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2024
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Mavodze, Nyiko Allan. (2024). The impact of big data analytics on the competitiveness of South African smart manufacturing enterprises [Masters dissertation, University of the Witwatersrand, Johannesburg]. WIReDSpace. https://hdl.handle.net/10539/50165

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The impact of big data analytics on the competitiveness of South African smart manufacturing enterprises

A research report submitted

By

Nyiko Allan Mavodze

Student number: 458057

Supervised by Dr Oro Ufuo Oro

A research report submitted to the Faculty of Commerce, Law and Management, University of the Witwatersrand, in partial fulfilment of the requirements for the degree of Master of Business Administration

Johannesburg, 2024

DECLARATION

I, Nyiko Allan Mavodze, hereby declare that the research work reported in this thesis my own work and was thoroughly done by me, except where otherwise indicated in the references and acknowledgements.

It is submitted, in partial fulfilment of the requirements for the degree of Master of Business Administration at the University of the Witwatersrand. This thesis has not, either in whole or in part, been submitted for a degree or diploma to any other universities.

Signed: Date: 27 October 2024

ACKNOWLEDGEMENTS

First, I express my heartfelt and sincere gratitude to my wife for her continued support in all my academic pursuits. I also extend my gratitude to my family and friends for their support and contributions towards creating an environment that has allowed me to succeed.

My sincere gratitude and appreciation go to my supervisor, for his support and guidance, which have contributed significantly to the successful completion of this research.

Lastly, I dedicate this research to my son and daughter. This research serves as proof that dedication and hard work yield results. Time is precious, so choose carefully how you invest it.

I give thanks to God for being the source of hope and blessings.

ABSTRACT

Smart manufacturing is recognized for its potential to significantly enhance strategic decision-making and competitive advantage (Al-Khatib, 2022). However, despite its transformative potential, many manufacturers, particularly in South Africa, struggle to fully leverage big data due to limitations in capacity and capability (World Economic Forum, 2021; Rockwell Automation, 2024). This study aims to identify the barriers and benefits associated with big data analytics adoption within South African smart manufacturing enterprises.

Literature highlights that while big data analytics can significantly enhance manufacturing operations and competitiveness, many organizations face challenges related to high costs, skills shortages, and infrastructural limitations (Kamble et al., 2018; Pradhan & Agwa-Ejon, 2018). This study fills a gap by examining these issues within the South African context, applying qualitative methods to gain deeper insights into these barriers and benefits.

The study employed a qualitative approach, starting with a questionnaire that yielded 172 respondents. This questionnaire comprised both quantitative questions (e.g., participants' demographics) and open-ended qualitative questions, providing a comprehensive understanding of the respondents' insights. Following this, in-depth qualitative interviews were conducted with nine participants. The data were analysed using thematic analysis and ATLAS.ti software to identify key themes and insights.

Findings reveal that many South African manufacturers are in the early stages of adopting smart manufacturing, with significant barriers including financial and resources constraints, poor/lack infrastructure, skills gaps, and organizational resistance. Identified the benefits of big data analytics include improved operational efficiency, predictive maintenance, and enhanced decision-making, are recognized as critical to achieving competitive advantage. The study emphasizes that South African smart manufacturing enterprises must address these barriers to fully leverage big data analytics. It highlights the urgency of overcoming financial constraints, bridging skills gaps, and fostering a supportive organizational culture to enhance long-term competitiveness and sustainability.

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LIST OF ACRONYMS

4IR – Fourth industrial revolution

AI – Artificial Intelligence

ANSI – American National Standards Institute

CPS – Cyber Physical Systems

IIoT – Industrial Internet of Things

IoT – Internet of Things

ISA– International Society of Automation

TAM - Technology Acceptance Model

DIT - Diffusion of Innovation Theory

CHAPTER 1. INTRODUCTION

1.1 Background of the study

The fourth industrial revolution has introduced a wide range of digital and technological capabilities, significantly transforming manufacturing industry (Sahoo & Lo, 2022). Characterized by interconnected production systems, transformed manufacturing capability is called smart manufacturing (Mourtzis et al., 2022). Smart manufacturing generates a high volume and variety of data from interconnected production systems (Tao et al., 2018), which is categorized as big data (Belhadi et al., 2019) and the capability of analyses this data is referred big data analytics.

A survey conducted across 17 countries, involving over 1500 manufacturers, found that 95% are currently adopting or fully adopted smart manufacturing capabilities (Rockwell Automation, 2024). Although industry is experiencing constant growth in smart manufacturing adoption, there's evidence to argues that most manufacturers lack the capacity and capabilities to leverage and exploit the data (World Economic Forum, 2021). A World Economic Forum (2021) study that surveyed over 1300 manufacturing executives found that only 16% have scaled data-driven use cases in production process. The global manufacturing landscape has now advanced to utilizing big data analytics in unlocking the benefits of smart manufacturing. However, Gumbi & Twinomurinzi (2020) argues that among South African firms there is a lack of awareness and knowledge of smart manufacturing.

Understanding the barriers to adoption and utilization big data analytics in smart manufacturing can generate insight that can enable South African Manufacturers to effectively compete at a global scale. Casual observation indicates that the South African manufacturing industry lacks the capacity to compete in a global market (Statistic South Africa, 2022). This shortcoming is attributed to the inability to manage the vast amounts of data associated with smart manufacturing (Eybers & Mayet, 2021). Recent research in this area using South African data has failed to investigate the factors responsible for this weakness (Dhamija, 2022).

1.2 Research problem

In today's rapidly evolving global manufacturing landscape, smart manufacturing has emerged as a pivotal strategy for enterprises seeking to gain a competitive edge (Lin et al., 2020). The effective utilisation of big data analytics is recognized as a key driver in unlocking the full potential of smart manufacturing, offering significant benefits such as predictive production planning, improved energy and resource efficiency, and enhanced labour productivity (Ma et al., 2020; Schuh & Scheuer, 2022). Research further suggests that leveraging big data analytics can directly and positively impact the competitive advantage of smart manufacturers (Al-Khatib, 2022; Raut et al., 2021). Similarly, Schuh & Scheuer (2022) suggests that improving labour productivity through smart manufacturing can only be achieved by effectively using data and formulating sustainable data-driven strategies.

However, despite the increasing adoption rate of smart manufacturing technologies (Rockwell Automation, 2024)., many manufacturers encounter substantial barriers in adopting and utilizing big data analytics (World Economic Forum, 2021). According to a study conducted by Deloitte (2017), South Africa is in the early stages of adopting smart manufacturing technologies, suggesting a need for significant development to fully integrate these advanced capabilities.

While South African manufacturers are gradually enhancing their smart manufacturing capabilities, there is limited research examining the specific barriers to the adoption of big data analytics and the associated benefits within this context. This knowledge gap may prevent many South African manufacturers from fully realizing the competitive advantages offered by smart manufacturing technologies. Thus, this study aims to investigate the barriers to the adoption of big data analytics and to explore the perceived benefits of its utilisation in enhancing the competitive advantage of smart manufacturing enterprises in South Africa. By addressing these critical issues, the research will provide valuable insights to help manufacturers navigate the challenges of big data analytics adoption and leverage its full potential to improve their competitive positioning.

1.3 Research objectives

The objectives of this study are:

- To identify the barriers to big data analytics adoption among South African smart manufacturing enterprises.
- To discover the benefits of utilising big data analytics in smart manufacturing.

1.4 Research questions

The research questions of this study are:

- What are the barriers to adopting big data analytics among South African smart manufacturing enterprises?
- What are the perceived benefits of adopting big data analytics for smart manufacturers in South Africa?

1.5 Rationale of the study

The impact of big data analytics on competitive advantage is well-researched, yet little has been explored in a South African context, particularly from the perspective of smart manufacturing enterprises (Pradhan & Agwa-Ejon, 2018). Insights from this study can bolster the confidence of the South African manufacturing industry in adopting big data analytics and understanding the perceived benefits of utilizing big data is crucial for grasping its impact.

The motivation behind adopting smart manufacturing ultimately revolves around gaining a competitive advantage. As the South African manufacturing industry ramps up its smart manufacturing capabilities, it's vital to understand the role of big data analytics in achieving competitive advantage. Technological advancements can entail significant costs and risks, and understanding potential barriers to gaining a competitive advantage is crucially important. Research by Azeem et al. (2021), highlighted the case of a South African mine that was able to improve its yield and profit by analysing production data and then formulating

a data- driven production procedure. Evidently, in the fourth industrial revolution, data is considered a commodity, holding the potential to enhance competitiveness for smart manufacturers.

Thus, this study is driven by the necessity to identify barriers to adopting big data analytics in smart manufacturing. It aims to empower industry practitioners to navigate smart manufacturing by shedding light on associated barriers to unlocking competitive advantages. Additionally, the study aims to raise awareness of the benefits of utilizing big data analytics in smart manufacturing.

This study will contribute valuable insights to manufacturing industry practitioners, providing an understanding of the barriers and associated benefits of adopting big data analytics within a South African context. The International Journal of Technology Management listed in DHET Accredited journal lists for publications is the nominated journal.

A clear understanding of these aspects can boost confidence in adopting new technologies. Furthermore, this study enhances the current body of work on technology management.

1.6 Limitations of the study

Smart manufacturing is still developing in South African. This limitation was evidently on the findings of the research, interview data collection was only limited to a few companies with smart manufacturing. These limitations negatively affect the generalisability of the results of this study.

1.7 Assumptions of the study

The study used LinkedIn to identify potential participants based on the professional backgrounds captured in their profiles, assuming that this information is accurate and reflects the participants' experience in the manufacturing industry. Verifying each profile would require significant time and resources; thus, the study operates under the assumption that participants' listed backgrounds are valid. Furthermore, it is assumed that participants answered

questions honestly and factually, as validating each response in detail would also require substantial time and effort.

Therefore, guided by existing literature, participants included in this study met specific criteria to ensure relevance and expertise. Participants were required to (1) have a minimum of five years of experience in the manufacturing industry, (2) demonstrate willingness to participate, (3) be knowledgeable in manufacturing technologies and engineering, and (4) possess work experience that includes practical understanding of smart manufacturing as defined in this study. These criteria aimed to select individuals well-suited to contribute valuable insights into the adaptation barriers to big data analytics in smart manufacturing.

1.8 Delimitations of the study

This study limits itself to smart manufacturing even though big data analytics could also apply to the other models of manufacturing. This limit is explained by time and other resources required to collect data from the sample of all manufacturing enterprises. Smart manufacturing firms are only those who integrate various fourth industrial revolution technologies into their operations.

1.9 Definition of terms

Smart manufacturing – refers to the transformation of manufacturing operations through integration of digital systems linking both the physical and cyber capabilities (Sahoo & Lo, 2022).

Big data analytics – a methodical approach to analysing and managing a large volume of data in order to gain insight (Ikegwu et al., 2022).

Competitiveness – refers to an organization's capacity to thrive in a specific market or setting (Chaudhuri & Ray, 1997). It is a gauge of their potential to outperform and prevail in contrast to their competitors.

Competitive advantage – refers to a company's distinctive qualities or advantages that set them apart from rivals and enable them to perform better than others in a certain market or sector (Porter, 1985).

Dynamic capabilities – refers to the ability of a firm to integrate, develop, and reconfigure competencies in order to exploit opportunities and handle challenges presented by the changing environment (Teece, 2018).

1.10 Structure of the research report

This research report is structured as described below:

Introduction: An introductory chapter providing the background of the research, the research problem, the reasons for undertaking the research, and delimitation of the study.

Literature Review: A detailed literature review on the smart manufacturing, big data analytics, and research frameworks adopted by the study and highlights the research gaps.

Research Methodology: Outlines the research method that will be used to conduct the study and gather the data.

Research Results: Presents and describes the results gathered from the research instrument.

Conclusion: Summaries key findings, recommendations for future research and reflection on the significance and contribution of the research.

CHAPTER 2. LITERATURE REVIEW

2.1 Introduction

The Fourth Industrial Revolution (4IR) has sparked a digital shift in the manufacturing sector. This is characterised by the integration of Internet of Things (IoT), Industrial Internet of Things (IIoT), Machine Learning, AI, and Cyber Physical Systems (CPS) into manufacturing systems and operations (Sahoo & Lo, 2022). As a result, manufacturing now features highly automated production systems and intelligent manufacturing systems (Mourtzis et al., 2022). Similarly, Sahoo & Lo (2022) suggests that the integration of 4IR technologies into manufacturing systems and operations results in smart manufacturing capabilities.

