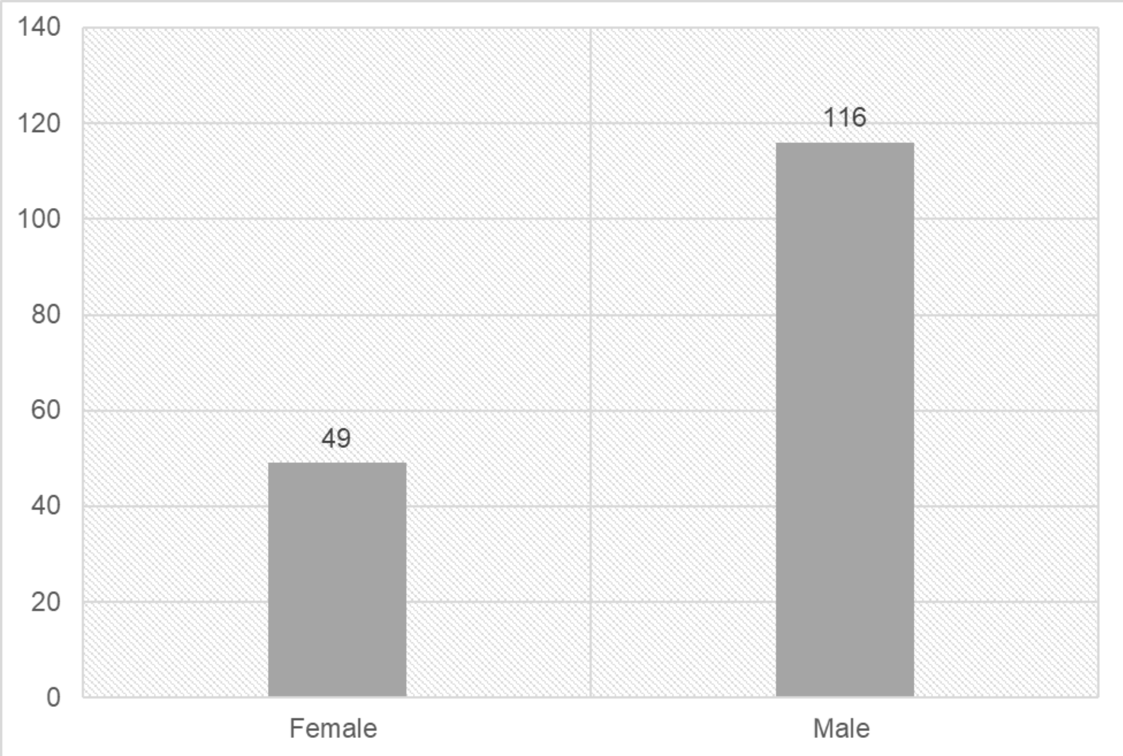

Figure 5.1: Gender of respondent

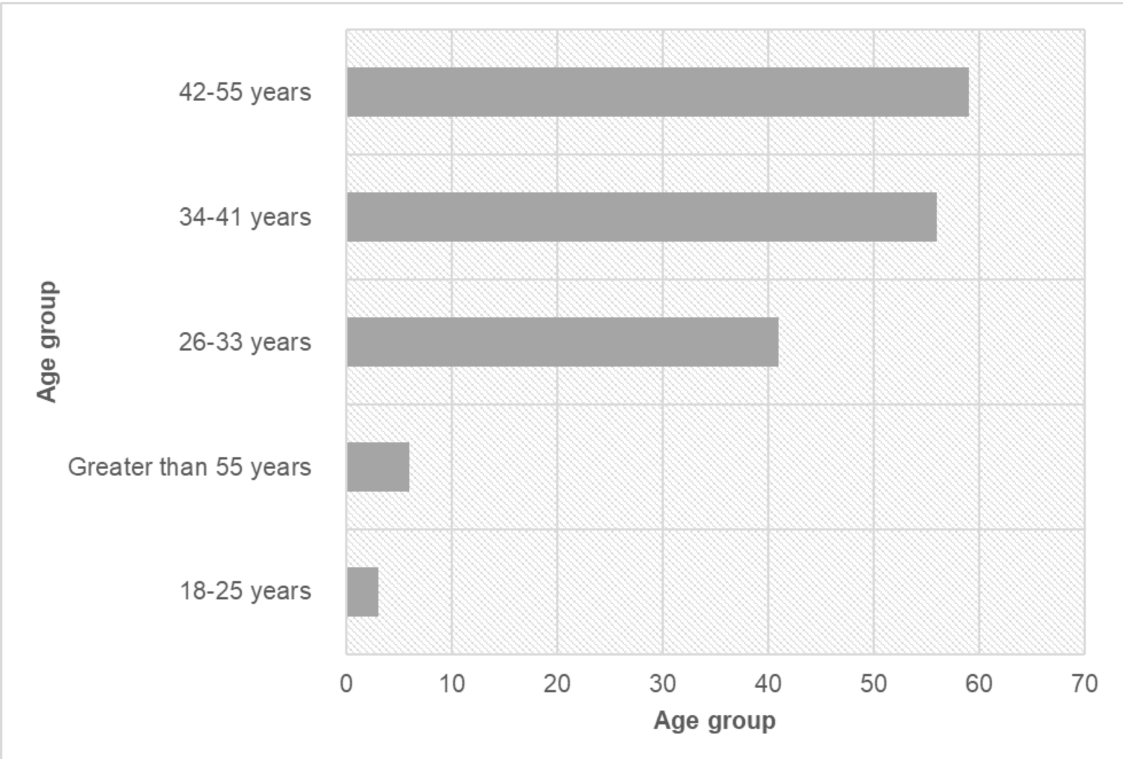

Figure 5.2: Categorisation of survey respondent age

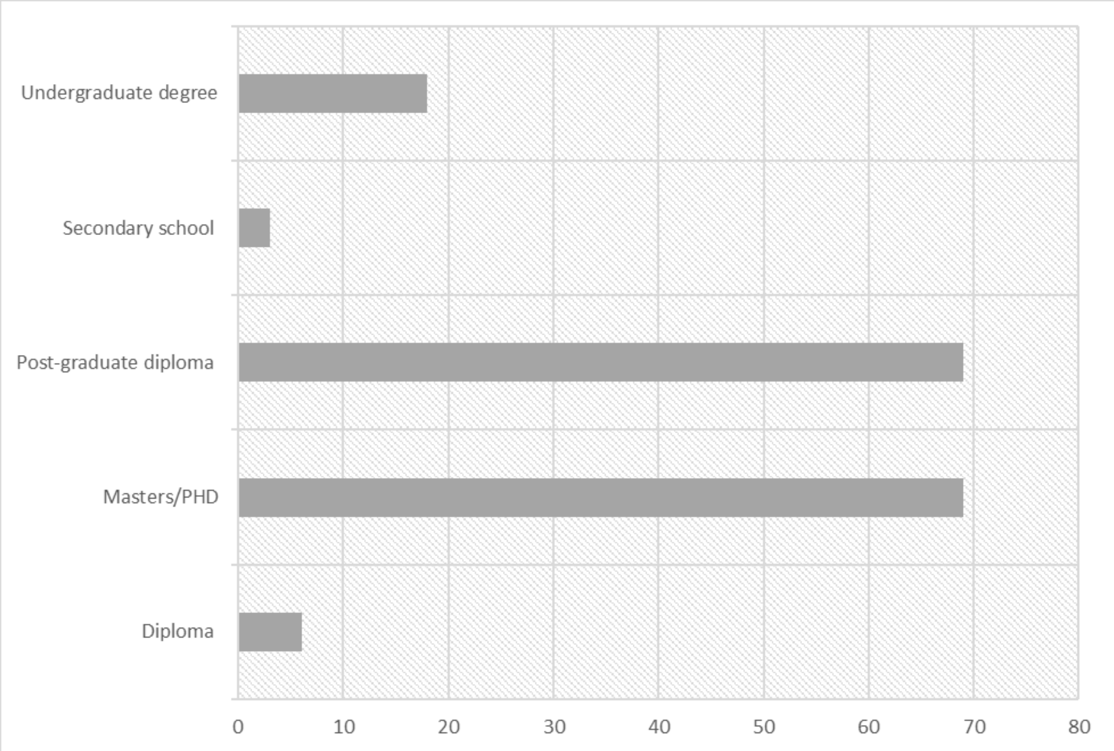

Figure 5.3: Survey respondents level of education

Question 5 is a demographic question related to the field of manufacturing specialisation that respondents' specialist skills. This question permitted respondents to choose multiple options from the specified list in addition to stating other specialist skills. Table 5.2 shows that in this sample population, 29% of respondents specialise in engineering, while 21% specialise in operations. The remainder is closely distributed between finance, supply chain, marketing, and sales specialisations. The fact that this sample population has a high level of education makes it plausible for respondents to have more than one field of specialisation. Interestingly, respondents stated that other specialisations include data analytics, chemistry, sustainability, economics, strategy, IT and human resource management.

Table 5.2: *Frequency of respondents manufacturing specialisations*

Specialisation Frequencies				
		Responses		Percent of Cases
		N	Percent	
Field of specialisation	1 Financial	34	16,7%	20,6%
	2 Engineering	60	29,4%	36,4%
	3 Supply Chain	22	10,8%	13,3%
	4 Marketing and Sales	23	11,3%	13,9%
	5 Operations	43	21,1%	26,1%
	6 Other	22	10,8%	13,3%
Total		204	100,0%	123,6%

Figure 5.4 illustrates the composition of respondents' positions within their respective organisations. In this survey population, 50% or 82 of all respondents are in some form of management position. At the same time, 42 or 25% of respondents are classified as professionals. Respondents in executive positions accounted for 20% or 33 responses in the sample. Graduates are essential assets in manufacturing organisations, and the survey contained insights from 6 graduates. One respondent selected other and stated they were a department supervisor, which can be considered management. However, in line with not adjusting the data, a decision was made not to change the respondent's designation.