Smart manufacturing capabilities are though to aid and influence strategic decision in competitive advantage (Al-Khatib, 2022). Although smart manufacturing has been identified as the next leap for manufacturers, the World Economic Forum (2021) reports that many manufacturers lack the capacity and capabilities to leverage and exploit the data produced in smart manufacturing operations. According to a report by Rockwell Automation (2024), the global manufacturing landscape has advanced to utilizing big data analytics to unlock the benefits of smart manufacturing. This however, this is argued not to be true within the South African context. According to Deloitte (2017), South African manufacturing enterprises have not yet recognized the value of the data they generate in their operations, and as a result, advanced analytics are generally not explored. A systematic review of Industry 4.0 adoption in South Africa suggests the need for further research to track the adoption progress and associated benefits, as there is currently a significant shortage of literature in this area (Dhamija, 2022).

Therefore, the purpose of this literature review is to synthesize existing literature to gain an understanding of the barriers to adopting big data analytics, the benefits of utilizing big data analytics, and how it enhances competitive advantage in smart manufacturing.

2.2 Smart Manufacturing

2.2.1 Understanding Smart Manufacturing

A full integration of 4IR technologies into manufacturing systems introduced a capability termed "smart manufacturing". Mourtzis et al. (2022) suggest that smart manufacturing primarily relates to advanced application of intelligent systems in manufacturing production and operations. Conversely, Mittal et al. (2018) suggest a more precise definition, stating that smart manufacturing refers to the outcome of applying Industry 4.0 communication and connectivity technologies across manufacturing processes.

Literature suggests that smart manufacturing is still regarded as a growing field of study and lacks a common definition that can be adopted by researchers (Ghobakhloo, 2018; B. Wang et al., 2021). However, this study shall adopt a definition conceptualised by Sahoo & Lo (2022) that the integration of 4IR technologies into manufacturing systems and operations results in smart manufacturing capabilities

2.2.2 Overview of smart manufacturing in South Africa

A study conducted by Deloitte (2017) examined the challenges and opportunities faced by the South African manufacturing industry in its journey towards digital transformation through the adoption of 'Industry 4.0' technologies. The study suggests that the adoption of Industry 4.0 technologies is still at a foundational stage (Deloitte, 2017). In support, a systematic review of Industry 4.0 adoption in South Africa suggests the need for further research to track the adoption progress and associated benefits, as there is currently a significant shortage of literature in this area (Dhamija, 2022).

According to Pradhan & Agwa-Ejon (2018), the adoption of the smart manufacturing capabilities across South African manufacturing industries faces barriers related to legal frameworks, skills deficits, and socio-economic issues. Shai et al. (2020) further highlights that the implementing smart manufacturing is highly costly and requires specialized skills. However, Gumbi & Twinomurinzi

(2020) argues that there is a lack of awareness and knowledge of smart manufacturing within the South African manufacturing industry. Gumbi & Twinomurinzi (2020) further expresses that there is limited research on the adoption and readiness of smart manufacturing.

According to a study conducted by Shai et al. (2020), smart manufacturing capabilities are anchored by the ability to gain insights from data. The study argues that this is also true for smart manufacturing in South Africa. Similarly, Deloitte (2017) suggests that South African manufacturing enterprises have not yet recognized the value of the data they generate in their operations. As a result, advanced analytics are generally not explored.

Gumbi & Twinomurinzi (2020) argues that the challenges and benefits of advanced smart manufacturing applications are yet to be contextualized for developing countries. Furthermore, the lack of contextualized research in smart manufacturing can be cited as a reason for the lack of awareness of its advantages (Gumbi & Twinomurinzi, 2020; Maisiri et al., 2021). Similarly, Maisiri et al. (2021) argues that the lack of context specific knowledge to support the sustainable adoption of advanced technologies, is one factor stifles competitiveness of the South African manufacturing industry.

Despite this, consensus among researchers seems to be that smart manufacturing adoption is in a foundation phase, and the cost of implementation and skills scarcity are some of the challenges South African firms are facing (Deloitte, 2017; Gumbi & Twinomurinzi, 2020; Maisiri & Van Dyk, 2021; Pradhan & Agwa-Ejon, 2018; Shai et al., 2020).

2.2.3 Benefits of smart manufacturing

Literature suggests that the impact of smart manufacturing can be categorized into three main areas: efficiency improvement, proactivity, and decision-making, all of which lead to numerous benefits for manufacturers (Haricha, 2021).

Efficiency

The efficiency impact of smart manufacturing is often measured through key performance indicators such as cost, quality, time savings, and flexibility (Haricha, 2021; Kamble et al., 2020).

Filz et al. (2020) claims smart manufacturing improves efficiency by reducing downtime and enhancing resource utilization. In support, empirical evidence from multiple studies shows that production processes can be streamlined using real-time data to conduct predictive analytics, which increases productivity and minimizes waste (Lee et al., 2020; Ma et al., 2020; Zhang et al., 2019). However, Mora et al. (2017) argues that organizations must first apply lean practices to realize the expected improvements in production process quality the rough smart manufacturing.

Proactivity

Smart manufacturing is thought to enable proactive actions and early-warning detection of production failures, abnormalities, and deviations through real-time data monitoring (Haricha, 2021). Research indicates that access to real-time data allows manufacturers to conduct predictive analytics to achieve predictive maintenance, minimizing failure and waste, and reducing costs (P. Kumar et al., 2021; Lee et al., 2020; Ma et al., 2020). Furthermore, through real-time monitoring and control of production processes, deviations can be detected, and corrective actions taken (Azeem et al., 2021; Dutta et al., 2022).

Zheng et al. (2018) suggests that the real-time data collection capability of smart manufacturing is a key enabler for optimal machine scheduling. Using data collected from sensors and manufacturing systems, deviations can be detected in real time, enabling proactive preventative measures that reduce downtime and breakdowns (Geary & Cosgrove, 2023; Sahoo & Lo, 2022).

Decision-Making

Real-time insights from smart manufacturing facilitate proactive decision-making, allowing decision-makers to make more informed choices and execute actions swiftly (Haricha, 2021). J. Davis et al. (2012) notes that smart manufacturing offers manufacturing intelligence, providing information in the right context and removing constraints in the decision-making process.

Enhanced decision-making is achieved through the high volumes of data generated by manufacturing systems. Advanced data analytics can extract insights from this data, enabling data-driven decisions that improve resource allocation, reduce risks, and enhance (M. O. Gökalp et al., 2021; Tao et al., 2018). The integration of Industry 4.0 technologies enables a seamless flow of information across the value chain. Literature further highlights that data synchronicity across manufacturing operations improves coordination, minimizes confusion, and enhances visibility (Cui et al., 2020).

2.3 Big Data Analytics

2.3.1 Understanding Big Data Analytics

The concept of big data was first introduced by Laney (2001). According to Belhadi et al. (2019), data can be classified as big data if it exhibits the following characteristics: value, velocity, variety, variability, and volume. Therefore, big data analytics is the process of analysing these massive and diverse data sets to uncover insights, market trends, and other valuable information that can inform data-driven business decisions (Ren et al., 2019). Big data analytics involves the application of statistical and mathematical modelling, econometrics, and simulation techniques to derive meaningful insights from large and complex data sets (Cetindamar et al., 2022).

The literature consistently highlights that big data analytics capabilities are a significant enabler of competitive advantage (Olabode et al., 2022). A study conducted by Kamble et al. (2020) on big data-driven supply chains introduced new metrics such as predictive quality, real-time fault detection, and predictive machine failure to evaluate manufacturing systems. In support, Majeed et al. (2021) states that big data analytics can transform conventional decision-making strategies into data-driven approaches through descriptive and predictive analytics. Research indicated that that the further advancement of using big data analytics to build data-driven decision-making strategies is a key differentiator among smart manufacturers (Al-Khatib, 2022; Majeed et al., 2021; O'Donovan et al., 2015).

2.3.2 Role of big data analytics in smart manufacturing

Smart manufacturing involves the comprehensive integration of various technologies, which collectively generate extensive data from diverse sources such as sensors, machines, production lines, and the supply chain (Bonnard et al., 2021). The application of big data analytics in a smart manufacturing environment can generate insight that bridges the need and preference gaps, it further offers the ability to conduct predictive analysis (Cetindamar et al., 2022). Big Data Analytics offers the opportunity to identify correlations, trends and insight between manufacturing data and business data. Listed below are some of the known applications and benefits cited in literature:

Predictive Maintenance - Conducting analytics on real-time data collected from sensors, equipment, and manufacturing systems can help improve predictive maintenance accuracy, and failure predictions can inform maintenance schedules in advance (Lee et al., 2020). The accuracy of predictive analytics aided by big data can help reduce unplanned downtime, minimize maintenance costs, and improve overall system efficiency (Azeem et al., 2021; Lee et al., 2020).

Quality control and defect detection - Big data analytics can use the real-time data from sensors, equipment, and manufacturing systems to identify patterns and deviations that emerge from the manufacturing process and improve quality deficiencies (Escobar et al., 2021; N. Kumar et al., 2021). A timely response in identifying quality deficiencies helps to minimize waste, improve the overall quality standards, and deliver high-quality products (Escobar et al., 2021; N. Kumar et al., 2021).

Supply chain optimization - Big data generated in smart manufacturing operations can be analysed to provide insight and improve demand forecasting and inventory management (Fatorachian & Kazemi, 2021; Lee et al., 2020). Optimizing the supply chain through the improvement of demand forecasting and investment management can reduce inventory carrying costs (Elhusseiny & Crispim, 2021; Fatorachian & Kazemi, 2021).

Production Optimization - Data collected from manufacturing systems can be linked and tested against processes to determine process efficiency and effectiveness (N. Kumar et al., 2021a). With big data analytics, manufacturers can optimize production processes, identify bottlenecks, and improve productivity (Azeem et al., 2021).

Real-time monitoring and control - In a case study conducted by Filz et al. (2020) it was found that monitoring the manufacturing process in real-time using data analytics improved the transparency of product quality. Monitoring and analysing energy consumption data through big data analytics can facilitate energy consumption optimization (Bu et al., 2021; Sahoo & Lo, 2022). Optimizing energy consumption can help reduce costs and improve contributions to sustainability initiatives and regulations (Bu et al., 2021). Big data analytics conducted on real-time data can improve the confidence levels and quality of data-driven decisions and help in the accurate implementation of corrective actions (Dutta et al., 2022; N. Kumar et al., 2021).

2.3.3 Barriers of adopting big data in smart manufacturing

Despite the numerous advantages of integrating big data into smart manufacturing, several barriers hinder its adoption. Listed below are some of the barriers in empirical studies:

Data Quality and Consistency - Moyne & Iskandar (2017) conducted a study on a semiconductor manufacturer, the study revealed that inconsistent data entry practices and fragmented data sources led to significant errors in production planning and quality control. Implementing stringent data governance policies improved data quality and consistency, leading to better decision-making outcome (Moyne & Iskandar, 2017).

Cybersecurity Risks - A study by Bernabei et al. (2023) investigated the cybersecurity threats faced by a smart manufacturing facility in the aerospace sector. The study highlighted the need for robust cybersecurity measures, including advanced encryption and real-time threat detection systems, to protect against such risks (Bernabei et al., 2023).

Scalability Issues - Wang et al. (2018) examined the scalability challenges in a smart textile manufacturing plant. The study found that as data volumes grew, the existing infrastructure struggled to process and store the data efficiently. The company had to invest in scalable cloud-based solutions to handle the increased data load effectively (Wang et al., 2018).

Skills Gap - Maisiri & Van Dyk (2021) conducted a survey that revealed a significant skills gap in data science and analytics. The study found that the lack of qualified professionals hindered the effective implementation of big data analytics, prompting companies to invest in extensive training programs and partnerships with educational institutions (Maisiri et al., 2021; Maisiri & Van Dyk, 2021).

Organizational Readiness and Culture - In a case study by Rauch et al. (2019), a large-scale food processing company faced resistance to adopting big data analytics due to a lack of organizational buy-in. The study showed that engaging employees through continuous communication and involving them in the change process were critical to overcoming resistance (Rauch et al., 2019). Adopting big data analytics requires a shift in organizational culture and how people make decisions (Al-Khatib, 2022). Resistance to change and a lack of awareness of the benefits can be barriers to adopting the capability (Behl, 2022).

High Initial Investment - An empirical study by Fernando et al. (2022) on SMEs in the manufacturing sector revealed that the high initial costs of big data infrastructure and analytics tools were a significant barrier. The study suggested that financial incentives and subsidies from government programs could help mitigate these costs and encourage adoption (Fernando et al., 2022).

2.4 Theoretical Frameworks

In considering the theoretical framework that underpins the slow adoption rate of smart manufacturing and the adaptation barriers to big data analytics in this context, both the Technology Acceptance Model (TAM) and the Diffusion of Innovation Theory (DIT) provide essential insights. The Technology Acceptance

Model (TAM), developed by Davis (1989), suggests that technology adoption within organizations is primarily driven by perceived usefulness and ease of use. In smart manufacturing, TAM implies that companies are more likely to adopt big data analytics when they recognize its potential benefits, such as enhanced operational efficiency (Venkatesh & Bala, 2008). Conversely, perceived complexity or disruption to established processes can act as barriers, particularly in manufacturing environments focused on process stability (F. Davis, 1989; Venkatesh & Davis, 2000). TAM thus frames how perceptions of utility and usability shape technology uptake in this sector (Davis, 1989; Venkatesh & Davis, 2000).

Complementing TAM, Diffusion of Innovation Theory (DIT) by Rogers (2003) explores the process of innovation adoption within social systems, categorizing adopters as innovators, early adopters, early majority, late majority, and laggards, each with distinct motivations (Rogers, 2003). DIT is especially relevant to smart manufacturing as it highlights the role of social influence and perceived relative advantage in adoption decisions (Ghobakhloo, 2018b). Early adopters may influence the wider industry by showcasing productivity gains through big data analytics, thereby encouraging later adopters to follow. However, some firms, particularly those in the late majority, might delay adoption until proven results become widespread (Gökalp et al., 2017).

Maturity models, discussed by Mittal et al. (2018), support both TAM and DIT by offering structured pathways for organizations to progressively develop digital capabilities. Through step-by-step improvements, maturity models help firms assess their digital readiness and address resistance, providing a framework for advancing to more sophisticated technology use (Mittal et al., 2018). Gökalp et al. (2021) further emphasize that maturity models enable organizations to identify growth opportunities, correct potential issues, and align capabilities with industry standards.

Integrating TAM and DIT provides a robust theoretical foundation for examining the adoption challenges in South African smart manufacturing. While TAM addresses the psychological and organizational factors influencing acceptance,

DIT contextualizes these processes within broader social dynamics, explaining how innovations diffuse across the industry. Together, these frameworks offer a comprehensive understanding of individual and collective barriers, which is essential for identifying strategies to accelerate big data analytics adoption and drive sustainable growth in this sector (Davis, 1989; Ghobakhloo & Ching, 2019; E. Gökalp et al., 2017; Venkatesh & Bala, 2008).

2.5 Chapter Conclusion

This chapter reviewed and synthesized literature on big data analytics and smart manufacturing. Further literature was reviewed to better understand the smart manufacturing landscape in the South African context. The benefits of smart manufacturing were identified in the literature.

Big data analysis literature was also reviewed to gain a better understanding of the concept, understand its application in smart manufacturing, and lastly, understand adoption barriers and benefits. The reviewed literature created a foundation for identifying the relevant theoretical framework.

The next chapter describes the research methodology that was used to conduct this research study.

CHAPTER 3. RESEARCH METHODOLOGY

3.1 Introduction

In this chapter, the research methodology used to conduct the study is described. This chapter further details all the components involved in conducting the study, from research design, population, population framing and sampling, instrument for data collection, validation and reliability of the instrument, data analysis, and ethical considerations.

3.2 Research Paradigm

A paradigm is understood to be a fundamental set of beliefs that guide action (Guba, 1990). Creswell & Creswell (2018) further suggests that paradigms serve as a general philosophical orientation about the world and the nature of research that a researcher brings to a study. This study is anchored on the constructivism paradigm as it aims to gain a contextual understanding of the barriers to big data adoption in smart manufacturing.

The objectives of the study align with the constructivist paradigm by seeking to uncover the subjective perceived benefits of big data adoption from knowledgeable individuals within the industry. Epistemologically, constructivism views knowledge as subjective, created through interaction between the researcher and participants, emphasizing context-specific understanding over universal truths (Guba, 1990).

This approach allows for a deep exploration of participants' views and the contexts in which they work (Creswell & Creswell, 2018). Creswell & Creswell (2018) further highlights that constructivism is generally employed in qualitative research. This study is anchored on constructivism due to its ability to provide a nuanced and detailed exploration of individual and collective experiences, offering more insights. This flexibility ensures that the research can adapt to emerging patterns and themes, yielding a comprehensive and contextually relevant analysis.

3.3 Research Design

Research design refers to the strategic framework for conducting research, encompassing the plan for collecting, measuring, and analysing data to answer research questions (Creswell & Creswell, 2018). According to Neuman (2014) research design is a comprehensive plan that ensures the practical execution of research, enabling researchers to derive evidence-based answers to their research questions.

Research methodology and research design are closely intertwined. Methodology encompasses the overarching approach to the research process, including philosophical assumptions, ethical considerations, and the social-organizational context of the research (Neuman, 2014). Thus, methodology provides the philosophical and procedural foundation upon which the design is constructed, ensuring that the research is methodologically sound and practically feasible.

Following the constructivism paradigm guidance, this shall adopt a qualitative research methodology. Qualitative research is characterized by a naturalistic and interpretative approach, with a focus on collecting data within a context which participants experience the issue under study (Creswell & Creswell, 2018). Similarly, Burns & Grove (1993) highlights that a qualitative approach is systematic and subject in describing experiences, Lincoln & Guba (1985) emphasizes that qualitative research focuses on the unique experiences of individuals, highlighting their distinctiveness.

Further to this, this study collected qualitative data using interview and questionnaires. These two data collection instruments use open-ended questions to gain in depth insight into the participant's experiences and perspectives. This study can be considered exploratory because big data analytics and smart manufacturing concepts have not yet been broadly studied within the South African context.

3.4 Study Population and Sample

This study employed purposive sampling to identify potential participants from a predefined population determined through LinkedIn, using the search parameters specified in Section 3.4.2.

3.4.1 Study Population

The population and sample for this study consisted of technology and engineering professionals working in the manufacturing sector in South Africa. According to Burns and Grove (1993), a population is defined as a group of individuals, events, or objects that meet the inclusion criteria for a study.

To mitigate potential challenges in participant selection, this study utilized LinkedIn, the largest professional networking platform, to identify suitable candidates across various manufacturing sectors. The South African manufacturing sector employs approximately 1.654 million individuals, with only 21.8% classified as skilled workers (Statistics South Africa, 2023), resulting in an estimated skilled workforce of around 360,572 individuals. However, the degree of variability within this skilled population is not well-documented.

Through LinkedIn, a targeted search identified 421 profiles relevant to the study, establishing the target population size for the questionnaire as 421. Subsequently, purposive sampling will be employed to select candidates for the interviews, ensuring that participants possess the necessary expertise and experience relevant to the research objectives.

3.4.2 Sampling Technique

Purposive sampling is a involves identifying and selecting participants that are particularly knowledgeable and experienced in an area of interest (Creswell & Creswell, 2018). Therefore, with guidance from literature participants included in this study meet the following:

- Have been working in the manufacturing industry for at least 5 years or more.

- Willing to participate
- Be well versed in manufacturing technologies and engineering.
- Work experience shall include working knowledge and understanding of smart manufacture, as defined in this study.

To identify potential participants on LinkedIn, the search parameters below was applied when conducting the search to identify the target population:

- The researcher exclusively conducted the search on their personal LinkedIn profile.
- The search results were filtered to only include 1st degree connections, denoting direct connections/profiles reachable via messenger.
- The search results were refined based on location, specifically limiting them to South Africa.
- The results were subjected to further filtering to include specific industries, as delineated in the LinkedIn search parameters. These industries were:
  - Manufacturing
  - Appliances, Computer, electrical and electronics manufacturing
  - Oil and gas
  - Glass, ceramics, and concrete manufacturing
  - Automation machinery manufacturing
  - Medical equipment manufacturing
  - Food and beverage manufacturing
  - Furniture and home furnishing manufacturing
  - Textile manufacturing; Paper and forest product manufacturing
  - Glass product manufacturing
  - Metal valve, ball, and roller manufacturing
  - Metalworking machinery manufacturing

3.4.3 Sampling procedure

This study utilised two research instruments to collect data, employing purposive sampling for both instruments based on a population identified through a LinkedIn search, which applied the parameters and criteria outlined in Section 3.4.

Scholars contend that determining a specific sample size is typically unnecessary in qualitative studies, as the main objective is to reach information saturation. This point is achieved when the data collected becomes repetitive, and no new insights are gained from further participants (Creswell & Creswell, 2018; Lincoln & Guba, 1985; Neuman, 2014; Strauss & Corbin, 1990).

To purposefully sample participants with expertise in smart manufacturing, a sample of 172 participants was selected for the questionnaire, from which 9 were chosen for interviews.

3.5 Data collection

This study begins with a survey questionnaire consisting solely of open-ended questions, allowing the research to gather rich data from a larger sample. Although surveys are generally used as quantitative instruments, scholars argue that responses to open-ended questions can be considered qualitative data Creswell & Creswell (2018; Neuman, 2014). Neuman (2014) further elaborates that open-ended questions enable participants to answer freely, providing their views and insights.

The second phase of data collection involves in-depth exploratory interviews. Interviews are considered valuable data collection instruments in qualitative studies (Neuman, 2014). Unlike questionnaires, interviews enable researchers to interact with participants and observe non-verbal cues (Creswell & Creswell, 2018). This study employs semi-structured interviews for data collection.

3.5.1 Survey Questionnaires with Open-Ended Questions

Given the abundance of digital resources and platforms, questionnaires can be administered quickly. Questionnaires offer a chance of anonymity as respondents' identities are irrelevant to the study (Smith & Quelch, 1993).

According to a study conducted by Ekerljung et al. (2013), the layout of a questionnaire and the setup of questions significantly influence the outcomes of

a study. Therefore, this study categorized questions into two sections, each focusing on specific themes as detailed below.

- Participation Demographics: This section captures participants' career-related and profession information and their current employers' technological capabilities.
- Open-Ended Questions: This section aims to identify barriers and benefits to the adoption of big data analytics in smart Manufacturing.

Refer to APPENDIX B for the full questionnaire detailing all the questions that were used to gather the qualitative data.

3.5.2 Semi-structured interview

In addition to the questions covered in the questionnaire, interviews were conducted to elicit more detailed information related to the issue under study. A semi-structured interview approach was adopted, primarily focused on specific questions while allowing flexibility through follow-up questions. According to Guba & Lincoln (2005), in a constructivist paradigm, the interaction between interviewer and interviewee is central to creating data. Multiple scholars highlight that semi-structured interviews offer the opportunity to pose impromptu follow-up questions based on the interviewee's responses (Cooper & Schindler, 2014; Denzin & Lincoln, 2005; Neuman, 2014; Strauss & Corbin, 1990).

Strauss & Corbin (1990) argue that semi-structured interviews require knowledge of the issue under study, as the questions must be knowledge-based. Cooper & Schindler (2014) further elaborate that a semi-structured interview should be conducted using an interview guide to ensure that discussions are guided by the questions prepared prior to the interview. Consequently, an interview guide was prepared prior to the interviews (see APPENDIX B).

- The interview followed the prescribed nuances suggested by Neuman:
- The interviewer demonstrated interest in the responses and encouraged further elaboration.

- The interview resembled a friendly conversational exchange, though with somewhat more guidance from the interviewer.
- The interview included jokes, side stories, and digressions, all of which were recorded.
- Open-ended questions were utilized, and probing was frequent.
- The pace of the interview is controlled by both interviewer and participant
- The interviewer adapted to the participant's norms and language usage.

As detailed in APPENDIX C, the interview guide is structured as follows: an introduction explaining the research objectives and the ground rules of the interview, followed by questions covering the participant's background and the main questions related to the study.

3.5.3 Pretesting the research instruments

Reynolds et al. (1993) highlights that a research instrument be admitted to a trial to identify flaws and improve its reliability. Grimm (2010)’s view is that it is necessary to conduct pretesting of survey questionnaires, as this will determine if the questions are clear and understood by the participants.

Therefore, questionnaire for this study was pretested with three randomly selected respondents by the researchers, following the sampling criteria outlined in Section 0. During the pretesting phase, minor mistakes were identified in the instruments, primarily related to grammar and framing. The affected questions were rephrased to correct grammatical errors, while lengthy questions were condensed and reworded to elicit the necessary information more effectively.

3.5.4 Data collection process

This study obtained informed consent from participants before collecting data. A consent and information sheet (see APPENDIX A) informed prospective participants about the research's objectives and nature, assured them of anonymity, and explained how the collected data would be used. Participants were also informed of their right to skip questions or withdraw from the study at

any time. This practice aligns with Neuman (2014) guidance that a study must obtain informed consent before data collection.

The researcher distributed a link to the questionnaires through the professional networking platform LinkedIn to the purposively chosen and consenting participants. The questionnaire was hosted on Qualtrics, an online survey platform, and included a consent requirement before continuing with the survey, ensuring each participant's consent was recorded along with their data.