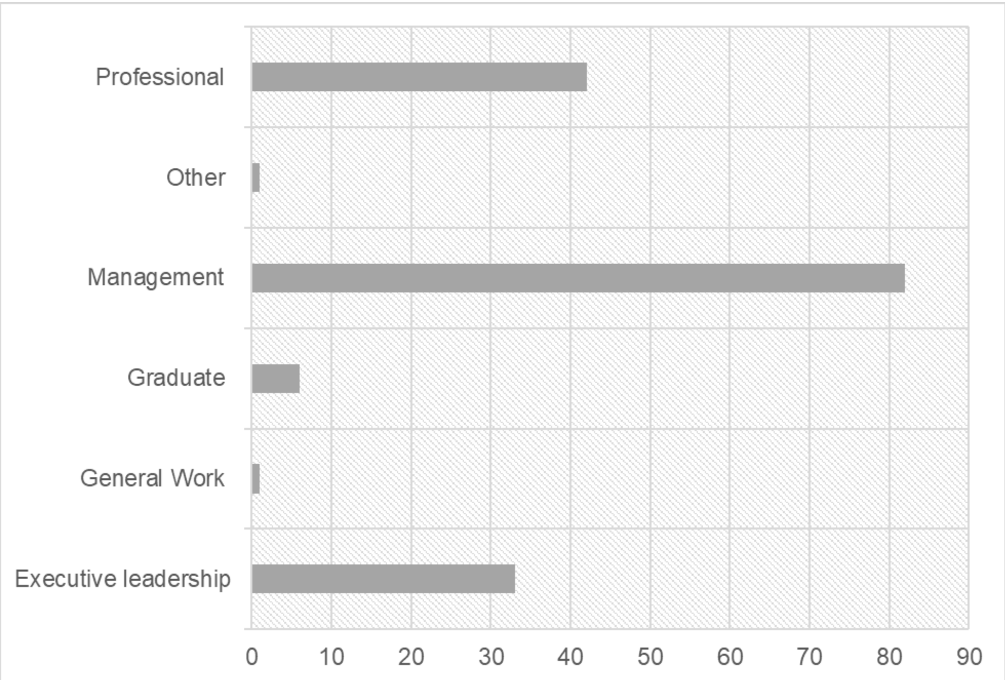

Figure 5.4: Level within organisation

In Figure 5.5, the respondent provided the number of years that they have worked for their respective manufacturing organisations. This distribution of the respondents is pretty balanced and aligns with the age classifications of respondents. Employees who were employed for longer than 10 years but not more than 20 years accounted for the most significant proportion of respondents, with 45 responses, 27% of the total survey population. Notably, only 14 or 8% of respondents worked with their current employers for more than 20 years. This is understandable, considering that the manufacturing sector is highly competitive and continuously evolving (Sharma & Singh, 2020; Belhadi et al., 2019)

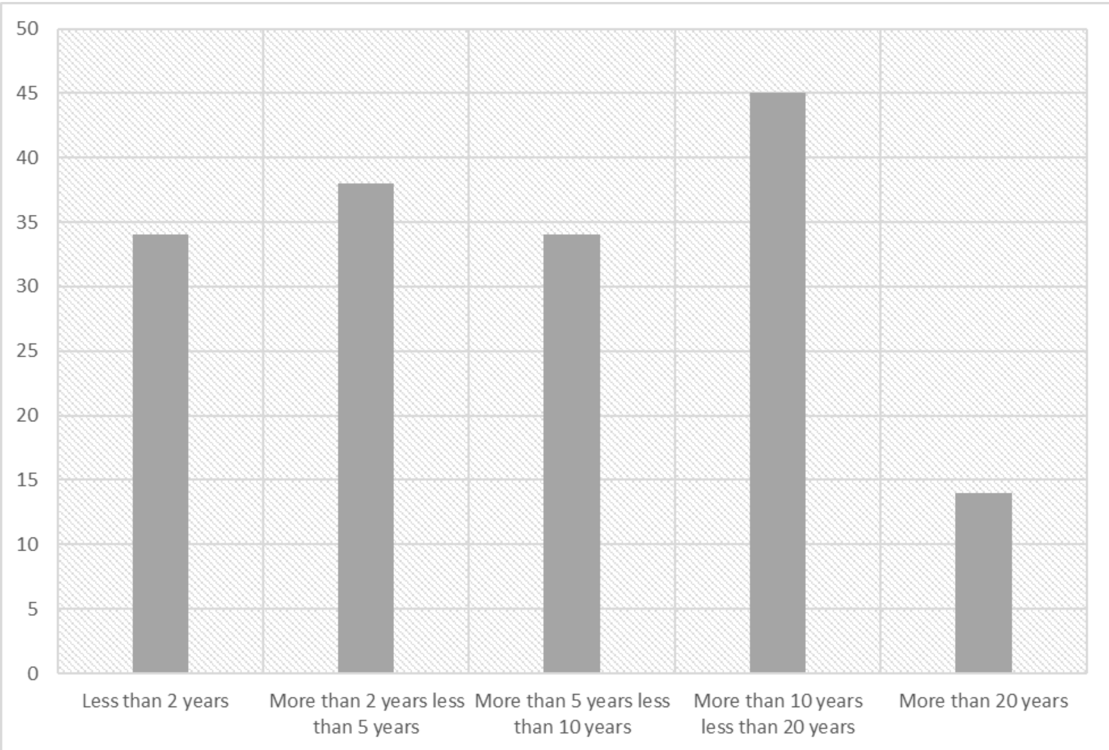

Figure 5.5: Years of employment

It is crucial to understand whether the organisations represented by the respondents in the survey have increased their dependency on BDA in the last five years. Belhadi et al. (2019), Dubey et al. (2019a) and Wamba et al. (2017) have expressed that big data is an essential tool that ensures manufacturing organisations remain competitive. Figure 5.6 shows that 142 or 86% of the sample population has indicated that their respective manufacturing organisations have increased their dependency on big data. Only 19 or 12% of respondents have indicated that big data use has stayed the same over the last five years in their respective organisations. Of the four selected respondents, two were unsure if using big data has increased or not, while the other respondents stated that big data use was only noticeable in specific functions like finance.

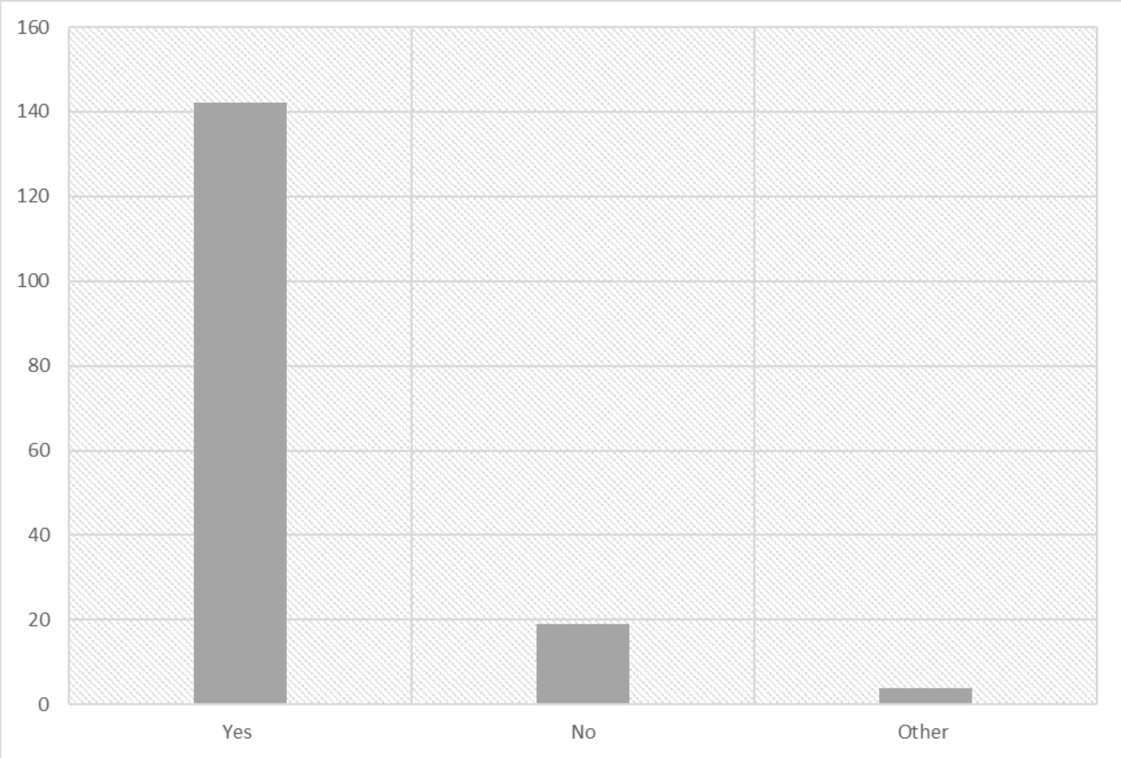

Figure 5.6: Has the use of BDA increased in the last 5 years

The final demographic question relates to the basis for using BDA in manufacturing organisations. The respondents were allowed to select multiple options such as operational and financial reporting, strategic operational improvement, strategic commercial improvement executive review and others. Table 5.3 shows that 25% of respondents use big data for operational reporting. This is aligned with Wamba et al. (2017), Belhadi et al. (2019), and Dubey et al. (2019a), who all share the view that advances in sensor technology generate large volumes of data to improve organisational performance. This view is further solidified in Table 5.3, where 23% of respondents believe that BDA to be a strategic tool to improve operational performance.

Financial reporting accounts for 20% of respondents using big data, while 16% of respondents use big data to improve commercial performance. From Table 5.3, the researcher has intuitively deduced that big data is being used for multiple applications by respondents across manufacturing organisations.

Table 5.3: *Basis for using big data*

Big Data USE - Frequencies				
		Responses		Percent of Cases
		N	Percent	
BDAUSE[a]	1 Operational reporting	100	25,0%	61,0%
	2 Financial reporting	79	19,8%	48,2%
	3 Strategic operational improvement	92	23,0%	56,1%
	4 Strategic commercial improvement	62	15,5%	37,8%
	5 Executive review	55	13,8%	33,5%
	6 Other	12	3,0%	7,3%
Total		400	100,0%	243,9%
a. Dichotomy group tabulated at value 1.				

Table 7.1 in Appendix B demonstrates the descriptive statistics generated for the survey questions relating to the research hypothesis. The table shows that the sample population has, on average, somewhat agreed with the survey question about BDAC's influence on manufacturing FPer.

5.3 Exploratory data analysis

In Chapter 4, the research design section stated that this research will be exploratory. To understand the higher level BDAC constructs in manufacturing organisations, this research employed the PLS-SEM analysis method. This method simply explains complex hierarchical models (Hair et al., 2011; Esposito, 2010; Wamba et al., 2017).

5.4 Measurement model evaluation

In the preceding chapter, Esposito (2010), Hair et al. (2014) and Wamba et al. (2017) state that in SEM, the outer model evaluation process tests the reliability and validity of the model variables. Measuring the effects of the outer (measurement) model specification safeguards the reliability and validity of the independent variables and the research constructs. This section will evaluate the measurement model by employing the above mentioned evaluation techniques.

5.4.1 Outcomes from the reliability test

In determining the reliability of the hypothesis questions, two forms of reliability tests were performed on the underlying data. The Cronbach alpha and composite reliability tests were generated using SmartPLS-4. The rationale for using two tests for reliability was guided by Becker et al. (2012) and Hair et al. (2014), who both stated weaknesses in the Cronbach alpha test which was deemed sensitive and could underestimate the results. This is guided by the Cronbach alpha and composite reliability ranges, which of Hair et al. (2021) states that the internal reliability value should be bigger than 0.7 while the stronger and more robust composite reliability should exceed 0.8.

The researcher followed a multi-stage process of iterative recalibrating the model to ensure the specified conditions were met. This research utilises a higher-order reflective-formative model. As such, much consideration was given to verifying the outer model. In Table 5.6, the second and third construct Cronbach alpha values should be between 0.80 to 0.92. Meanwhile, the first-order Cronbach alpha values range from 0.80 to 0.91 in Table 7.2. of Appendix B. The Composite reliability values for the higher-order constructs in Table 5.6 are also above the 0.8 specified level, ranging from 0.80 to 0.95. The first-order constructs also demonstrate a similar trend with values that range between 0.80 to 0.93. From these results, the reliability of the outer model was verified.

5.4.2 Outcomes from the validity test

The purpose of the convergent and discriminate tests is to evaluate the validity of the measurement model. Two prescribed methods to test convergent validity are the factor analysis method and the AVE method (Hair et al., 2021; Esposito et al., 2010). Discriminate validity is tested using the HTMT test (Hair et al., 2021; Rasoolimanesh, 2022).

Hair et al. (2011) state that a factor analysis indicates how well the interdependent variables measure the latent construct. Purwanto (2021) and Hair et al. (2021) state that higher-order reflective models' prescribed loading factor value should be greater than 0.7. This implies that the indicator/independent variable adequately measures the latent variable/construct. Purwanto (2021) states that a factor loading value greater than 0.5 is considered adequate. For the purpose of this research, values less than 0.5 will be removed across all order levels. Guided by Purwanto (2021) and Hair et al. (2021), the identified factor loading values in Table 5.4 were identified and removed from the model.