Unlike the survey questionnaire, the interviews began with the researcher initiating introductions and greetings to establish rapport. Participants were verbally informed about the study, its purpose, and the ethical considerations related to their participation. The questions were asked according to the semi-structured interview guide (see Appendix D). Interviews also included a consent procedure before starting, both for record-keeping purposes and to obtain a signed consent form from each participant. Once consent was obtained, appointments were scheduled based on participant availability. The interviews were conducted online using Microsoft Teams, and recordings of each interview were kept for records.

3.6 Validity and Reliability

Early research in qualitative research suggests that should not be assessed using the conventional criteria of validity and reliability due to its unique ontological and epistemological foundations (Lincoln & Guba, 1985; Strauss & Corbin, 1990). Golafshani (2003) assert that the quality of a study should be evaluated according to the criteria of its own paradigm. Lincoln & Guba (1985) support this view, emphasizing that maintaining the trustworthiness of a research report is contingent upon addressing relevant issues within the paradigm.

3.6.1 Validity

Validity in qualitative research can be evaluated by the extent to which the researcher provides enough detail for readers to interpret the meaning and

context of the findings (Pope et al., 1998). The quality of research is thus linked to the generalizability of the results and the testing and enhancement of the study's validity or trustworthiness. This chapter's discussion of research methodology processes aligns with the goal of ensuring internal validity.

However, Golafshani (2003) advocates for triangulation, using multiple data sources to strengthen a study’s credibility. In this study, data were collected using questionnaires and interviews, as detailed in section 3.5. This approach aims to develop a comprehensive understanding of the issues, thereby enhancing the study's credibility and validity.

3.6.2 Reliability

Literature suggests that in qualitative research, the term "dependability" is used rather than reliability (Creswell & Creswell, 2018; Golafshani, 2003; Lincoln & Guba, 1985; Morse et al., 2002). A study is considered dependable when it is accurate and consistent (Golafshani, 2003). To ensure the dependability of this study, all collected data was meticulously recorded and transcribed. Excerpts from the data were then used to highlight key insights and support the findings. Additionally, the research supervisor conducted continuous reviews and scrutinized the data analysis process.

3.7 Data Analysis

In this study, an inductive approach was employed in collecting the qualitative data. Therefore, thematic analysis is used to analyse the questionnaire instrument included both closed-ended and open-ended questions.

3.7.1 Thematic Analysis

Thematic analysis is considered a qualitative analytics tool and is widely used to analyse classifications and identify emerging themes from the data (Boyatzis, 1998). It is considered appropriate for studies that seek to discover through

interpretation. Thematic analysis enables research to identify relationships between concepts through the analysis of themes (Marks & Yardley, 2004).

The thematic analysis method outlined by Clarke and Braun (2017) has gained widespread adoption due to its recursive process (Kiger & Varpio, 2020). It comprises six iterative steps of non-linear analysis, enabling researchers to thoroughly review data and identify themes worthy of closer examination (Kiger & Varpio, 2020).

Detailed below are the six steps of conducting a thematic analysis as outlined by Clarke and Braun (2017):

- **Step 1: Familiarizing yourself with the data -** This step involves actively and repeatedly reading through the collected dataset in order to become familiar with it. This step provides valuable orientation to the dataset and is foundational to the preceding steps (Kiger & Varpio, 2020). For this study, the dataset consists of open-ended question responses collected from the two instruments. For the interview data this step includes the transcription of the interviews recording, which also improved familiarity of data.
- **Step 2: Generating Initial Codes**

  The process of coding helps to organize raw data by identifying phrases or words with common meanings relevant to the question posed. A code can be thought of as a segment or element of raw data that can be assessed for meaning (Kiger & Varpio, 2020). Coding further facilitates generating insights as it is a way of systematically interrogating the dataset and identifying meaning and observing phenomena (Kiger & Varpio, 2020).
- **Step 3: Searching for Themes**

  The process of theme identification involves examining the generated codes and direct excerpts from the dataset to identify themes of broader significance (Kiger & Varpio, 2020). Themes are constructed through sorting, combining, comparing, and analysing the relationship between codes. This study shall take the inductive approach to derive themes directly from the dataset.
- **Step 4: Reviewing Themes**

  The step of reviewing themes involves closely evaluating the generated codes under each theme to ensure a proper fit and adequacy with supporting data

(Kiger & Varpio, 2020). The data within each theme must be cohesive and coherent, and themes ought to be different enough to stand alone (Clarke & Braun, 2017). This is an iterative process of sorting data extracts and modifying themes to better reflect the codes within them. Themes can be added, separated, mixed, or removed during this process.

- **Step 5: Defining and Naming Themes**
  In this step, the researcher defines and narrates the description of each theme and contextualizes its importance to the research question of the study (Kiger & Varpio, 2020). Themes must be adequately described to create a coherent narrative of unique insights and understanding regarding the answers to the research questions (Kiger & Varpio, 2020). Some excerpts can be selected and represented in the report in order to contextualize and support the narrative.
- **Step 6: Producing the report**
  Major elements of this step are completed in Step 5. This step involves writing the final analysis and descriptions of the research findings. The report must provide a concise and logical narrative, accounting for how the data was interpreted, and detailing the accuracy of theme selection and interpretation. The thematic analysis report form is detailed in Section 4.2.2.

3.8 Ethical Consideration

According to Smith & Quelch (1993), research is considered ethical if it considers, respects, maintains, and protects informed consent, voluntary participation, and anonymity. The study was conducted ethically, with careful attention given to observing, recognizing, and protecting the rights of the respondents. A formal ethics clearance was acquired from Research Ethics Committee at the Faculty of Commerce, Law, and Management of the University of Witwatersrand, refer to APPENDIX D. No data relating to this study was collected prior to receiving written **permission to conduct the study** from the research committee.

Smith & Quelch (1993) defines informed consent as the potential participants' agreement to participate in the study, for which the researcher shall collect

relevant information. **Consent** was obtained from each participant prior to collecting data for the study. Furthermore, potential participants were informed of their **right to voluntary participation**, and they decide whether to consent, decline, or withdraw from the study at any time, without penalty or punishment.

The **anonymity** of the respondents was maintained throughout the study. Maintaining anonymity meant that the participants of the study shall not be linked to their responses, even with the research (Burns & Grove, 1993; Smith & Quelch, 1993). To achieve this, this study did not collect any information relating to the identity of respondents; the consent received from respondents was in the form of a box tick; therefore, the identity of the respondents is completely detached from their responses.

The **confidentiality** of potential participants was maintained throughout the study. Confidentiality refers to protecting information or not publishing information that may lead to the identification of potential participants (Polit & Hungler, 1997). To achieve this, this study did not collect any information relating to the identity of respondents.

3.9 Chapter Conclusion

This study adopted qualitative research methods based on the constructivist paradigm due to the nature of the research. A survey questionnaire with open-ended questions was chosen as the research instrument, followed by in-depth interviews. Participants were purposively selected by the researcher. The collected data was analysed using thematic analysis.

This chapter detailed all the components involved in conducting the study, including the research paradigm, research design, target population and sample, instruments for data collection, validation and reliability, data analysis, and ethical considerations.

The next chapter presents the research findings derived from the data collected through the two instruments and highlights the key results.

RESEARCH RESULTS AND FINDINGS

4.1 Introduction

This chapter presents and describes the results gathered from two research instruments. To meet the objectives set on this study and to answer the research questions posed at the study employed a qualitative approach to explore participants' experiences and perspectives. The research began with a questionnaire distributed to 421 potential respondents via LinkedIn, resulting in 172 completed surveys. The questionnaire included both quantitative (participants demographics) and open-ended qualitative questions, providing a comprehensive understanding of the respondents' insights.

Additionally, nine in-depth interviews were conducted, allowing for deeper exploration of the themes identified in the open-ended questionnaire responses. These qualitative responses were analysed using ATLAS.ti, a computer-assisted qualitative data analysis tool, which facilitated the identification of key themes and insights.

The analysis of the collected data is divided into two sections. The first section presents a demographic overview of the participants and their respective organizations, utilizing descriptive statistics to summarize the quantitative data. The second section provides a thematic analysis, focusing on the results and interpretation of the open-ended responses from both the questionnaire and interviews.

4.2 Questionnaire results and analysis

The primary inclusions as detailed in Section 0 dictated that industry professionals with knowledge in manufacturing shall be the prime focus of the study. Therefore, exclusions were applied based on the type of role and the industry that respondents specialized in. This was done to improve the quality of the study.

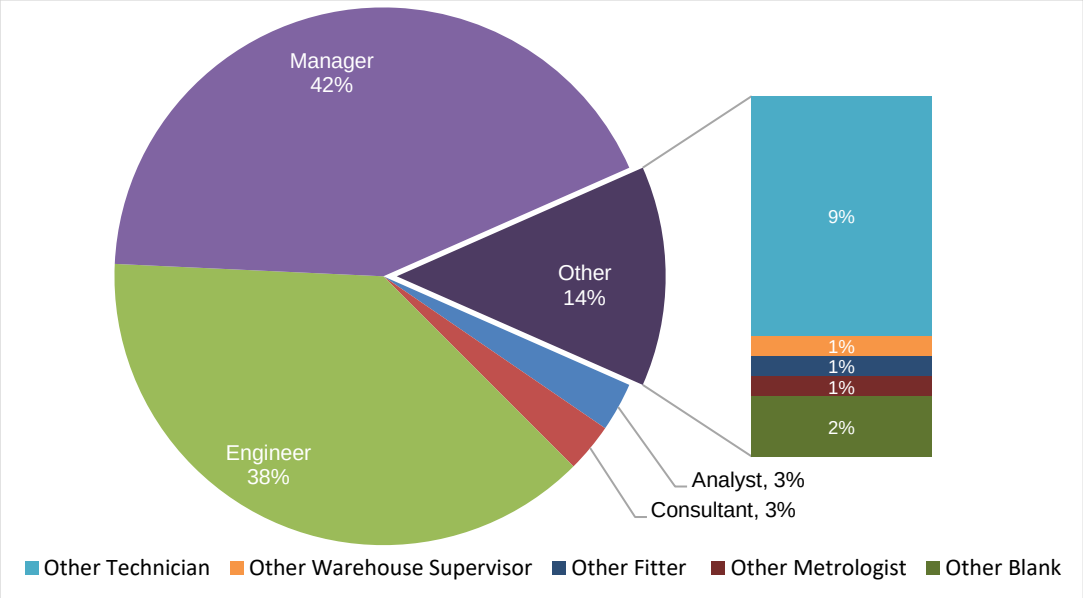
4.2.1 Demographic

This demographics section profiles the participants and their organizations based on their characteristics, knowledge, and awareness of salient characteristics of the companies they work for. These details enabled the researcher to conduct a more thorough descriptive statistical analysis of the collected data.

4.2.1.1 Participant's Demographics

Considering that the questionnaire was distributed to professionals working in the manufacturing industry. The questionnaire included four questions about professional specifics and experience to enhance understanding of the participants' professions and experiences.

Figure **1** describes that, of the 172 participants, managers and engineers are the biggest groups, representing 42% and 38%, respectively. Analysts and consultants represented the smallest group of respondents, both at 3%. 'Other' represents a manual entry field to cater to other roles not covered in the given options. The majority of 'other' category are technicians. This indicates that the survey captured perspectives from key decision-makers and technical experts within the manufacturing sector.

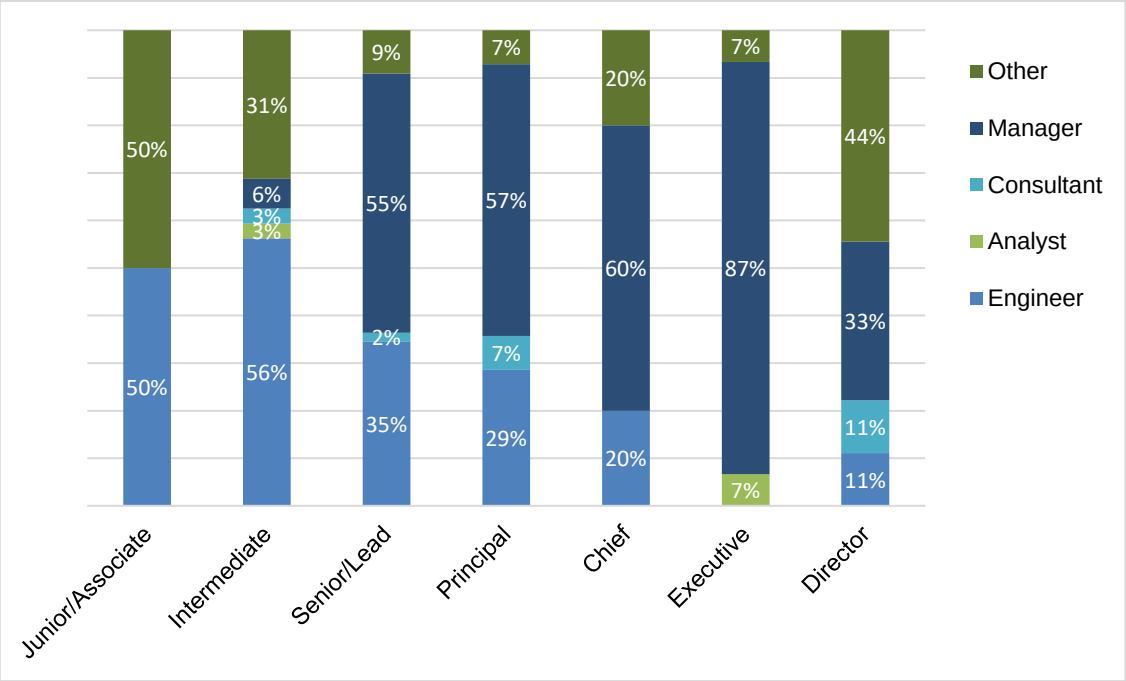


Source: Research questionnaire: Q1.1 data

Figure 1: Roles held by respondents

Figure 2 below presents a cross tabulation of the respondent roles and their seniority levels. Given that most respondents are managers and engineers, Figure 2 highlights that 87% of the managers are executives, with seniors/leads, principals, and chiefs following behind, and 33% are directors. The second biggest group is that of engineers, and their seniority levels are mostly intermediate and junior/associate.