Table 5.4: Independent variables removed because of factor loading values- 1st iteration

First-order factor loading	
BDAMOD4 <- BDAMOD	-0,334
Second-order factor loading	
BDAIDM3 <- BDA Management Capabilities	0,430
BDAMOD4 <- BDA Infrastructure Flexibility	-0,292
Third-order factor loading	
BDACOEC2 <- BDAC	0,484
BDACOEC3 <- BDAC	0,356
BDACOMP4 <- BDAC	0,443
BDAMOD1 <- BDAC	0,406
BDAMOD2 <- BDAC	0,456
BDAMOD4 <- BDAC	-0,196

Removing the independent variables with factor loading estimates lower than 0.5 improved the revised model factor loading value. However, a second review of the factor loading values highlighted that an additional variable needed to be removed.

Table 5.5: Independent variables removed because of factor loading values- 2nd iteration

Third-order factor loading	
BDACOEC4 <- BDAC	0,495

The revised model constructs based on the factor loading values have been recorded in Table 7.2 in Appendix B. Table 7.3 in Appendix contains all of the outer model factor loading values

The AVE results for the second and third-order latent test results are close to the 0.5 value prescribed by Hair et al. (2021) in Table 5.6. The third-order construct BDAC has an AVE value of 0.48, which may raise questions about why the decision was made to include this variable in the model design. The result value is close to the prescribed value of 0.5 when applying the root-squared method guided by Hulland (1999). The Root AVE now becomes

0.69, which is deemed sufficient in terms of the acceptable ranges, Hulland (1999) advised. The convergent reliability is confirmed based on the AVE and factor analysis results.

The discriminant reliability is confirmed in Table 5.7, where a significant proportion of HTMT values did not exceed the stipulated level of 0.85 or 0.9 (Hair et al., 2021; Rasoolimanesh, 2022). In reviewing Table 5.7 and acknowledging the complexities associated with higher-order reflective-formative models while guided by Becker et al. (2012). The researcher has decided to keep the first-order latent construct BDATK in the model in the model because it was the only first-order construct reflecting on a second-order construct after rounds of calibration. Becker et al (2012) advocates for a holistic approach to discriminate validity in reflective-formative models such as these. The researcher includes this variable in the model because it refers to BDA technical knowledge which is relevant in this study which is positioned in the manufacturing industry. This variable needs to be included because technical knowledge around equipment sensors provides much insight on how to improve FPer. Using both the HTMT values and some justification, discriminant validity is confirmed for the outer model.

Table 5.6: Summary of higher order validity and reliability results

Model Construct	**Construct**	**Cronbach's alpha**	**Composite reliability (rho_a)**	**Composite reliability (rho_c)**	**Average variance extracted (AVE)**
2nd order	**BDAEC**	0,919	0,921	0,939	0,756
	BDAIF	0,800	0,808	0,883	0,717
	BDAMC	0,920	0,922	0,932	0,535
3rd order	**BDAC**	0,952	0,955	0,956	0,481

Note: BDA Expertise Capabilities (BDAEC), BDA Infrastructure Flexibility (BDAIF), BDA Management Capabilities (BDAMC)

Table 5.7: *HTMT results overview*

HTMT	BDAEC	BDAIF	BDAMC	BDAC	BDACOMP	BDACON	BDADPER	BDAIDM	BDAPLAN	BDAPODC	BDATK
BDAEC											
BDAIF	0,569										
BDAMC	0,752	0,564									
BDAC	0,931	0,737	0,990								
BDACOMP	0,569	1,250	0,564	0,737							
BDACON	0,741	0,593	0,976	0,937	0,593						
BDADPER	0,382	0,266	0,402	0,436	0,266	0,358					
BDAIDM	0,684	0,465	1,016	0,905	0,465	0,794	0,396				
BDAPLAN	0,625	0,477	0,968	0,856	0,477	0,695	0,342	0,787			
BDAPODC	0,630	0,519	0,580	0,662	0,519	0,525	0,498	0,520	0,533		
BDATK	1,088	0,569	0,752	0,931	0,569	0,741	0,382	0,684	0,625	0,630	

Note: BDA Expertise Capabilities (BDAEC), BDA Infrastructure Flexibility (BDAIF), BDA Management Capabilities (BDAMC)

5.5 Inner model evaluation

Concluding the outer model evaluation and establishing its credibility the analysis now proceeds to systematically evaluate the structural model using the PLS-SEM guidelines provided in Figure 4.2 of Chapter 4.

5.5.1 Collinearity test results

High levels of multicollinearity have been acknowledged to bias regression estimates. In order for a model to be robust and have reliable estimates, multicollinearity must be tested and controlled using standardised methods. In the model, collinearity was conducted using the SmartPls-4 software. In Chapter 4, under the PLS-SEM model section, it was highlighted that there are differing opinions on a suitable VIF value. Hair et al. (2021) propose that variables with VIF values greater than 5 be removed, while Henseler et al. (2015) propose that VIF values greater than 10 be removed. For the purposes of this research, a middle ground of VIF values greater than 7.5 be removed, giving allowance for the model design, which is reflective of higher order.

The VIF inner model was assessed because the structural model is reflective-formative in design. Hair et al. (2021) advise that the measurement model VIF estimates should be verified to establish if the advised thresholds have not been breached; if the estimates have breached the threshold limits, the explanatory variable must be excluded from the measurement model. Guided by Hair et al. (2021), the VIF inner model limits are less than 5. The findings of the VIF tests revealed that this research model did face a challenge relating to collinear variables influencing the model estimates. The Inner VIF model values in Table 7.6 did not exceed 1.6, while the outer model VIF values in Table 7.5 did not exceed the researcher's prescribed guidance of 7.5.

5.5.2 Structural Model Assessment

Guided by the research methodology from Chapter 4, the structural model assessment is developed from the diagnostic result obtained from the bootstrapping algorithm in SmartPLS-4. The path coefficient identifies the strength of the relationship between the constructs in the structural model, which reveals that all three higher order construct levels have a significant relationship between each other because the t-values are larger than 2 and the p-values are smaller than 0.05 (Hair et al., 2021).

Table 5.8: Path coefficient values of the inner structural model

Path coefficients - Mean, STDEV, T values, p values	**Original sample (O)**	**Sample mean (M)**	**(STDEV)**	**T - Values**	**P values**
BDA Expertise Capabilities -> BDATK	1,000	1,000	0,000	**89630, 887**	**0,000**
BDA Infrastructure Flexibility -> BDACOMP	1,000	1,000	0,000	**26116, 776**	**0,000**
BDA Management Capabilities -> BDACON	0,863	0,864	0,022	**39,721**	**0,000**
BDA Management Capabilities -> BDAIDM	0,892	0,892	0,020	**45,636**	**0,000**
BDA Management Capabilities -> BDAPLAN	0,875	0,875	0,026	**34,204**	**0,000**
BDAC -> BDA Expertise Capabilities	0,885	0,885	0,019	**47,484**	**0,000**
BDAC -> BDA Infrastructure Flexibility	0,634	0,631	0,063	**10,121**	**0,000**
BDAC -> BDA Management Capabilities	0,919	0,918	0,015	**60,076**	**0,000**
BDAC -> BDADPER	0,220	0,219	0,095	**2,327**	**0,020**
BDAC -> BDAPODC	0,615	0,618	0,045	**13,563**	**0,000**
BDAPODC -> BDADPER	0,321	0,323	0,104	**3,073**	**0,002**

The next step is to evaluate the coefficient of determination (R^2) of the structural model, demonstrating that the variance in latent variables is because of the independent explanatory variables (Esposito, 2010). R^2 values range from 0 to 1, with values closer to 1 implying stronger predictive power (Henseler et al., 2015; Hair et al., 2021).

In Table 5.9, it becomes apparent that while the overall model is sound based on all the variables in the model having p-values of smaller than 0.05 and t-values larger than 2. Some variables have questionable R^2 values.

Table 5.9: Coefficient of determination (R^2)

R-square-Mean, STDEV, T values, p values	**Original sample (O)**	**Sample mean (M)**	**(STDEV)**	**T values**	**P values**
BDA Expertise Capabilities	0,783	0,784	0,033	23,852	0,000
BDA Infrastructure Flexibility	0,402	0,402	0,078	5,170	0,000
BDA Management Capabilities	0,844	0,843	0,028	30,193	0,000
BDACOMP	1,000	1,000	0,000	13059, 440	0,000
BDACON	0,744	0,747	0,037	19,944	0,000
BDADPER	0,238	0,251	0,064	3,716	0,000
BDAIDM	0,796	0,797	0,035	22,994	0,000
BDAPLAN	0,765	0,766	0,044	17,243	0,000
BDAPODC	0,379	0,384	0,056	6,802	0,000
BDATK	1,000	1,000	0,000	44816, 210	0,000

Cohen's f^2 test measures the impact of the predicted variable on the latent construct. The guiding principle by Hair et al. (2021) is that the f^2 values are considered weak when less than 0.2 and stronger when greater than 0.35. In Table 5.10, not all the predictor variables in the model can describe the variances amongst other predictors.

The Stone-Geisser's (Q^2) was run to determine the extrapolative impact of the independent variables in a predictive model. Hair et al. (2021) state that a value greater than 0 indicates significant predictive power. In Table 5.11, the Q^2 estimates for the inner model constructs were greater 0; therefore, predictive relevance was proven.

Hair et al. (2021) and Henseler et al. (2015) suggest that the SRMR should be used to evaluate the fit of the PLS-SEM model. SMSR value of less than 0.08 indicates a good-fitting model (Hair et al., 2021). The SRMR values shown in Table 5.11 are above the threshold values and imply that further evaluation is required to understand the influence of BDAC on manufacturing FPer.

Table 5.10: *Cohen's f^2 test results*

f-square -Mean, STDEV, T values, p values	**Original sample (O)**	**Sample mean (M)**	**(STDEV)**	**T values**	**P values**
BDA Expertise Capabilities -> BDATK	58004,013	57769,342	76535,005	0,758	0,449
BDA Infrastructure Flexibility -> BDACOMP	163088,790	207789,550	3877648,652	0,042	0,966
BDA Management Capabilities -> BDACON	2,910	3,043	0,602	4,838	0,000
BDA Management Capabilities -> BDAIDM	3,906	4,059	0,849	4,603	0,000
BDA Management Capabilities -> BDAPLAN	3,255	3,427	0,856	3,801	0,000
BDAC -> BDA Expertise Capabilities	3,604	3,729	0,726	4,966	0,000
BDAC -> BDA Infrastructure Flexibility	0,672	0,703	0,232	2,898	0,004
BDAC -> BDA Management Capabilities	5,406	5,595	1,185	4,562	0,000
BDAC -> BDADPER	0,040	0,047	0,037	1,067	0,286
BDAC -> BDAPODC	0,609	0,636	0,152	4,021	0,000
BDAPODC -> BDADPER	0,084	0,096	0,061	1,378	0,168

Table 5.11: *Stone-Geisser's* (Q^2) *test result*

LV prediction summary	Q²predict	RMSE	MAE
BDA Expertise Capabilities	0,779	0,477	0,361
BDA Infrastructure Flexibility	0,394	0,790	0,620
BDA Management Capabilities	0,842	0,405	0,288
BDACOMP	0,395	0,789	0,619
BDACON	0,699	0,555	0,431
BDADPER	0,164	0,926	0,736
BDAIDM	0,637	0,616	0,471
BDAPLAN	0,600	0,649	0,472
BDAPODC	0,372	0,804	0,654
BDATK	0,779	0,477	0,361

Table 5.12: *SRMR – Model Fit*

SRMR	Original sample (O)	Sample mean (M)	95%	99%
Saturated model	0,115	n/a	n/a	n/a
Estimated model	0,120	n/a	n/a	n/a

This reflective-formative research model design was selected for this research. Guided by the research method prescribed in Chapter 4, an extensive array of statistical techniques was performed on the data to establish statistical relevance to extract value-adding inference around the research constructs, and while the end results may not be as desired, further analysis and deeper interrogation are required. The outer model was evaluated in accordance with the research method, and a bootstrapping algorithm was run to draw inferences on the survey population (Hair et al., 2021). Sarstedt et al. (2016) and Dijkstra and Henseler (2015) acknowledge that higher-order factors bias the model fit results. Becker et al. (2012) suggest employing the root mean square error (RMSE) as an adjunct test along with the SRMR test for higher-order latent construct models. Lower RMSE values indicate that the model is simpler to interpret and generalisable to interpret by capturing the core relationships and patterns in the underlying data. The RSME values for all the higher-order constructs in Table 5.11 indicate an RSME range between 0.4 and 0.8 at an average of 0.6, indicating that the model is parsimonious.

The researcher employed a rigorous systematic process for each hypothesis with repeated attempts to re-calibrate the measurement and structural models. The amended research model is shown in Figure 5.7.

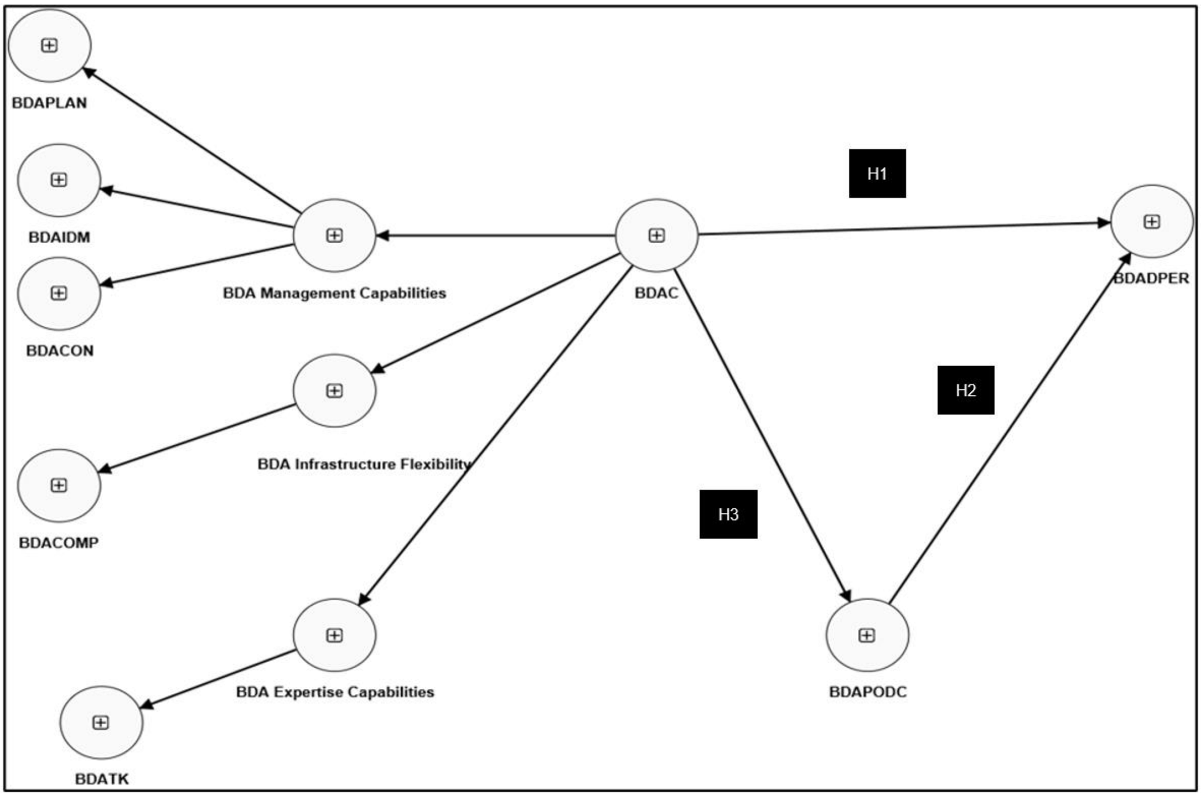

Figure 5.7: Revised research model

5.5.3 Evaluating the structural model relationship

The hypothesis questions in this research were guided by the seminal studies undertaken by Kim et al. (2011), Wamba et al. (2017) and Akter et al. (2016), focusing on BDAC and organisational performance. The key departure points are focusing exclusively on the manufacturing sector and focusing on a practitioner level because all employees who work in the manufacturing sector have access to some version of a technological device that houses big data.

5.5.3.1 Hypothesis 1 path assessment

The first hypothesis being assessed in this research was transposed to the research undertaken by Wamba et al. (2017), which attempted to understand how BDAC influences organisational performance. Hypothesis one of this research proposes a positive link between BDAC and the performance of manufacturing organisations. The outcomes of the evaluation are reflected in Table 5.13.

Table 5.13: *Hypothesis one – path model estimates*

Hypothesis Construct	Path Coefficient	T-value	P-value
BDAC -> BDADPER	0.220	2.327	0.020

From Table 5.13, it is confirmed that BDAC is positively linked to the performance of manufacturing organisations, albeit not strongly linked with a path coefficient of 0.220 ($t=2.37$; $P<0.02$). The test result concur with rejecting the null hypothesis as BDAC influence manufacturing FPer (BDADPER) albeit modestly. This result aligns with the research finding disclosed in Wamba et al. (2017) and Akter et al. (2016), who did have higher path coefficient estimates. The results for hypothesis one confirm that while BDAC positively influences manufacturing FPer, it does so modestly.

5.5.3.2 Hypothesis 2 path assessment

The purpose of hypothesis question two is to define the linkages between PODC and the impact on manufacturing organisations' performance. Belhadi et al. (2019) framework of BDAC established a model through which manufacturing organisations can harness big data generated from the IIoT, ICT and advances in monitoring technologies to resolve manufacturing process-related challenges emanating throughout the value chain by improving the competences relating to the process-related challenge. Wamba et al. (2017) and Akter et al. (2016) concentrated on a similar construct, evaluating how distinct dynamic capabilities influenced organisational performance. The results to evaluate this hypothesis is displayed in Table 5.14.

Hypothesis two in Table 5.14 displays a positive yet slightly improved path coefficient when compared to hypothesis one. The path coefficient for measuring the influence of big data process-orientated dynamic capabilities (BDAPODC) on BDADPER (manufacturing FPer) is 0.321 (t=3.073; P<0.002). Based on the results of the statistical tests, the null hypothesis can be rejected as BDAPODC has a positive influence on BDADPER.

Table 5.14: *Hypothesis two-path model estimates*

Hypothesis Construct	Path Coefficient	T-value	P-value
BDAPODC -> BDADPER	0.321	3.073	0.002

5.5.3.3 Hypothesis 3 path assessment

Hypothesis three aims to assess BDAC's influence on the process-orientated capabilities of manufacturing organisations. Belhadi et al. (2019) are of the view BDAC can improve the PODC capabilities of manufacturing organisations. A similar approach to generate insights on how big data can improve internal organisational capabilities was used by Wamba et al. (2017). The path coefficient scores are illustrated in Table 5.15.

Table 5.15: *Hypothesis three-path model estimates*

Hypothesis Construct	Path Coefficient	T-value	P-value
BDAC -> BDAPODC	0.615	13.563	0.000

The path coefficient results in the table are much improved from the prior two hypothesis tests. The path coefficient results are positive, with BDAC explaining 0.615 (t=13,563; p<0.000) of the variance in BDAPODC. The null hypothesis is rejected because BDAC positively influences PODC of manufacturing organisations. Intuitively, this link was established through the literature review, which illustrated the advancement of manufacturing organisations as a result of being the first adopter of technology to improve processes and competitiveness.

Chapter 6: Discussion of analysis findings

6.1 Introduction

The primary goal of this research was to understand BDAC's influence on manufacturing organisations' performance. Advances in technology coupled with transformative capabilities of the IIoT in an industry characterised by being pioneers in innovation to remain competitive in a continuously organically and inorganically evolving environment and guided by the evolution of manufacturing systems and processes starting from the first IR to the expectations of the industry beyond the fourth IR (Sharma & Singh, 2020; Dogaru, 2020). Using this foundation of technological evolution, a summary of theories underpinning the main constructs of this study allowed the research to establish path linkages between BDAC, FPer and PODC (Akter et al., 2016; Belhadi et al., 2019; Wamba et al., 2017). The primary objectives of the research are expressed in Figure 3.1 of Chapter 3.

This research is positioned as a baseline to understand if manufacturing organisations that generate large volumes of big data that can harness their resources and leverage existing capabilities to improve existing processes and organisational performance. As this research is slanted towards establishing a baseline perspective, all three research questions focus on understanding the direct linkages between BDAC, FPer and PODC. The chapter will focus on discussing research outcomes from Chapter 5. The first part of this chapter will analyse key observations identified in the demographic questions because this research requires a greater understanding of the sample population characteristics of the manufacturing industry, which is needed to contextualise the latter discussion of the three research questions.

6.2 Discussion on demographic survey questions

In Chapter 4, the population sample was described as employees of (practitioners) manufacturing organisations and who used some form of BDA for decisions with the goal of improving organisational performance. Similar research on this topic positioned the population sample to concentrate on IT managers (Wamba et al., 2017; Akter et al., 2016; Gupta & George., 2016). However, this research will not restrict the respondents by their designation because, in manufacturing, BDA is used across many activities and applications from operations, marketing, strategy and new product development (Wamba et al., 2017; Belhadi et al., 2019; Kuo & Kusiak, 2019). The demographic question becomes integral in providing context. Hughes et al. (2016) share that demographic questions clearly describe the sample population to make the research findings generalisable.

The gender of the sample population comprised of 70% male and 30% female respondents. The composition of this representation in this sample is aligned with the view of Samuel et al. (2020), who share that there is lower female representation compared to males in science, technology, engineering and mathematics (STEM) related careers. In this sample population, 70% of all respondents fall within two age categories, starting from 34 to 55 years old. This is an essential fact because more experienced respondents have established ways of working and may need more support to embrace BDA fully. Sutherland (2020) shares that there needs to be a balance between people and technology for BDA to succeed because there is a risk that the rate of innovation surpasses the availability of skills.

In terms of skills and technical expertise, 98% of respondents who qualified for this survey have acquired a level of education that exceeds that of a post-graduate degree. This would imply that all respondents have above-average competency in using BDA tools and applications. The respondents in the sample have indicated that they have more than one area of specialisation, and this flexibility is due to the high level of skill they have acquired through years of studying. Half of the respondent in this sample have indicated that they are in management positions, and 27% of the survey population indicated that they have been employed for more than 10 years but less than 20 years with their current employer.

The survey question relating to whether the use of BDA has increased in use at the respondents organisations over the last 5 years and has had an overwhelming yes response with 86% of respondents. The final demographic question relates to the type of applications big data reports are predominantly used for in the respondents' organisations. The respondents highlighted that big data-generated reports were predominantly used to report on operational and financial performance and to strategically improve operational activities. These responses align with Wamba et al. (2017), Belhadi et al. (2019), and

Dubey et al. (2019a), assertions that large volumes of data are generated from operational activities and used to improve internal operational efficiencies.

6.3 Hypothesis 1 discussion

Hypothesis 1 in this research aimed to verify if the theoretical assertion that big data does improve FPer from manufacturing perspective. This research question was expressed as:

Does BDAC have positive influence on the on manufacturing FPer?