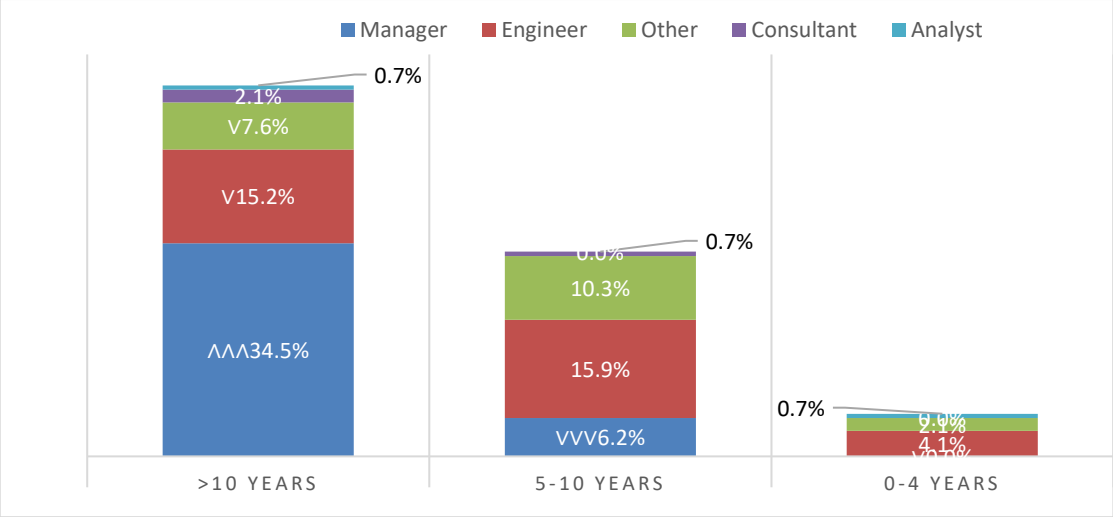
Therefore, this fair distribution of the roles and seniority levels provides a good representation and thus does not bias the response to certain roles and seniority levels, hence improving the quality of the responses.



Source: Research questionnaire: Crosstabulation of Q1.1 and Q1.2 data

Figure 2: Seniority levels of respondent's roles

In addition to the above, the quality of the responses is also influenced by the level of experience of the people participating in answering the questionnaires. Highly experienced people are relatively likely to give good-quality responses when compared to people with relatively low experience. As per Figure 3, 33.1% of the total respondents have between 5-10 years of experience and 60% with at least 10 years of experience. Of the 60% of the respondents who have more than 10 years of experience 34.5% are managers while 15.2% are engineers.



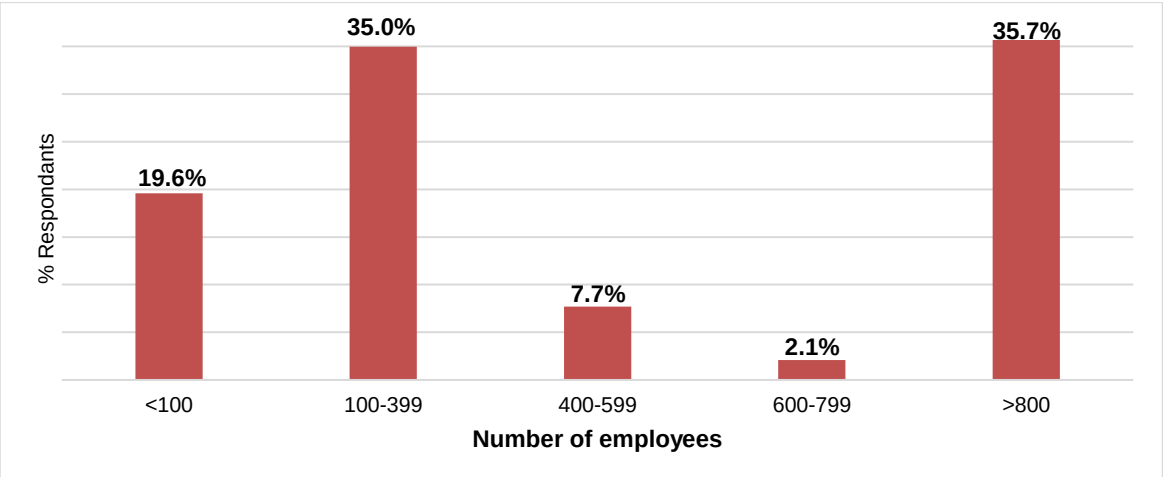
Source: Research questionnaire: Crosstabulation of Q1.1 and Q2 data

Figure 3: Years of experience and roles held by respondents

Overall, the results effectively captured insights from a diverse group of participants, including both management and technical perspectives, thereby providing valuable insights into the role of big data analytics and other factors impacting the competitive advantage of smart manufacturers.

4.2.1.2 Organisation's Demographics

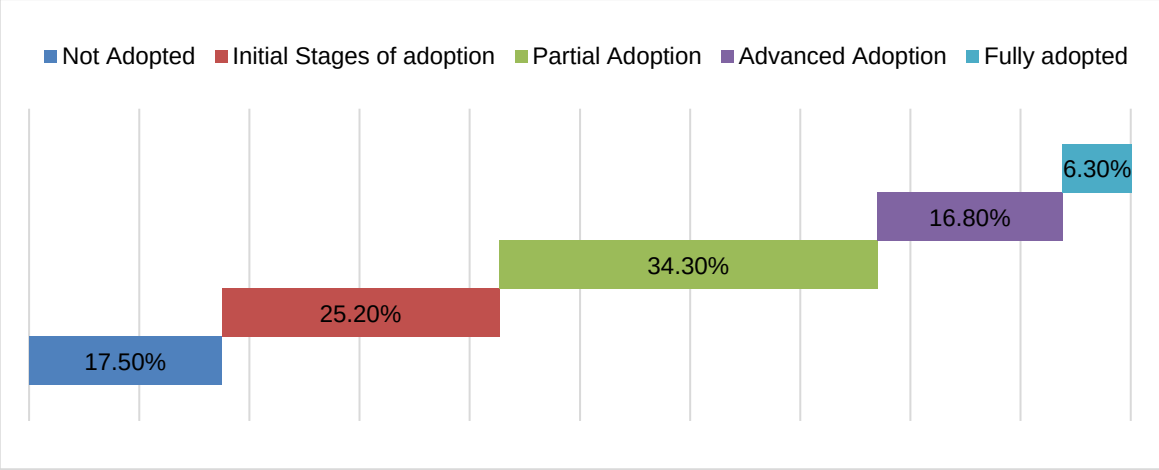
Besides the quality and distribution of the respondents, the quality and nature of the organisation they are coming from also influence the quality of the responses. This section of the demographic analysis focuses on the capabilities of the respondent's organization.



Source: Research questionnaire: Q3 data

Figure 4: Respondent's organisation size

Figure 4 below shows the distribution of the organisation's size using the number of employees are the indicator of size. Most respondents come from organizations with sizes between 100 to 399 employees and organizations with more than 800 employees. Both two groups represent approximately 35% of the total respondents, with 19.6% employed by organizations with fewer than 100 employees. The two size categories with the smallest numbers are between 400 to 799 employees. The size of the organization plays a significant role in understanding different causalities related to smart manufacturing adoption and barriers faced in adoption, as well as the utilization of big data analytics and the barriers faced in utilization.

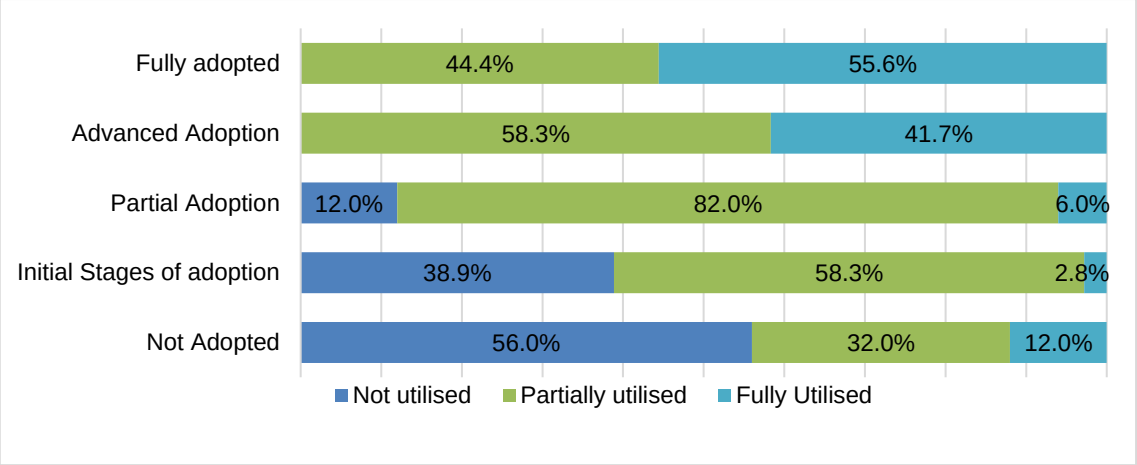


Source: Research questionnaire: Q4 data

Figure 5: Level of smart manufacturing adoption

Figure 5 illustrates the respondents' organizations' capabilities regarding the adoption of smart manufacturing. Of the respondents, 17.50% reported no initiation of smart manufacturing capabilities, while 25.20% are in the early phases of adoption. The largest group, comprising 34.30%, has partially adopted smart manufacturing. Additionally, 16.80% have made significant progress in adoption, and 6.30% have fully embraced smart manufacturing.

Overall, a substantial proportion of respondents' organizations are either in the early exploration or partial adoption phases, while a smaller percentage has made significant progress or fully embraced smart manufacturing.



Source: Research questionnaire: Crosstabulation of Q4 and Q5 data

Figure 6: Smart manufacturing adoption and big data analytics utilisation

Figure 6 aims to highlight the utilization of big data analytics at different levels of smart manufacturing adoption. For organizations that have fully adopted smart manufacturing, they fully utilize big data analytics, with a frequency of usage at 55.6%, and 44.4% partially use it.

4.2.2 Thematic Analysis

The questionnaire contained five open-ended questions; therefore, this section primarily focuses on the thematic analysis conducted on the responses. The dataset was cleaned, with invalid responses excluded from the analysis. All questions in the questionnaire required text input to proceed with the survey, resulting in a varying degree of invalid responses across all questions. Note that the demographic details of participants detailed in Section 4.2.1 are also valid to this thematic analysis section.

4.2.2.1 Benefits of integrating big data analytics

This section reports the results of the thematic analysis on questions that relates to identifying the benefits of big data analytics in smart manufacturing.

The word cloud in Figure 7, suggests that most respondents agree that integrating big data analytics into smart manufacturing is crucial for achieving a competitive advantage. They emphasize that big data analytics enable predictive maintenance, optimize operational efficiency, improves decision making and

reduce costs by minimizing waste and energy consumption. Additionally, big data enhances product quality control and fosters innovation by providing valuable insights into market trends and customer needs. Overall, leveraging big data is seen as essential for improving manufacturing practices, driving efficiency, and maintaining a competitive edge in the industry.

Source: Research questionnaire data

Figure 7. Necessity of big data analytics

Through the thematic analysis, the identified themes are examined in detail, with key findings highlighted and supported by relevant respondent excerpts.

Theme: Operational Efficiency and Process Optimization

A significant number of respondents emphasized that big data analytics plays a crucial role in improving operational efficiencies and optimizing production processes.