For some time, BDAC has been considered a tool through which an organisation can attain a superior level of performance (Garmaki et al., 2016; Müller et al., 2018; Ghasemaghaei, 2021). In manufacturing organisations, the strategic relevance of BDA is widely communicated because it can be applied across a spectrum of processes and applications that can holistically improve not only current performance but mitigate future challenges (Mikalef et al., 2017; Belhadi et al., 2019; Arinez et al., 2020; Chien et al., 2020; Choi et al., 2022). Organisations in very competitive sectors, such as manufacturing, have been shown to derive value from BDA (Müller et al., 2018).

To understand this relationship, there needs to be an understanding of the organisational IT capabilities (infrastructure, management and personal expertise) that directly influence organisational performance (Garmaki et al., 2016; Mikalef & Pateli, 2017). The view emanates from the theoretical proposition in the RBV and DCT, which state that in order for organisations to maintain a competitive position, resources and capabilities need to be deployed using the VRIN principle (Barney, 1991). In the case of this research, this principle needs to be integrated with an organisational IT capability to ensure that IT resources can impact and influence the performance of an organisation (Kim et al., 2011; Akter et al., 2016; Garmaki et al., 2016).

Organisational IT capabilities have been emphasised as the main influencing factor of BDAC (Belhadi et al., 2019; Garmaki et al., 2016; Wamba et al., 2017). BDAC is regarded as the transmission mechanism through which to improve FPer; however, it brings with it many complexities, as highlighted by Schroeck et al. (2012) four V’s (volume, velocity, veracity, and variety). This complexity around BDAC necessitated that higher-order capabilities be designed to evaluate BDAC incorporating tangible and intangible IT capabilities which operate in unison within the dynamic organisational system (Akter et al., 2016; Garmaki et al., 2016; Wamba et al., 2017). Like IT capabilities, BDAC also requires the application of DCT to consolidate, disseminate and facilitate data tools and applications to improve organisation performance and competitiveness (Wamba et al.,2017; Dubey et al., 2019a).

Assessing the link between BDAC and the performance of manufacturing organisations in hypothesis 1 was determined from the results of the structural PLS-SEM tests. The path coefficient reported in Table 5.13 was 0.220 ($t=2.37$; $P<0.02$) These results align with the findings from the research undertaken by Wamba et al. (2017) and Akter et al. (2016). The findings from the two studies mentioned above are congruent with those of Fainshmidt et al. (2016), who state that higher-order dynamic capabilities positively influence the performance of organisations. The path weighting result for this construct is smaller than the 0.71 path coefficient value in Akter et al. (2016) as well as the 0.56 path weighting in Wamba et al. (2017) for the BDAC and organisational performance relationship.

The researcher postulates that the differences between the path coefficients are attributed to the differing sample populations between the two research sets. Akter et al. (2016) and Wamba et al. (2017) identified their respective units of analysis focused on BDA managers and IT managers primarily focused on maintaining IT infrastructure. The unit of analysis in this survey is differentiated by its concentration on the manufacturing sector and positioning at the practitioner level. The respondents in this survey reported that they have a cross spectrum of specialisations ranging from engineering, finance, supply chain, operations and marketing. In addition, 50% of the sample survey population reported that they were in management positions, which infers that the primary use of BDA would be improving the functional area they directly manage. Therefore, they would have a partial view of how BDAC improves the manufacturing organisation's overall performance.

Accessing the influence of BDAC through higher-order capabilities is essential, lower-order dynamic capabilities can also provide much insight into the factors that can improve and organisations competitive position. This research model comprised of the following three higher-order constructs, namely BDA infrastructure flexibility, BDA management capabilities and BDA expertise capabilities. Table 6.1 identifies that all second-order path coefficients in this model have been shown to have a positive and significant relationship with the third-order construct BDAC. BDA management capabilities were reported to have the most robust path coefficient, 0.919, followed by BDA expertise capabilities, which realised a path coefficient value of 0.885 and then BDA infrastructure flexibility with a path coefficient of 0.634.

Table 6.2 compares the differing path coefficient weighting between related research on BDAC and FPer. Having already established that the path coefficient weightings differ from Wamba et al. (2017) and Akter et al. (2016) because of differing units of analysis and the fact that Gupta and George (2016) used a formative PLS-SEM as opposed to reflective-formative some interesting observation can be derived from the results of the current and past research.

Table 6.1: *H_1-Path coefficients - 2nd order constructs*

Path coefficients - 2nd order constructs	Path coefficient	T Value	P values
BDAC -> BDA Expertise Capabilities	0.885	47.484	0.000
BDAC -> BDA Infrastructure Flexibility	0.634	10.121	0.000
BDAC -> BDA Management Capabilities	0.919	60.076	0.000

Table 6.2: *H_1 -Path coefficient comparison between similar research*

Comparable 2nd order construct	Current Research	Gupta & George (2016)	Akter et al. (2016)	Wamba et al. (2017)
	Path (β)	Path (β)	Path (β)	Path (β)
BDA Expertise Capabilities	0.885	0.37	0.96	0.96
BDA Infrastructure Flexibility	0.634	0.42	0.91	0.96
BDA Management Capabilities	0.919	0.31	0.94	0.93

From Table 6.2 it is evident that BDA management capabilities are important drivers in ensuring that manufacturing organisations can achieve sustainable and competitive performance through BDA supporting the underlying thought process of decision makers

(Akter et al., 2016; Gupta & George, 2016). Ghasemaghaei (2021) characterised BDA as the future enabler for competitive organisational performance, which needs to be managed by managing the organisation's big data resources and capabilities. This view aligns with Barney's (1991) perspective on managing organisational resources to improve organisational FPer. BDA expertise capabilities have a lower path weighting when compared to Akter et al. (2016) and Wamba et al. (2017), which is attributed to the differences in the sample populations between the studies. The respondents in this research have high levels of technical expertise related to manufacturing and support functions.

As such, they may not have BDA skills directly comparable to Akter et al. (2016) and Wamba et al. (2017), resulting in a moderately lower path influence. The BDA infrastructure flexibility path coefficient positively influences BDAC, but the influence is smaller in magnitude than that of Akter et al. (2016) and Wamba et al. (2017). In Chapter 2, it was established that the manufacturing industry is a first-line adopter of new technologies, and as such, the infrastructure has long been in place (Cheng et al., 2018a; Choi et al., 2022). In summary, BDAC can improve the performance of manufacturing organisations; however, to be competitive, manufacturing organisations need to be proactive in managing big data resources and improve expert capabilities in BDA.

6.4 Hypothesis 2 discussion

The intention of hypothesis 2 was to identify the nature of the relationship between PODC and manufacturing organisational performance. This research question was expressed as:

Do process-orientated dynamic capabilities (PODC) and manufacturing FPer have a positive relationship?

The role of dynamic capabilities play in developing competitive advantages contributing to improved organisational performance has been extensively researched (Protogerou et al., 2012; Lin & Wu, 2014; Drnevich & Kriauciunas, 2011). The second research question pertains to a sub-section of dynamic capabilities. PODCs are defined as a firms ability to transform and adapt to the continuously evolving dynamism of the business environment and reconfigure resources to ensure that dynamic capabilities (direct and indirect) can make the necessary adjustments ahead of competitors (Eisenhardt & Martin, 2000; Wamba et al., 2017; Belhadi et al., 2019).

A key theme that emerged from the evolution of manufacturing and the future of manufacturing sections in Chapter 2 was the ability of the manufacturing sector to recognise changing market conditions and reconfigure resources and capabilities. Kim et al. (2011) share that organisational IT resources are not parallel independent streams of resources and capabilities working towards a singularly defined outcome but rather an entangled composition of resources and capabilities all working simultaneously to improve distinct organisational processes. Expanding this viewpoint, Kim et al. (2017) posits that organisations that are focused on singular capabilities are not competitive over the long term.

Transposing this perspective to the manufacturing sector creates a challenging paradox to overcome to ensure that manufacturing organisations maintain long-term competitiveness. Wamba et al. (2017) reaffirm this view that BDAC consists of many entangled elements that must work in harmony to ensure FPer is maintained and incrementally improved. Visualising this concept within the manufacturing ecosystem may appear challenging had it not been for Figure 2.4 from Belhadi et al. (2019), in which manufacturing process challenges were identified (quality, operations, environmental, asset maintenance and occupational health) and recorded in big data analytics faculties which cleaned unstructured data and organised the data so that it could be warehoused and mined to generate transparent insight that support decision making, improve performance and enhance knowledge.

This context demonstrates the entanglement effect on IT resources and capabilities mentioned by (Wamba et al. 2017; Akter et al., 2016; Kim et al., 2011). Manufacturing organisations undertake many direct (operational) and indirect (value chain) activities. In terms of direct activities, sensors submit real-time data on a variety of aspects relating to organisational performance. In most instances, the data generated from these processes is unstructured and needs some form of transformation to be data mined and generate meaningful results that can improve operational processes (Belhadi et al., 2019).

BDA generated from the manufacturing process applies to current processes and can assist in mitigating future challenges. In the Future of Manufacturing section in Chapter 2, three key challenges were identified as significant disruptors to the manufacturing industry. Advances in technology are expected to significantly influence processes along with the competitive position of the manufacturing industry in future (Dubey et al., 2019; Chien et al., 2020; Choi et al., 2022). Digital twining, 3D printing, Blockchain, AI and IIoT are expected to influence manufacturing processes in the future significantly (Chien et al., 2020; Choi et al., 2022; Tao et al., 2018a; Helu,2020). The global adoption of an environmentally conscious approach to manufacturing is also expected to influence manufacturing activities as manufacturers are expected to shift to cyber-physical systems as a way to utilise big data to generate opportunities and new level of insights and reduce costs of prototyping, test new sustainable material and manage waste emitted from existing processes (Dubey et al., 2016; Ren et al., 2019). For manufacturing organisations to be competitive and improve performance, BDAC must be infused into PODC to maintain organisational performance and competitiveness.

Wamba et al. (2017) concedes that the understanding of linkages and influence of BDAC and PODC is not well developed, and the researcher has also realised this. However, in the manufacturing context, PODCs are deemed a significant construct because, universally, manufacturing organisations are characterised by the goal of optimising processes (Yelles-Chaouche et al., 2021). Wamba et al. (2017) regard this construct as a mediating effect; however, this research will view PODC as a direct influence of FPer because of the focus on manufacturing and how improving a single process can improve organisational competitiveness.

Half of the respondents in this survey are in management positions with an operational concentration. As such, they are accountable for the performance of the process they directly manage. From Table 6.3, it is evident that this PODC does have a confirmed impact on the performance of manufacturing firms, aligning to the findings in Wamba et al. (2017). The magnitude of influence would be more significant in this research, which focuses exclusively on manufacturing and places high importance on process optimisation. However, the researcher expected that this impact would be more significant given the challenges facing manufacturing companies on the horizon.

Table 6.3: H2 – Path coefficient comparison between related research

Path -coefficient	Current Research	Wamba et al. (2017)
	Path (β)	Path (β)
BDAPODC -> BDADPER	0.320 (t=3.073)	0.28 (t=3.30)

6.5 Hypothesis 3 discussion

The final hypothesis in this research is important because it seeks to understand if BDAC does have an influencing role PODC of manufacturing organisations. This research question was expressed as:

Is there a positive association between BDAC and PODC in manufacturing organisations?

The linkages between organisational resources and dynamics capabilities have been extensively researched (Chen et al., 2014; Lin & Wu, 2014; Wamba et al., 2017; Akter et al., 2016). PODC, while acknowledged, has been given limited attention than the concentration research on the influence of dynamic IT capabilities on organisational performance (Wamba et al., 2017). Kim et al. (2011) describe PODC as the organisation's capability to adapt resources and capabilities to the current processes to retain a competitive footing in the dynamic business environment. Research into the influence of BDAC on FPer has been around for a while, but the influence of PODC on FPer has largely been unexplored. PODC should not be viewed as similar to the explorative and exploitative capabilities concept in which organisations search for new opportunities and find existing resource capabilities to exploit (Birkinshaw et al., 2016). PODC represents an organisation's continuous effort to reconfigure resources and capabilities to maintain and grow its competitive performance in line with its strategic goals (Kim et al., 2011). The manufacturing sector is continuously evolving and, therefore, needs to improve the dynamic capabilities of existing processes to remain competitive (Wamba et al.,2017; Dubey et al., 2019a).

Manufacturing is considered fast-paced, and organisations must continuously adapt to remain competitive (Belhadi et al., 2019; Dubey et al., 2019a). Organisational IT capabilities through BDA have been positioned to effectively support institutions in identifying, managing and redeploying capabilities to empower faster and astute DDDM (Ghasemaghaei et al., 2017). BDAC is much needed in manufacturing to empower process managers to change and adapt processes so that FPer is not compromised before competitors can seize the advantage.

Most of the survey respondents are process managers and have indicated using a cross-section of BDA reports in the decision-making. Over 80% of respondents in the survey have expressed that the use of a BDAC application increased in their respective organisations. Based on these generalised observations of survey respondents and guided by Belhadi et al. (2019) and Wamba et al. (2017), it is plausible to infer that BDAC would significantly influence PODC in manufacturing organisations.

In Table 6.4, the hypothesis is that BDAC does positively influence PODC in manufacturing firms. It has been established that this research construct is under-researched, as confirmed by Wamba et al. (2017). The estimated path coefficient values are in line with Wamba et al. (2017), which is the only comparable study on this construct. The results from this research has a lower magnitude of influence than the comparable study. The underlying reasons behind this can be attributed to the focus of the sample population being at a practitioner level compared to IT managers which related studies had preferred to be the sample population.

This differentiation in the sample has an influence on the results for this research construct because, at a practitioner level, the influence of BDAC on PODC is not in the same light as the technicians who re-calibrate equipment to perform optimally. The fact that the sample population is management-driven and uses a variety of reports indicates that BDAC does play a contributing role in ensuring that processes are continuously adapting resulting in an inclusive improvement in organisational performance and competitiveness. This view is reaffirmed by the findings in Table 6.2, which shows that BDA Management Capabilities are the most significant second-order construct influencing BDAC in manufacturing organisations. From this sample, it can be deduced that the respondents are focused on managing processes across disciplines and are not specialists in the field of IT and, therefore, need to comprehend the magnitude and significance of BDAC fully has had on PODC and ultimately improving firm performance.

Table 6.4: *H_3 – Path coefficient comparison between related research*

Path -coefficient	Current Research	Wamba et al. (2017)
	Path (β)	Path (β)
BDAC -> BDAPODC	0.615 (t=13.563)	0.84 (t=34.70)

6.6 Conclusion

The research aims to understand BDAC's influence on manufacturing organisations' performance. This research confirms that BDAC positively influences performance in manufacturing organisations directly via strategic management of dynamic capabilities and identified PODC. The findings disclosed in Chapter 4 and the subsequent discussion of the findings in Chapter 5 confirmed the study objectives. They were guided by the underlying theoretical constructs of RBV, DCT and PODC, which were applied through an IT capabilities lens in a manufacturing ecosystem and formed the basis through which the research hypothesis could be statistically tested using a PLS-SEM model that was reflective and formative.

This allowed for the complexity and specificity of that sample population to be empirically tested. The results for all three of the hypothesised constructs were deemed statistically significant, with the only differentiation being the characteristics of the sample population, which was manufacturing, and practitioner focused. Related research on similar constructs and statistical methods was focused on insights from IT and prominent data professionals. The research results provide insightful perspectives on the nature of big data capabilities in manufacturing organisations that can practically contribute to managers and academics. This will be discussed in the last chapter of this research.

Chapter 7: Conclusion

7.1 Introduction

The underlying objective of this study was to establish a baseline from which to understand how BDAC influences manufacturing organisations' performance directly and indirectly through its influence on the multiple concurrent process streams occurring in an evolving dynamic ecosystem. Academic research examining the influence of BDAC on organisational performance positioning big data as a tool or application that supports manufacturing organisations in navigating the complex dynamism of the business environment (Dubey et al., 2019a; Belhadi et al., 2019; Akter et al., 2016; Wamba et al., 2017; Lee et al., 2011; Mourtzis er al.,2016).

Current and seminal research on this phenomenon grounds the research construct from the organisational dynamic capabilities theoretical perspective, with the resource base view providing the overarching theoretical base (Dubey et al., 2019a; Belhadi et al., 2019; Akter et al., 2016; Wamba et al., 2017; Birkinshaw et al., 2016). This research represents a combination of theory and contextualisation of the evolution of the manufacturing industry, and the impact technology has had on performance and competitiveness historically and in the future. These views aided in developing the research model in Figure 3.1, through which the research objectives were explored.

This chapter will consolidate the results of Chapters 5 and 6 from an academic and management viewpoint. The chapter will propose avenues of future research by expanding the dimensions of the existing research constructs. The chapter will conclude by discussing the limitations experienced during this research.

7.2 Contribution to existing theory

Chapter 2 established that the RBV view was the overarching theoretical construct through which the influence and direct and indirect IT dynamic capabilities of FPer were explored. This research contributes to existing academic research relating to strategic management and informational systems, expanding the existing knowledge on the nature of the relationship between BDAC and PODC on FPer from the perspective of manufacturing organisations. Guided by emerging literature on the influence of BBDAC and PODC on FPer by Wamba et al. (2017), Akter et al. (2016), Kim et al. (2011) and Gupta and George (2016), this research expanded on the views from the studies mentioned above. A key focus of the research was to understand how manufacturing organisations who are regarded as the first-in-line pioneers of technological innovation harnessed the big data made available from IIoT to improve competitiveness and overall performance (Dubey et al., 2019a; Belhadi et al., 2019; Cheng et al., 2018a; Choi et al., 2022). The intention of this research is to expand on the limited research on PODC on FPer and BDAC on PODC as mentioned by Wamba et al. (2017) and Belhadi et al. (2019)

There has been a comprehensive review of the influence of IT capabilities on FPer in academia (Kim et al.,2011; Mikalef & Pateli, 2017). The underlying realm of influence of BDAC as a construct is still continuously debated. Belhadi et al. (2019) and Wamba et al. (2017) share the view that BDAC is a composition of interactive resources in the form of commercial, personal and technology. At the same time, Jagadish et al. (2014) and Lee (2017) believe that for BDAC to successfully influence FPer, the technical and system-related challenges need to be corrected.

The research expands the outcomes from the research undertaken by Wamba et al. (2017), Akter et al. (2016) and Kim et al. (2011), who all postulate that in order for BDAC strategies to be successful, it requires the successful integration of expert knowledge of IT system, be flexible in amending the IT infrastructure, and most importantly management needs to have the skills to manage resources and capabilities to achieve improved FPer.

Expanding on the existing theoretical interpretation of the identified constructs, this research employed a reflective-formative third-order hierarchical PLS-SEM model. The results from this research were statistically significant for all three research questions and aligned to the results of Wamba et al. (2017) and Akter al. (2016). BDAC does have a positive relationship on the performance of manufacturing organisations, much like the related seminal research, but the magnitude of the influence in the second-order construct differed. The differing unit of analysis between the sets of research influenced the path weightings of the second-order constructs. The research was focused on the manufacturing sector, while the seminal research studies were flexible on the industry but focused on IT managers with technical knowledge. This research was broader regarding respondents and concentrated on practitioners who use BDA. The underlying rationale was that manufacturing sector employees were the early pioneers of BDA, which was established in the second chapter. The literature on big data in manufacturing recognised that BDA infrastructure was already well-established in manufacturing organisations (Singh & Sharma, 2020; Dubey et al., 2019a). In addition, the sample respondents in the survey were from a technical discipline, and more than half the sample were in management positions.

Wamba et al. (2017) share that PODC is an under-researched area. Kim et al. (2011) and Wamba et al. (2017) have attempted to understand this research construct, but the insights generated additional questions. This research is well-positioned to expand the existing body of knowledge regarding the BDAC, PODC and FPer. Manufacturing organisations consist of many concurrent processes that are all integrated and contribute to the overall level of organisational performance. The second research question established that PODC positively influences manufacturing organisations' performance. This aligns with the results from Wamba et al. (2017). The magnitude of influence in this research is more significant than the seminal work because of the focus on manufacturing and the core characteristic of performance being process optimisation (Yelles-Chaouche et al., 2021).

The final hypothesis question of this research is focused on the establishing the link and influence of BDAC and PODC. As mentioned already, research on PODC is limited; this research supplements the existing academic understanding by identifying that from a manufacturing vantage point, BDAC positively influences PODC aligning to Wamba et al. (2017). The empirical results reveal that BDA management capabilities are the most influential construct to BDAC influencing PODC. Ferraris et al. (2019) state that firm performance improves with structured and appropriate management of BDAC. This is evident from the results from the model, which demonstrate that the magnitude of influence of BDAC on PODC is significant when compared to Wamba et al. (2017).

7.3 Contribution to existing management practices

The rapid technological advances have added a new complexity that organisations must navigate to ensure they achieve the performance levels required to remain competitive (Dubey et al., 2019a; Belhadi et al., 2019). The findings in this research conform with the literature on BDA and its influence of organisational growth (Comuzzi & Patel, 2016; Birkinshaw et al., 2016; Coleman et al., 2016). This research highlights the significant role of BDAC in directly influencing FPer and PODC from a manufacturing perspective. The empirical analysis outcomes align with related research on the impact of dynamic IT capabilities influencing organisational strategy formulation and performance (Kim et al., 2011; Dubey et al., 2019a; Chen et al., 2014). The findings of this research are a snapshot reflection from a defined point in time. Because big data systems continuously evolve, any insights extracted by management may only herald gains over the short term. The results of this research highlight the influential role of BDA management capabilities of BDAC and, subsequently, FPer and PODC, inferring that there needs to be a comprehensive strategy to manage big data resources and associated dynamic capabilities.

BDAC can be effective and provide real value for manufacturing organisations. A comprehensive big data strategy must be formulated and interwoven as essential enabling pillars supporting the strategic organisational objectives (Comuzzi & Patel, 2016). This research highlighted BDA planning, investment decisions and control as critical drivers for managing extensive data capabilities. The key drivers make intuitive sense within the context of manufacturing organisations, especially considering that most manufacturing companies face a delicate balancing act between maintaining performance, capital expenditure, and return on investment. Big data has to be a phased-in strategy with defined time intervals and measurable key performance metrics. In this way, organisations can maintain performance and competitiveness while incrementally improving concurrent manufacturing processes (Kim et al., 2011).

7.4 New research suggestions

This research presented a challenge in that the hypothesis construct was adapted from a generalised perspective to align with a manufacturing perspective. In addition, this research expanded on the boundaries of the type of respondent permitted to participate in the research. The underlying reason for this change was that the research occurred a few years after the initial seminal studies, and workers have become more adept at using big data when making decisions. Therefore, this study concentrated on the influence of big data capabilities in manufacturing from the practitioners' perspective. The research findings have proved to be aligned with Wamba et al. (2017). However, the results indicated that related areas of research construct could be explored.