For instance, one respondent noted, *"Big data analytics can be used to improve operational efficiencies including optimizing production processes"*. Another respondent highlighted the potential of big data to enhance production capabilities and quality: *"It can result in more efficient production and higher quality"*.

This aligns with the literature, which suggests that big data analytics enables manufacturers to streamline operations, reduce waste, and enhance overall

productivity (Escobar et al., 2021; N. Kumar et al., 2021). By analysing vast amounts of data from various sources, manufacturers can identify inefficiencies and implement improvements that lead to more effective and efficient manufacturing processes.

Theme: Predictive Maintenance and Downtime Reduction

Several respondents emphasized the role of big data in predictive maintenance and reducing downtime.

For example, one respondent stated, *"Predictive Maintenance: By analysing historical data and sensor readings, manufacturers can predict when equipment is likely to fail and schedule maintenance proactively"*. This capability to anticipate and address maintenance needs before they lead to downtime is a critical advantage in manufacturing.

This finding is consistent with studies showing that predictive maintenance, enabled by big data analytics, can significantly reduce unplanned downtime and maintenance costs (N. Kumar et al., 2021; Lee et al., 2020). Real-time data analysis helps in monitoring equipment performance and predicting potential failures, thus optimizing maintenance schedules and minimizing disruptions.

Theme: Data-Driven Decision Making

Data-driven decision making emerged as a key theme, with many respondents highlighting the importance of making informed decisions based on data analysis.

One respondent mentioned, *"Data analytics provides real-time insight into the market for competitive advantage and insight into the manufacturing processes for efficiency improvement and cost reduction"*. Another noted, *"Big data can help prevent downtimes, predict maintenance needs, and create safer working environments".*

The literature supports this view, indicating that big data analytics enables organizations to make informed decisions that improve efficiency, enhance product quality, and drive profitability (Azeem et al., 2021). The ability to analyse data in real time allows for quick adjustments and strategic decision-making that can lead to a significant competitive edge.

Theme: Competitive Advantage and Innovation

The responses frequently linked the integration of big data analytics to gaining a competitive advantage and fostering innovation.

For example, one respondent noted, *"Manufacturers that leverage big data analytics effectively can respond more quickly to market changes, adapt to customer demands, and innovate faster than their competitors"*. Another mentioned, *"Big data can help in determining design flaws and save time in development, which can support design choices for successor products".*

This is supported by existing literature, which highlights that big data analytics enables companies to stay ahead of competitors by enhancing their ability to innovate, adapt to market changes, and respond to customer needs (Ren et al., 2019). The insights gained from data analysis can drive product development and operational strategies that maintain and enhance competitive positioning.

Theme: Challenges and Considerations

While the benefits of big data analytics are well acknowledged, several respondents also pointed out challenges associated with its integration. These include issues related to data quality, the need for skilled personnel, and the financial investment required.

For example, one respondent noted, *"The implementation of big data analytics requires the entire value chain to have a significant need for it. Top management buy-in and understanding are necessary to initialize such an undertaking".*

The literature also identifies similar challenges, such as the need for high-quality data, the shortage of skilled professionals, and the significant costs associated with big data analytics implementation (Gumbi & Twinomurinzi, 2020; Maisiri & Van Dyk, 2021; Shai et al., 2020)). Addressing these challenges is crucial for realizing the full potential of big data analytics in smart manufacturing.

4.2.2.1.1 Summary

In summary, the qualitative data underscores several key insights into the role of big data analytics in manufacturing. Operational efficiency, competitive

advantage, and innovation are identified as major benefits, supported by existing literature on the transformative potential of data analytics. Key benefits include predictive maintenance, optimized operations, improved decision-making, cost reduction, and better product quality control.

4.2.2.2 Barriers and challenges to big data analytics

This section reports the results of the thematic analysis on questions that relates to identifying the barriers and challenges in the effective use of big data analytics.

The analysis of the collected data reveals several critical themes that encapsulate the challenges organizations face with big data analytics. The emerging themes were visualized in a word cloud, as shown in Figure 8. These themes are: Resource Constraints, which include financial limitations and inadequate infrastructure; Skills and Training, highlighting the shortage of skilled personnel and the need for further training; Cultural and Organizational Barriers, reflecting resistance to change and the prevailing organizational culture; and Security and Privacy Concerns, focusing on issues related to data security and privacy.

Source: Research questionnaire data

Figure 8: Word Cloud for big data implementation challenges

Theme: Resource Constraints

Resource constraints emerged as a prominent theme, reflecting the financial and infrastructural limitations faced by organizations.

For example, one respondent noted *"Resource Constraints: Implementing and maintaining big data analytics infrastructure was costly. Organizations lacked the financial resources or IT infrastructure required for such initiatives."*

Respondents highlighted significant challenges due to the high costs associated with big data analytics infrastructure and a lack of sufficient financial resources. This theme underscores the financial burden and resource limitations that hinder the adoption and effective use of big data analytics. This finding aligns with the literature, which emphasizes that the high costs of big data technologies and the need for substantial investments in IT infrastructure can impede adoption (Kamble et al., 2018; P. Kumar et al., 2021). According to Kamble et al. (2018), the capital expenditure required for hardware, software, and skilled personnel can be a substantial hurdle for many organizations.

Theme: Skills and Training

The shortage of skilled personnel and the need for additional training were recurring concerns among respondents.

One respondent remarked, "Difficulty in obtaining adequately skilled personnel for data analysis and recommendations."

Organizations frequently cited difficulties in finding adequately skilled personnel for data analysis and the necessity for further training of existing staff. This theme highlights the gap in skills and the importance of investing in training programs to build data analytics capabilities. This skills gap is well-documented in academic literature, which highlights that the demand for data science expertise far exceeds the supply (Kamble et al., 2020; Pradhan & Agwa-Ejon, 2018) argue that the scarcity of qualified data professionals and the need for continuous skill development are critical issues impacting the success of big data initiatives.

Theme: Cultural and Organizational Barriers

Resistance to change and organizational culture were significant barriers affecting the implementation of big data analytics.

Noted excerpt from one respondent: "Resistance to adoption due to fear of job displacement and preference for traditional methods."

Resistance to change and challenges related to organizational culture were commonly reported. Participants indicated that internal resistance, including fear of job displacement and a preference for traditional decision-making methods, impedes the adoption of big data analytics. This resonates with research that indicates resistance to change is a common challenge in technology adoption, driven by concerns over job security and entrenched (Dutta et al., 2022; Rauch et al., 2019). Rauch et al. (2019) suggests that overcoming organizational inertia and cultural resistance is essential for successful technology integration.

Theme: Security and Privacy Concerns

Data security and privacy concerns were major issues mentioned by respondents.

A respondent highlighted this challenge, stating "Security concerns with cloud platforms and privacy challenges with growing data."

Concerns about data security and privacy, particularly with the use of cloud platforms and the increasing volume of data, were prevalent. This theme emphasizes the need for robust security measures and privacy protocols to protect sensitive information. This concern is corroborated by existing literature, which underscores the complexities of securing vast amounts of data and ensuring compliance with privacy (Bernabei et al., 2023; Sahoo & Lo, 2022). Sahoo & Lo (2022) point out that the increased use of cloud computing for big data analytics raises specific security and privacy challenges that organizations must address to protect sensitive information.

4.2.2.2.1 Summary

In summary the analysed qualitative data to identify challenges and barriers in implementing big data analytics. Challenges include resource constraints, skills and training gaps, cultural and organizational barriers, and security concerns. These insights deepen our understanding of big data adoption complexities and inform future research and practice.

4.3 Interview results and analysis

The interviews, involving nine participants, were transcribed, cleaned, and analysed using ATLAS.ti software. This tool facilitated the coding and thematic analysis of the qualitative data by locating, annotating, and visualizing key features. To ensure data quality and validity, the study first examined the demographics of the interviewees and their organizations, confirming they were from advanced smart manufacturing environments and had relevant expertise.

4.3.1 Demographics

All the participants hold key roles in their respective organizations, including production engineer, system integration engineer, production manager, quality director, production engineering manager, manufacturing engineering manager, process control technician, and maintenance director. The interviewees have extensive experience in their respective roles. Table 1 below details the roles held by each interviewee and the manufacturing sector they work in.

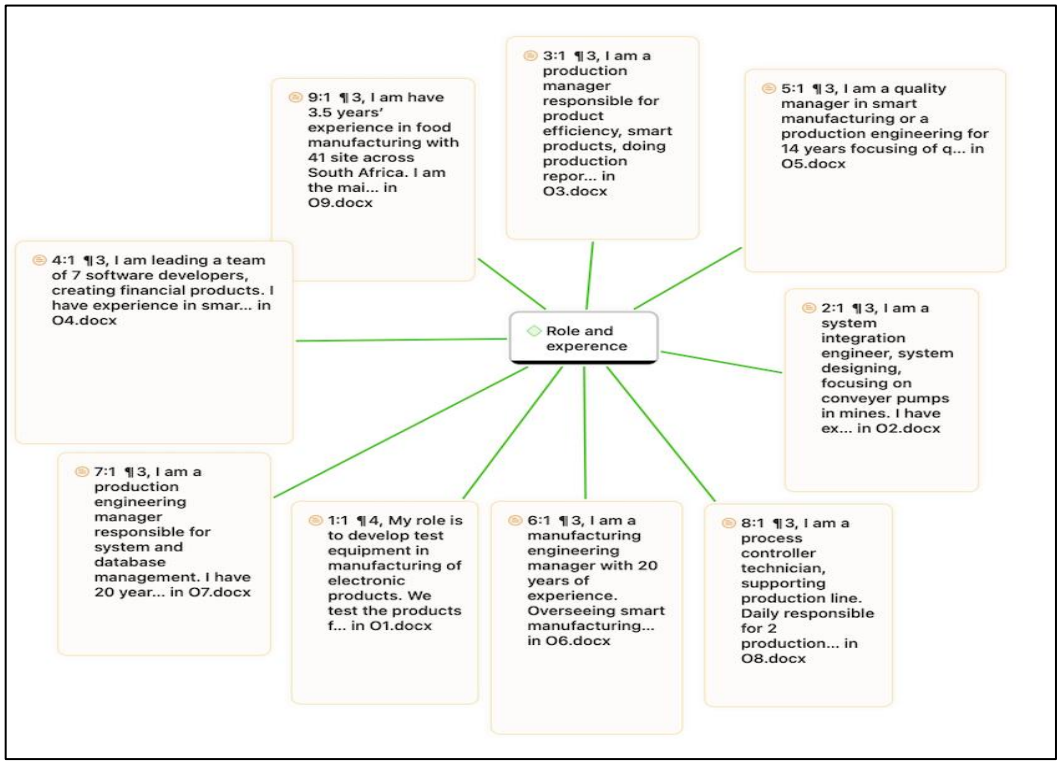
Table 1: Interviewees demographics

ID	Role held	Years of Experience	Manufacturing Industry Sector
1	Production Engineer	12 Years	Electronics Manufacturing
2	System Design and Integration Engineer	9 Years	Robotics Automation Consulting
3	Production Manager	+20 Years	Electronics Manufacturing
4	Software Developer (Ex Production Engineer)	+10 Years	Electronics Manufacturing
5	Quality Director	14 Years	Electronics Manufacturing
6	Manufacturing Engineering Manager	20 Years	Aerospace Manufacturing
7	Production Engineering Manager	20 Years	Electronics Manufacturing
8	Process Control Technician	+10 Years	Beverage Manufacturing
9	Maintenance Director	+30 Years	Food Manufacturing

Source: ATLAS.ti using the interview data

All interviewees confirmed their extensive expertise and exposure to smart manufacturing environments, gained through current and previous roles within the manufacturing industry. They emphasized the transformative role of big data analytics in enhancing various aspects of manufacturing operations. Key applications include optimizing quality control, refining manufacturing processes, ensuring process traceability, maintaining equipment, reducing downtime, preventing equipment misuse, monitoring production productivity, and tracking faults.

Additionally, Figure 9 provides a snapshot of the interviewees' responses regarding their roles and experience. The diversity of roles and depth of experience contribute to high-quality responses to questions on big data analytics in smart manufacturing.