This research was entirely focused on respondents from the South African manufacturing industry. While the seminal works of Wamba et al. (2017) and Akter et al. (2016) reported that respondents originated from China and the United States of America respectively. Each research population is undoubtedly at different stages of development and complexity in the BDAC life cycle. It would be advantageous to undertake a similar research project and incorporate manufacturing respondents from different geographical locations. This would broaden the scale and scope of insights from an academic and real-world perspective.

This research focused on front-facing perceptive constructs such as big data capabilities, process capabilities and firm performance. Dubey et al. (2019a) posit that organisational culture is influential in determining if BDA is successfully implemented in organisations. An extension of this research would be to assess if manufacturing organisations adopt a positive culture towards adopting big data. This would be interesting from the standpoint of a manufacturing firm where the cultural inclination is to ensure that targets are achieved. Big data offers a potential platform to ensure that targets are realised but also poses a risk to job security, which could negatively impede the implementation of BDA.

The seminal research was conducted in advanced geographical manufacturing centres, so their management of big data strategies would be more progressive. In South Africa, the socioeconomic climate may need to be more accepting of big data applications. Sutherland (2020) further adds that South Africa needs more big data professionals. This implies that organisational management would question the integrity of big data-related product offerings. This can create situations when management does not believe in the results obtained via big data (Mikalef et al., 2018). Managing large data strategies from a manufacturing point of view requires further research.

The demographic survey questions revealed some rather interesting observations regarding the attributes of the manufacturing industry in South Africa. The survey revealed that that manufacturing employees are technically orientated, highly educated and in some form of leadership or management. Based on these characteristics it would be advisable to expand the boundaries of research to include the mediating effect of big data expert capabilities amongst practitioners in the manufacturing sector.

This research's primary objective was to understand BDAC's boundary condition drivers on manufacturing FPer. Emerging literature has put forth the view that AI can dramatically change how manufacturing organisations operate, as AI can analyse and process data in a way that established methods cannot and, therefore, yield a deeper level of insights to empower strategic decision-making (Arinez et al., 2020; Tao et al., 2018b). Dubey et al. (2020) and Akter et al. (2016) introduce the concept of higher-order distinct expert capabilities as mediators that effectuate BDAC and enhance FPer. This type of research is limited to a manufacturing context and would be a positive perspective to the existing research views and real-world business applications. Chapter 2 highlighted the expectant challenges of sustainability and GVC; AI could greatly support manufacturing organisations in overcoming these challenges, but to do so, manufacturing organisations need to establish if there are distinct expert capabilities with existing dynamic capabilities to develop, execute and maintain complex AI project to garner a competitive advantage.

7.5 Restrictions of this research

This research was limited because 96 or 36% of all respondents did not complete the survey. This limitation could have influenced model results because these sample respondents embodied a different set of demographic characteristics, which may have changed the dimension of insights if the path weighting were balanced equally between BDA management capabilities, expert capabilities and infrastructure capabilities.

The respondents needed clarification regarding how the survey questions which IT capability focused related to BDAC. This concept is relatively unknown, and the link to IT capabilities may have needed to be clarified to influence how the respondents answered the survey and potentially influence the model results. This research was cross-sectional and only collected data which formulated insights for a specific period in time.

7.6 Conclusion

The objective of this study was to understand the nature of the between BDAC and the performance of manufacturing organisations. This explorative study embraced a positivist philosophy to establish the causal linkages between BDAC, PODC and FPer. Using the PLS-SEM method of analysis, the empirical findings support the hypothesis that BDAC influences manufacturing firms' performance.

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Appendix A

Demographic questions

Q1. Are you employed in any of the following South African manufacturing sub-sectors:

Agro processing

Automotive

Chemicals

ICT and electronics

Metals

Textiles, clothing and footwear

Other (please specify)

Q2. Gender

Male

Female

Other

Q3. Age group

18-25 years

26-33 years

34-41 years

42-55 years

Greater than 55 years

Q4. Education Level

Primary school

Secondary school

Diploma

Undergraduate degree

Post graduate diploma

Masters/PHD

Q5. Field of specialisation

Financial

Engineering

Supply Chain

Marketing and Sale

Operations

Other (Specify)

Q6. Level in organisation

Graduate

General Work

Professional

Management

Executive Leadership

Other Specify

Q7. Years employed in current organisation

Less than 2 years

More than 2 years less than 5 years.

More than 5 years less than 10 years.

More than 10 years less than 20 years.

More than 20 years.

Q8. Has your organisation increased its dependence on big data (large volumes of information) over the last five years.

Yes

No

Other

Q9 Basis for using big data.

Operational reporting

Financial reporting

Strategic operational improvement

Strategic commercial improvement

Executive review

Other (specify)

Survey question

	1. IT Planning		
	1.1	We continuously examine the innovative opportunities for the strategic use of IT (Using computers, software, and digital networks to send, receive and process data).	Likert Scale 1-7
	1.2	We enforce adequate plans for the introduction and utilisation of IT (Using computers, software, and digital networks to send, receive and process data).	
	1.3	We perform IT planning (Aligning IT strategies to support business goals) processes in systematic and formalised ways.	
	1.4	We frequently adjust IT plans (Refers to an organisations management of infrastructure, projects and resources) to better adapt to changing conditions..	

2. IT Investment Decision making		
2.1	When we make IT investment decisions, we think about and estimate the effect they will have on the quality and productivity of the employees' work.	Likert Scale 1-7
2.2	When we make IT investment decisions, we consider and project about how much these options will help end users make quicker decisions.	

2.3	When we make IT investment decisions, we consider and estimate whether they will consolidate or eliminate jobs.	
2.4	When we make IT investment decisions, we think about and estimate the amount and cost of training that end users will need.	
2.5	When we make IT investment decisions, we consider and estimate the time managers will need to spend overseeing the change.	
3. IT Control		
3.1	In our organisation, the responsibility and authority for IT direction and development are clear.	Likert Scale 1-7
3.2	We are confident that IT project proposals are properly appraised.	
3.3	We constantly monitor the performance of IT function.	
3.4	Our IT department (Team responsible for managing IT infrastructure, systems and services) is clear about its performance criteria.	
4. Connectivity		
4.1	Compared to rivals within our industry, our organisation has the foremost available IT systems and connections.	Likert Scale 1-7
4.2	All remote, branch, and mobile offices are connected to the central office.	
4.3	Our organisation utilises open systems network mechanisms (Allows for open sharing of information across different hardware, software, internal and	

	external vendors) to boost connectivity.	
4.4	There are very few identifiable communications bottlenecks within our organisation.	
5. Compatibility		
5.1	Software applications (Programs) can be easily transported and used across multiple platforms.	Likert Scale 1-7
5.2	Our user interfaces provide transparent access to all platforms and applications.	
5.3	Information is shared seamlessly across our organisation, regardless of the location.	
5.4	Our organisation provides multiple interfaces or entry points for external end users.	
6. Modularity		
6.1	Reusable software modules (Code) are widely used in new system development.	Likert Scale 1-7
6.2	End users utilise object-oriented tools to create their own applications.	
6.3	IT personnel utilise object-oriented technologies to minimise the development time for new applications.	
6.4	The legacy system within our organisation restricts the development of new applications.	
7. Technical Knowledge		
7.1	Our IT personnel are very capable in terms of programming skills.	Likert Scale 1-7
7.2	Our IT personnel are very capable in terms of managing project life cycles.	

7.3	Our IT personnel are very capable in the areas of data and network management and maintenance.	
7.4	Our IT personnel are very capable in the areas of distributed processing or distributed computing.	
7.5	Our IT personnel create very capable decision support systems (Expert systems, artificial intelligence, data warehousing and mining).	
	8. Technology Management Knowledge	
8.1	Our IT personnel show a superior understanding of technological trends.	Likert Scale 1-7
8.2	Our IT personnel show superior ability to learn new technologies.	
8.3	Our IT personnel are very knowledgeable about the critical factors for the success of our organisation.	
8.4	Our IT personnel are very knowledgeable about the role of IT as a means, not an end.	
	9. Business Knowledge	
9.1	Our IT personnel understand our organisation's policies and plans at a very high level.	Likert Scale 1-7
9.2	Our IT personnel are very capable in interpreting business problems and developing appropriate technical solutions.	
9.3	Our IT personnel are very knowledgeable about business functions.	
9.4	Our IT personnel are very knowledgeable about the business environment.	
	10. Relational Knowledge	

10.1	Our IT personnel are very capable in terms of planning, organising, and leading projects.	Likert Scale 1-7
10.2	Our IT personnel are very capable in terms of planning and executing work in a collective environment.	
10.3	Our IT personnel are very capable in terms of teaching others.	
10.4	Our IT personnel work closely with customers and maintain productive user/client relationships.	
11. Process-oriented Dynamic Capabilities		
11.1	Our company is better than competitors in connecting (e.g., communication and information sharing) parties within a business process.	Likert Scale 1-7
11.2	Our company is better than competitors in reducing cost and human labor within a business process.	
11.3	Our company is better than competitors in bringing complex analytical methods to bear on a business process.	
11.4	Our company is better than competitors in bringing detailed information into a business process.	
12. Firm Performance		
12.1	Over the past 3 years, our financial performance has been outstanding.	Likert Scale 1-7Strongly Agree
12.2	Over the past 3 years, our financial performance has exceeded our competitors'.	
12.3	Over the past 3 years, our sales growth has been outstanding.	

12.4	Over the past 3 years, we have been more profitable than our competitors.	

Appendix B

Table 7.1: Descriptive statistics for survey questions

Population Descriptive Statistics

	N	Mean	Std. Deviation	Variance
BDAPLAN1	165	5,782	1,353	1,831
BDAPLAN2	165	5,564	1,411	1,991
BDAPLAN3	165	5,558	1,385	1,919
BDAPLAN4	165	5,345	1,351	1,826
BDAIDM1	165	5,527	1,328	1,764
BDAIDM2	165	5,618	1,248	1,557
BDAIDM3	165	4,976	1,572	2,472
BDAIDM4	165	5,376	1,295	1,677
BDAIDM5	165	4,764	1,629	2,653
BDACON1	165	5,018	1,593	2,539
BDACON2	165	4,994	1,446	2,091
BDACON3	165	5,036	1,456	2,120
BDACON4	165	5,297	1,358	1,845
BDACOEC1	165	4,533	1,628	2,649
BDACOEC2	165	5,788	1,278	1,634
BDACOEC3	165	4,533	1,905	3,631

BDACOEC4	165	4,267	1,772	3,141
BDACOMP1	165	4,509	1,646	2,711
BDACOMP2	165	4,521	1,697	2,880
BDACOMP3	165	4,927	1,732	3,001
BDACOMP4	165	4,327	1,659	2,753
BDAMOD1	165	4,497	1,404	1,971
BDAMOD2	165	3,788	1,654	2,737
BDAMOD3	165	4,521	1,412	1,995
BDAMOD4	165	4,618	1,609	2,588
BDATK1	165	4,824	1,772	3,139
BDATK2	165	4,903	1,699	2,888
BDATK3	165	5,327	1,445	2,087
BDATK4	165	4,982	1,539	2,369
BDATK5	165	4,618	1,753	3,072
BDAMK1	165	4,885	1,612	2,599
BDAMK2	165	5,103	1,540	2,371
BDAMK3	165	5,012	1,572	2,473
BDAMK4	165	5,133	1,524	2,322
BDABK1	165	5,279	1,412	1,995
BDABK2	165	4,873	1,573	2,475
BDABK3	165	5,030	1,446	2,090

BDABK4	165	4,921	1,518	2,303
BDARELKN1	165	5,018	1,495	2,236
BDARELKN2	165	5,133	1,342	1,800
BDARELKN3	165	4,891	1,393	1,940
BDARELKN4	165	4,776	1,499	2,247
BDAPODC1	165	4,479	1,528	2,334
BDAPODC2	165	4,339	1,605	2,576
BDAPODC3	165	4,503	1,613	2,602
BDAPODC4	165	4,533	1,520	2,309
BDADPER1	165	4,552	1,763	3,108
BDADPER2	165	4,412	1,677	2,812
BDADPER3	165	4,618	1,697	2,878
BDADPER4	165	4,412	1,576	2,485
Valid N (listwise)	165			

Std. Deviation and Variance use N rather than N-1 in denominators.