Source: ATLAS.ti using the interview data

Figure 9: Role and experience of interviewees

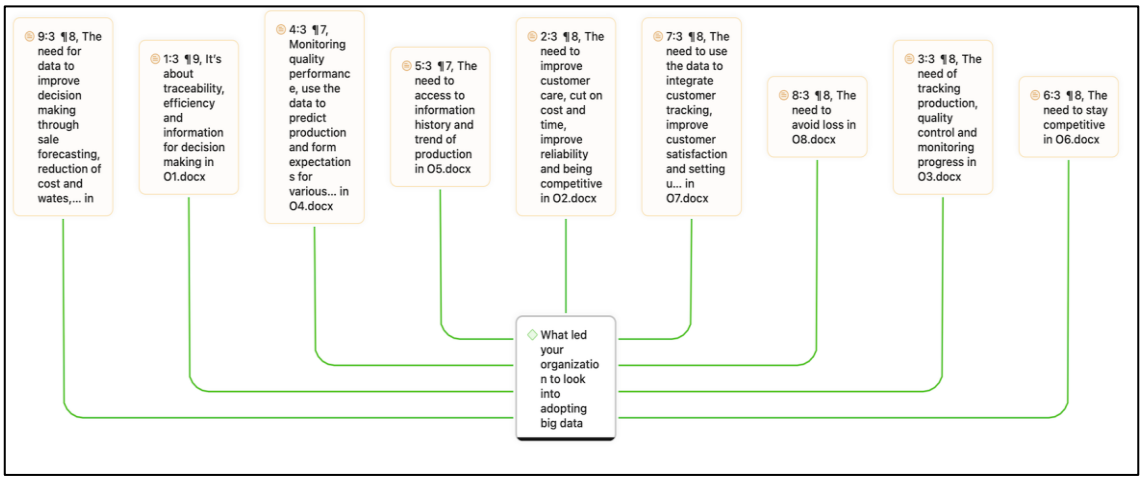
Furthermore, interviewees highlighted the critical role of big data analytics in enabling real-time decision-making by collecting and analysing data from advanced sensor networks. This technology is also pivotal in the calibration,

personalization, and customization of products and production lines, allowing manufacturers to tailor solutions to specific needs. Some organizations are leveraging big data analytics to achieve unprecedented levels of efficiency by precisely tracking production processes through sensor data.

4.3.2 Thematic Analysis

4.3.2.1 Reason behind the adoption of big data analytics

The interviewees provided a variety of reasons for their organizations' adoption of big data analytics. Three common themes emerged from their responses: the need for efficiency, the need to remain competitive, and the need to be innovative. Figure 10 below presents snapshots of the interviewees' responses regarding the reasons behind the adoption of big data analytics.



Source: ATLAS.ti using the interview data

Figure 10:Reasons behind adopting big data analytics

Theme: The need for efficiency

In this theme, interviewees emphasized that their organizations adopted big data analytics primarily to enhance production efficiency. They highlighted that the drive for efficiency stemmed from several key issues, including improved decision-making. Interviewees noted that big data analytics significantly accelerates decision-making processes by enabling organizations to swiftly identify and address production challenges.

By leveraging insights derived from big data, organizations can optimize operations, reduce waste, and lower costs, ultimately leading to more efficient production. Additionally, big data analytics was noted to be instrumental in mitigating losses, refining production controls, enhancing reliability, and closely monitoring and accounting for waste and downtime on production lines.

Theme: The need to be competitive

The second prominent reason organizations adopted big data analytics was to enhance their competitive positioning. Interviewees highlighted that, by leveraging big data, their respective organizations were able to identify emerging market trends and stay ahead of their rivals.

While other interviews highlighted the strategic use of analytics as a means to provide a significant competitive edge by enabling organizations to better understand market demands, deliver high-quality products, and price them competitively.

Collectively, big data analytics facilitates several key advancements in this area. It enables organizations to track and integrate customer data more effectively, enhance customer satisfaction, optimize resource allocation, and improve troubleshooting processes. Ultimately, these capabilities help organizations maintain a competitive advantage and respond proactively to market dynamics.

Theme: The need to be innovative

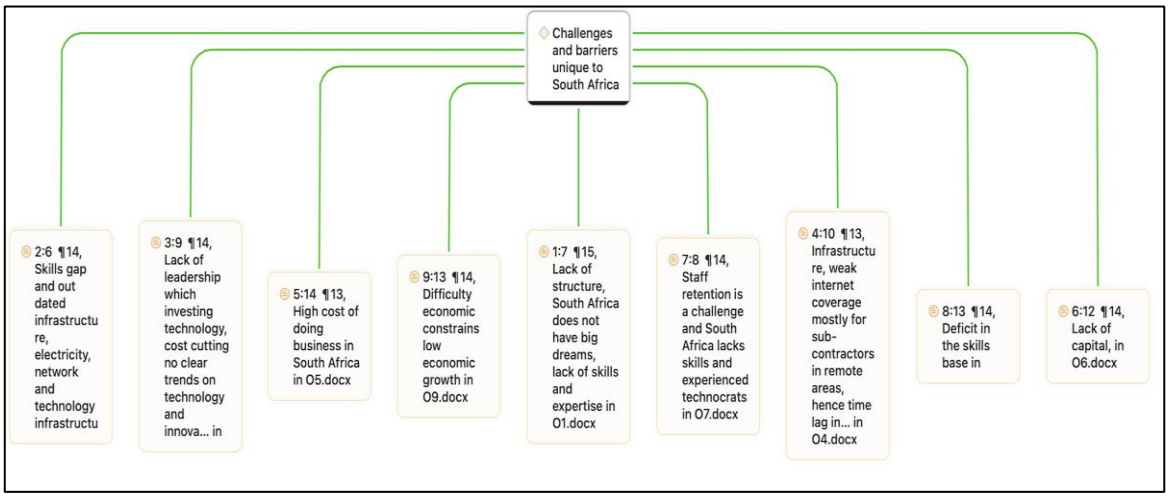
The third theme emerging from the analysis of responses was that organizations adopted big data analytics to drive innovation. Interviewees noted that big data analytics plays a crucial role in identifying existing system challenges and uncovering gaps within current processes.

Interviewees further highlighted that by leveraging these insights, organizations can utilize analytical reports to spearhead innovation, which may involve refining production processes, enhancing storage systems, and adopting more efficient ordering and dispatching systems. This approach not only fosters innovation but also boosts profitability and enhances production output.

4.3.2.2 Challenges in adopting big data analytics

The interviews revealed several internal and external challenges encountered in adopting and integrating big data analytics into smart manufacturing operations. The analysis of the responses identified four key themes: skills gaps, high costs and funding issues, inadequate infrastructure, and organizational culture.

Figure 11 below provides a snapshot of these challenges as highlighted by various representatives.



Source: ATLAS.ti using the interview data

Figure 11: Challenges in the adoption of big data analytics

Theme: Skills gap

Interviewees highlighted that their organizations face a significant skills gap challenge. They noted a shortage of big data analysts with the expertise to analyze data using appropriate indicators, establish relationships between relevant variables, and produce reports that substantially aid decision-making.

Further, interviewees pointed out that while data capture is accomplished, there is a lack of skills needed to analyze the data accurately and derive meaningful inferences. They also noted deficiencies in data visualization skills, which hinder the effective presentation of data in a way that is accessible and actionable for management.

It is further highlighted that in some cases, organizations struggle to measure variables correctly, which limits their ability to fully leverage the big data collected.

Additionally, the absence of data validation skills was cited as a common issue across many organizations.

Theme: high cost and funding

The second theme identified by interviewees was the high cost associated with implementing and maintaining an effective big data system. Key expenses highlighted include the initial investment in analytical applications, ongoing maintenance costs, and the expense of hiring skilled big data analysts.

Interviewees also noted challenges related to the substantial investment required and the difficulty in accurately estimating the return on investment (ROI) and payback periods for such investments.

Theme: Poor infrastructure

The third theme identified by interviewees was the challenge of inadequate infrastructure in integrating big data systems. They highlighted several infrastructure-related issues, including poor or unreliable internet connectivity, outdated system infrastructure, and incompatible applications. Additionally, interviewees noted that misaligned systems within the same organization and limited automation of manufacturing processes contribute to these challenges.

Power outages were also a concern, as organizations experienced data loss during transitions from the national electricity grid to backup generators. Furthermore, issues with data storage infrastructure were mentioned, with organizations lacking adequate systems for storing large volumes of historical data, which limits the ability to conduct trend analysis over time.

Theme: Organizational culture

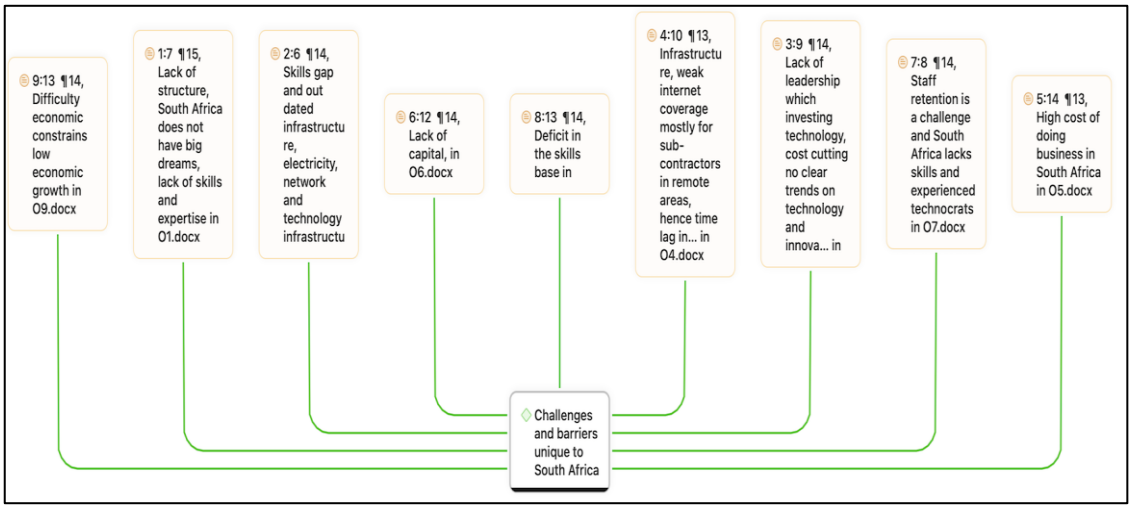
Organizational culture was also identified as a significant challenge in integrating big data analytics. Interviewees noted that some senior managers do not fully appreciate the value of big data analytics, which leads to reluctance in investing in such systems. Additionally, there is resistance to change among staff, who are often unwilling to adopt new and more efficient systems, preferring to continue using outdated and inefficient ones.

Further cultural challenges noted include issues related to data integrity, honest reporting, and transparency in managing big data. These cultural barriers can hinder the effective implementation and utilization of big data analytics within organizations.

4.3.2.3 Challenges and barriers specific to South African challenge

Among the internal and external challenges organizations face when integrating big data analytics, interviewees were also asked to identify challenges specific to South Africa. This question aimed to focus on issues unique to the South African context, as some organizations operate in multiple countries.

From the responses, three key themes emerged: the skills gap in South Africa, infrastructure challenges, and high costs or weak economic growth. Figure 12 below illustrates several responses related to the challenges and barriers of big data analytics specific to South Africa.



Source: ATLAS.ti using the interview data

Figure 12: Challenges and barriers specific to South African

Theme: Skills gap

Interviewees highlighted several challenges related to finding employees with specific skills in big data analytics. They noted that organizations often need to invest in training to equip employees with the necessary skills to integrate big data analytics into their roles and responsibilities. This training gap points to a

disparity between the skills produced by educational institutions and the needs of the market.

Additionally, interviewees mentioned a lack of ambition to develop applications with artificial intelligence (AI) that can automate the collection, analysis, and reporting of big data. Organizations also face difficulties in retaining staff skilled in big data analytics, reflecting the high demand for such expertise in the country.

The issue of inadequate leadership in technology at the governmental level was also raised. Representatives emphasized that the government needs to play a proactive role in developing policies that invest in bridging the skills gap in big data analytics.

Theme: Poor infrastructure

Poor infrastructure was identified as a significant challenge in South Africa, where frequent power outages and unreliable internet connectivity in remote areas hinder the effectiveness of big data analytics. Organizations that engage subcontractors to collect data from these remote regions often face difficulties due to limited or non-existent internet coverage.

These infrastructure issues impede real-time data collection and analysis, which in turn slows down decision-making and prevents organizations from fully realizing the benefits of adopting big data analytics.