Table 7.2: *Revised constructs*

	Original model	**Revised model**
1	BDAPLAN1	BDAPLAN1
2	BDAPLAN2	BDAPLAN2
3	BDAPLAN3	BDAPLAN3
4	BDAPLAN4	BDAPLAN4
5	BDAIDM1	BDAIDM1
6	BDAIDM2	BDAIDM2
7	BDAIDM3	BDAIDM3 (removed)
8	BDAIDM4	BDAIDM4
9	BDAIDM5	BDAIDM5
10	BDACON1	BDACON1
11	BDACON2	BDACON2
12	BDACON3	BDACON3
13	BDACON4	BDACON4
14	BDACOEC1	BDACOEC1 (removed)
15	BDACOEC2	BDACOEC2 (removed)
16	BDACOEC3	BDACOEC3 (removed)
17	BDACOEC4	BDACOEC4 (removed)
18	BDACOMP1	BDACOMP1
19	BDACOMP2	BDACOMP2
20	BDACOMP3	BDACOMP3
21	BDACOMP4	BDACOMP4 (removed)

22	BDAMOD1	BDAMOD1 (removed)
23	BDAMOD2	BDAMOD2 (removed)
24	BDAMOD3	BDAMOD3
25	BDAMOD4	BDAMOD4 (removed)
26	BDATK1	BDATK1
27	BDATK2	BDATK2
28	BDATK3	BDATK3
29	BDATK4	BDATK4
30	BDATK5	BDATK5
31	BDAMK1	BDAMK1 (removed)
32	BDAMK2	BDAMK2 (removed)
33	BDAMK3	BDAMK3 (removed)
34	BDAMK4	BDAMK4 (removed)
35	BDABK1	BDABK1 (removed)
36	BDABK2	BDABK2 (removed)
37	BDABK3	BDABK3 (removed)
38	BDABK4	BDABK4 (removed)
39	BDARELKN1	BDARELKN1 (removed)
40	BDARELKN2	BDARELKN2

		(removed)
41	BDARELKN3	BDARELKN3 (removed)
42	BDARELKN4	BDARELKN4 (removed)

Table 7.3: *Outer Model factor loading values*

	Outer loadings
BDABK1 <- BDAC	0,660
BDABK2 <- BDAC	0,758
BDABK3 <- BDAC	0,825
BDABK4 <- BDAC	0,781
BDACOMP1 <- BDA Infrastructure flexibility	0,856
BDACOMP1 <- BDACOMP	0,857
BDACOMP1 <- BDAC	0,528
BDACOMP2 <- BDACOMP	0,903
BDACOMP2 <- BDA Infrastructure flexibility	0,903
BDACOMP2 <- BDAC	0,576
BDACOMP3 <- BDACOMP	0,775
BDACOMP3 <- BDA Infrastructure flexibility	0,777
BDACOMP3 <- BDAC	0,504
BDACON1 <- BDAC	0,643
BDACON1 <- BDACON	0,796
BDACON1 <- BDA Management Capabilities	0,682
BDACON2 <- BDACON	0,871
BDACON2 <- BDA Management Capabilities	0,758
BDACON2 <- BDAC	0,726
BDACON3 <- BDA Management Capabilities	0,689
BDACON3 <- BDACON	0,826
BDACON3 <- BDAC	0,672
BDACON4 <- BDACON	0,827
BDACON4 <- BDA Management Capabilities	0,734
BDACON4 <- BDAC	0,741
BDADPER1 <- BDADPER	0,915
BDADPER2 <- BDADPER	0,923
BDADPER3 <- BDADPER	0,836
BDADPER4 <- BDADPER	0,896
BDAIDM1 <- BDAC	0,737
BDAIDM1 <- BDAIDM	0,884
BDAIDM1 <- BDA Management Capabilities	0,823
BDAIDM2 <- BDA Management Capabilities	0,746
BDAIDM2 <- BDAIDM	0,795
BDAIDM2 <- BDAC	0,630

BDAIDM4 <- BDA Management Capabilities	0,680
BDAIDM4 <- BDAIDM	0,801
BDAIDM4 <- BDAC	0,624
BDAIDM5 <- BDAIDM	0,783
BDAIDM5 <- BDAC	0,614
BDAIDM5 <- BDA Management Capabilities	0,650
BDAPLAN1 <- BDAPLAN	0,879
BDAPLAN1 <- BDA Management Capabilities	0,741
BDAPLAN1 <- BDAC	0,620
BDAPLAN2 <- BDA Management Capabilities	0,730
BDAPLAN2 <- BDAPLAN	0,888
BDAPLAN2 <- BDAC	0,634
BDAPLAN3 <- BDA Management Capabilities	0,805
BDAPLAN3 <- BDAPLAN	0,888
BDAPLAN3 <- BDAC	0,734
BDAPLAN4 <- BDAPLAN	0,774
BDAPLAN4 <- BDAC	0,674
BDAPLAN4 <- BDA Management Capabilities	0,721
BDAPODC1 <- BDAPODC	0,845
BDAPODC2 <- BDAPODC	0,848
BDAPODC3 <- BDAPODC	0,913
BDAPODC4 <- BDAPODC	0,899
BDATK1 <- BDA Expertise Capabilities	0,852
BDATK1 <- BDAC	0,711
BDATK1 <- BDATK	0,854
BDATK2 <- BDA Expertise Capabilities	0,915
BDATK2 <- BDAC	0,827
BDATK2 <- BDATK	0,914
BDATK3 <- BDATK	0,848
BDATK3 <- BDAC	0,786
BDATK3 <- BDA Expertise Capabilities	0,849
BDATK4 <- BDAC	0,780
BDATK4 <- BDA Expertise Capabilities	0,891
BDATK4 <- BDATK	0,891
BDATK5 <- BDATK	0,838
BDATK5 <- BDAC	0,737
BDATK5 <- BDA Expertise Capabilities	0,837

Table 7.4: *Construct reliability and validity test*

Constructs	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
BDA Expertise Capabilities	0,919	0,921	0,939	0,756
BDA Infrastructure flexibility	0,800	0,808	0,883	0,717
BDA Management Capabilities	0,920	0,922	0,932	0,535
BDAC	0,952	0,955	0,956	0,481
BDACOMP	0,800	0,808	0,883	0,717
BDACON	0,850	0,852	0,899	0,690
BDADPER	0,915	0,932	0,940	0,798
BDAIDM	0,833	0,842	0,889	0,667
BDAPLAN	0,880	0,882	0,918	0,737
BDAPODC	0,899	0,902	0,930	0,768
BDATK	0,919	0,920	0,939	0,756

Appendix C

Table 7.5: *VIF outer model limits*

Outer model - List	VIF
BDABK1	2,797
BDABK2	4,429
BDABK3	5,327
BDABK4	4,778
BDACOMP1	2,009
BDACOMP1	2,009
BDACOMP1	2,446
BDACOMP2	2,330
BDACOMP2	2,330
BDACOMP2	2,943
BDACOMP3	1,469
BDACOMP3	1,469
BDACOMP3	1,776
BDACON1	2,717
BDACON1	1,936
BDACON1	2,065
BDACON2	2,413
BDACON2	2,816
BDACON2	3,250
BDACON3	2,200
BDACON3	2,025
BDACON3	2,568
BDACON4	2,032
BDACON4	2,514
BDACON4	2,966
BDADPER1	3,639

BDADPER2	5,302
BDADPER3	2,543
BDADPER4	4,394
BDAIDM1	3,303
BDAIDM1	2,389
BDAIDM1	3,087
BDAIDM2	2,210
BDAIDM2	1,809
BDAIDM2	2,506
BDAIDM4	2,067
BDAIDM4	1,824
BDAIDM4	2,361
BDAIDM5	1,781
BDAIDM5	2,200
BDAIDM5	1,868
BDAPLAN1	3,351
BDAPLAN1	3,609
BDAPLAN1	4,028
BDAPLAN2	3,591
BDAPLAN2	3,428
BDAPLAN2	3,877
BDAPLAN3	3,303
BDAPLAN3	2,578
BDAPLAN3	3,538
BDAPLAN4	1,712
BDAPLAN4	2,502
BDAPLAN4	2,144
BDAPODC1	2,169
BDAPODC2	2,255
BDAPODC3	3,795
BDAPODC4	3,452

BDATK1	2,472
BDATK1	2,791
BDATK1	2,472
BDATK2	3,773
BDATK2	4,960
BDATK2	3,773
BDATK3	2,507
BDATK3	3,413
BDATK3	2,507
BDATK4	3,853
BDATK4	3,129
BDATK4	3,129
BDATK5	2,407
BDATK5	2,969
BDATK5	2,407

Table 7.6: *VIF inner model*

Inner Model – List	VIF
BDA Expertise Capabilities -> BDATK	1,000
BDA Infrastructure flexibility -> BDACOMP	1,000
BDA Management Capabilities -> BDACON	1,000
BDA Management Capabilities -> BDAIDM	1,000
BDA Management Capabilities -> BDAPLAN	1,000
BDAC -> BDA Expertise Capabilities	1,000
BDAC -> BDA Infrastructure flexibility	1,000
BDAC -> BDA Management Capabilities	1,000
BDAC -> BDADPER	1,609
BDAC -> BDAPODC	1,000
BDAPODC -> BDADPER	1,609

Appendix D

Table 7.7: *Path coefficient – structural model*

Path coefficients	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
BDA Expertise Capabilities -> BDATK	1,000	1,000	0,000	89630,887	0,000
BDA Infrastructure Flexibility -> BDACOMP	1,000	1,000	0,000	26116,776	0,000
BDA Management Capabilities -> BDACON	0,863	0,864	0,022	39,721	0,000
BDA Management Capabilities -> BDAIDM	0,892	0,892	0,020	45,636	0,000
BDA Management Capabilities -> BDAPLAN	0,875	0,875	0,026	34,204	0,000
BDAC -> BDA Expertise Capabilities	0,885	0,885	0,019	47,484	0,000
BDAC -> BDA Infrastructure Flexibility	0,634	0,631	0,063	10,121	0,000
BDAC -> BDA Management Capabilities	0,919	0,918	0,015	60,076	0,000
BDAC -> BDADPER	0,220	0,219	0,095	2,327	0,020
BDAC -> BDAPODC	0,615	0,618	0,045	13,563	0,000
BDAPODC -> BDADPER	0,321	0,323	0,104	3,073	0,002

Table 7.8: R^2 *coefficients from the bootstrapping model*

R-square	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
BDA Expertise Capabilities	0,783	0,784	0,033	23,852	0,000
BDA Infrastructure Flexibility	0,402	0,402	0,078	5,170	0,000
BDA Management Capabilities	0,844	0,843	0,028	30,193	0,000
BDACOMP	1,000	1,000	0,000	13059,440	0,000
BDACON	0,744	0,747	0,037	19,944	0,000
BDADPER	0,238	0,251	0,064	3,716	0,000
BDAIDM	0,796	0,797	0,035	22,994	0,000
BDAPLAN	0,765	0,766	0,044	17,243	0,000
BDAPODC	0,379	0,384	0,056	6,802	0,000
BDATK	1,000	1,000	0,000	44816,210	0,000