Theme: High cost and weak economic growth

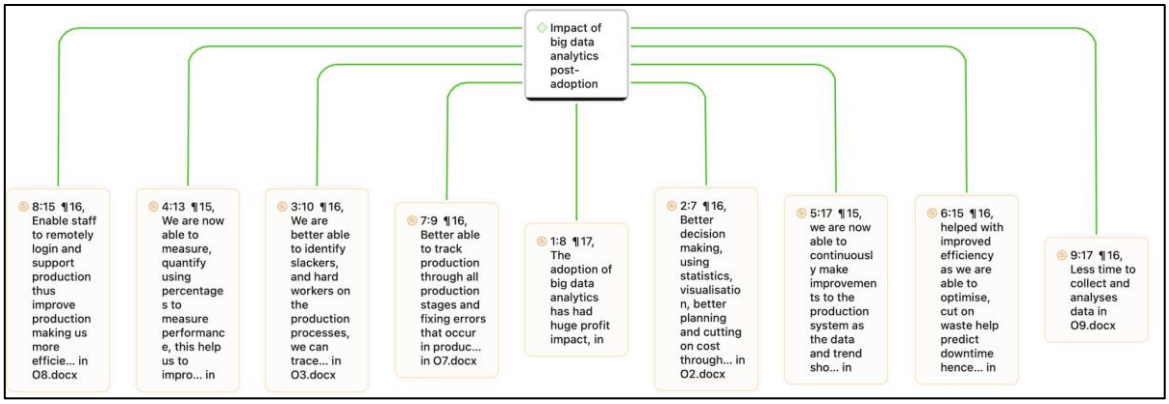
Interviewee responses highlighted the significant costs associated with implementing and maintaining big data analytics in South Africa. They noted that these costs include high wages required to hire and retain skilled professionals. Additionally, securing reliable electricity backup—whether through the installation of solar panels or the procurement of generators—involves substantial expenses related to fuel and maintenance.

Responses also pointed to the challenges posed by South Africa’s low economic growth, which limits investment and capital available for big data analytics. This economic environment contributes to subdued production capacity, leading some organizations to view full automation and comprehensive big data implementation

as financially unviable. Overall, these factors underscore the high cost of doing business in South Africa.

4.3.2.4 Impact of adoption of big data analytics

Interviewees were asked about the impact of adopting big data analytics on their smart manufacturing operations. All nine representatives reported that big data analytics had a positive impact on the manufacturing operations. The analysis of their responses identified three key themes: improved competitiveness, increased efficiency, and enhanced profitability. Figure 13 illustrates some of the representatives' insights into the positive effects of adopting big data analytics.



Source: ATLAS.ti using the interview data

Figure 13: Impact of adoption of big data analytics

Theme: Improved competitiveness

Interviewees highlighted that the adoption of big data analytics has enhanced competitiveness by enabling organizations to monitor both internal and external trends more effectively. This increased awareness allows them to better anticipate market forces and stay competitive against rivals.

Additionally, interviewees noted that big data analytics has facilitated waste reduction and production improvements. By leveraging these insights, organizations can employ competitive pricing strategies, produce high-quality products, and ensure timely dispatch. This has led to increased customer satisfaction and confidence, ultimately contributing to a larger market share for their various products.

Overall, the responses indicate that adopting big data analytics has significantly bolstered the competitiveness of these organizations.

Theme: Increased efficiency

Interviewees highlighted that organizations have achieved significant gains in production and allocative efficiency following the adoption of big data analytics. Improved data visualization capabilities was noted to have led to better planning, cost reduction, and waste management. Consequently, decision-making was highlighted to be more rapid and informed. For instance, one interviewee reported that their production has increased by 20-30%, while waste and costs have been reduced by 15-35% in certain organizations.

Interviewees also noted that organizations are now better equipped to quickly identify and address production bottlenecks and errors. Enhanced performance measurement has facilitated more effective target setting and evaluation of production methods, a notable benefit stemming from the integration of big data analytics.

Additionally, some interviewees observed that the adoption of big data analytics has enabled continuous improvements in production lines and more efficient equipment maintenance. Some organizations have leveraged remote monitoring to identify and correct production issues, further increasing production output.

Theme: Improved profitability

One interviewee reported that profits increased by 5-15% in some organizations, while production output rose by 6-20% in others. These gains in both profits and production were attributed to significant cost reductions, decreased waste, enhanced customer satisfaction and confidence, increased market share, improved product quality, better monitoring of production progress, and more effective planning.

4.3.2.5 Future anticipated big data analytics developments.

The interview participants provided insights into anticipated developments in big data analytics. Their responses revealed three key themes: increased use of AI, rising investment in big data analytics, and the introduction of new regulations.

Theme: Use of AI

Interview respondents anticipate a significant increase in the use of AI in big data analytics. They expect AI to automate data collection, analysis, and reporting, which will include expanded applications of machine learning, data mining, and the integration and standardization of various big data analytics tools. AI is projected to develop advanced data analysis models, accelerate the speed of analysis and reporting, and enhance decision-making capabilities. Additionally, the increased implementation of AI in big data analytics is anticipated to help address the skills gap by compensating for the shortage of human expertise in data analysis.

Theme: Rising investment in big data analytics

Interviewees also anticipated increased investment in big data analytics. This investment is expected to enhance infrastructure, including improvements in connectivity and the development of advanced applications. Additionally, funds are likely to be allocated to training programs designed to upskill personnel in big data analytics, support innovation within the field, and address troubleshooting needs. Overall, these investments aim to improve decision-making quality and drive further advancements in big data analytics.

Theme: Data regulations

The responses indicate a growing expectation for increased regulation concerning the storage and use of big data. Anticipated developments include enhanced cybersecurity measures and strengthen data integrity. This encompasses protecting privacy rights and ensuring the accuracy of big data.

4.3.2.6 Summary

Nine representatives from smart manufacturing organizations participated in interviews analysed using ATLAS.ti software. The analysis highlighted those big data analytics significantly enhances operational efficiency, competitive advantage, and innovation by improving predictive maintenance, optimizing processes, and reducing waste. The primary reasons for adopting big data include increasing production efficiency, gaining a competitive edge, and driving innovation. However, challenges such as a skills gap, high costs, inadequate

infrastructure, and organizational resistance impede integration. Specifically in South Africa, issues like the shortage of skilled professionals, poor infrastructure, and high operational costs are prominent. Despite these challenges, the adoption of big data analytics has led to increased competitiveness, higher efficiency, and improved profitability. Looking ahead, anticipated developments include greater use of AI, increased investment in analytics infrastructure and training, and stricter data regulations to enhance cybersecurity and privacy.

4.4 Chapter Conclusion

This chapter analysed the qualitative data collected from both questionnaires and interviews. The findings from both quantitative and qualitative analyses complement each other, providing a comprehensive understanding of the overall research results. Key findings indicate that smart manufacturing organizations are increasingly adopting big data analytics and reaping significant benefits from its implementation. These benefits include enhanced competitiveness, increased production output, and improved profitability, as organizations are better positioned to reduce waste, lower costs, and make more informed decisions.

However, organizations also face internal and external challenges, such as inadequate infrastructure and insufficient investment in big data analytics. Looking ahead, smart manufacturing organizations anticipate notable innovations in big data, particularly the increased use of AI to automate data collection, analysis, and reporting.

The next chapter will explore these findings in relation to existing studies and literature in the field.

CONCLUSION

5.1 Introduction

This chapter provides a comprehensive discussion of the results and Interpretation of the findings, drawing connections between the findings and existing literature while elucidating the implications of the study. By synthesizing the empirical data with prior research, a deeper understanding of the phenomenon under investigation is attained. By connecting these findings to relevant literature, this chapter offers valuable insights into the role of big data analytics in smart manufacturing and suggests avenues for future research and practical implications for industry stakeholders.

5.2 Summary of findings

This section provides feedback on the three key objectives and their corresponding research questions. Furthermore, the section provides a comprehensive summary of the complex dynamics shaping smart manufacturing in the era of big data and correlates these findings with existing literature.

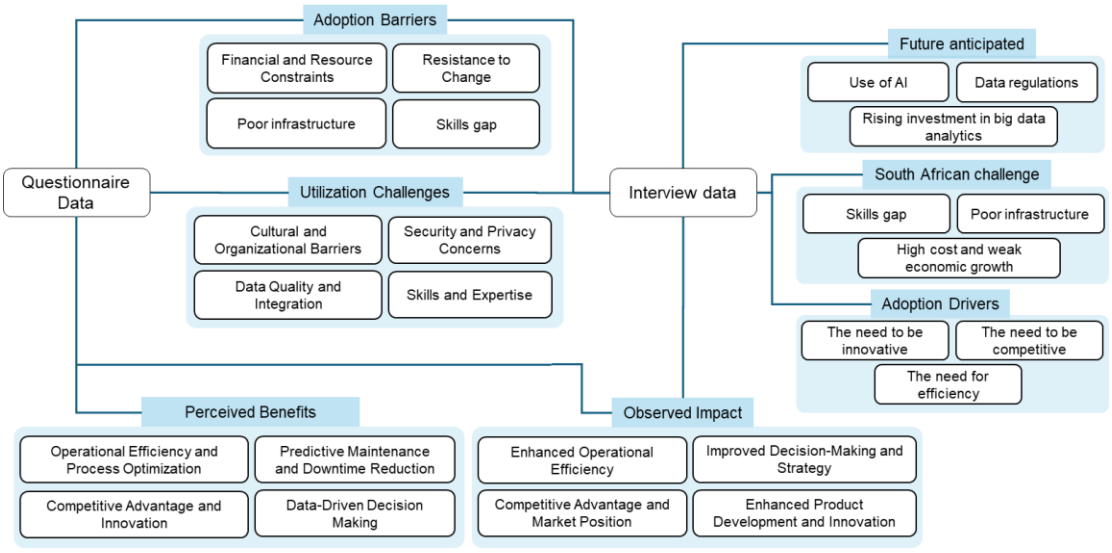


Figure 14: Findings thematic map

Figure **1** eeks to summarize the findings of the study by highlighting the key themes identified through the two research instruments. While both instruments

revealed common themes, the interview data provided a deeper understanding of the smart manufacturing landscape in South Africa.

Smart Manufacturing Adoption in South Africa

The study reveals that a significant proportion of respondents' organizations are either in the early stages of exploring or partially adopting smart manufacturing, while only a smaller percentage have achieved full adoption. These findings align with the literature, which indicates that smart manufacturing in South Africa is still in its nascent stages. The slow adoption rate is attributed to various barriers faced by manufacturing industries, as noted by Deloitte (2017), Dhamija (2022), and Shai et al. (2020).

A major challenge identified is poor infrastructure, particularly frequent power outages, which undermine the effectiveness of big data analytics and smart manufacturing, thereby impeding economic growth. This is consistent with Pradhan & Agwa-Ejon (2018) study, which highlights barriers such as inadequate legal frameworks, skill shortages, and socio-economic issues affecting the adoption of smart manufacturing capabilities in South Africa. Shai et al. (2020) further note that implementing smart manufacturing is costly and requires specialized skills.

Gumbi & Twinomurinzi (2020) emphasize a lack of awareness and knowledge about smart manufacturing within the South African manufacturing sector. This is corroborated by our findings, which also point to inadequate leadership and technological support at the governmental level as significant issues.

Research Objective 1: To identify the barriers to big data analytics adoption among South African smart manufacturing enterprises.

Financial and resources constraints - This study found that financial constraint is a significant barrier to the adoption of big data analytics. The financial burden associated with investing in big data infrastructure and maintaining it is a major challenge. This aligns with existing literature, which notes that the substantial capital required for hardware, software, and skilled personnel can impede

adoption (Dutta et al., 2022; Gumbi & Twinomurinzi, 2020). The capital expenditure for such technologies remains a critical obstacle.

Skills Gap – This study identified that there is a severe shortage of skilled professionals capable of analysing big data effectively. While data capture is achieved, the lack of expertise in data analysis, visualization, and interpretation limits the usefulness of the data. This skills gap is consistent with literature that notes the demand for data science expertise significantly exceeds supply (Shai et al., 2020). The need for targeted training programs to bridge this gap is evident.

Organizational Culture - Cultural resistance within organizations also emerged as a challenge. Some senior managers do not fully appreciate the value of big data analytics, leading to reluctance in investment. Furthermore, staff resistance to adopting new systems and reluctance to change old practices impede the effective integration of big data analytics. This finding resonates with research highlighting resistance to change as a common challenge in technology adoption (Dutta et al., 2022; Rauch et al., 2019).

Infrastructure Issues - Poor infrastructure, including frequent power outages and unreliable internet connectivity, was identified as a significant barrier. These issues hinder real-time data collection and analysis, affecting decision-making and overall effectiveness. Pradhan & Agwa-Ejon (2018) and Shai et al. (2020) also note that infrastructure challenges, alongside legal and socio-economic barriers, impact the adoption of smart manufacturing technologies.

Research Question 1: What Are the Barriers to Adopting Big Data Analytics Among South African Smart Manufacturing Enterprises?

Respondents confirmed that high costs, a skills gap, organizational culture, and infrastructure issues are significant barriers. These findings align with the literature, which identifies similar challenges such as high implementation costs, a shortage of qualified professionals, and cultural resistance (Gumbi & Twinomurinzi, 2020; Shai et al., 2020). The lack of awareness and knowledge about smart manufacturing further compounds these issues (Gumbi & Twinomurinzi, 2020).

Objective 2: To discover the benefits of utilising big data analytics in smart manufacturing.

Operational Efficiency - A key benefit of big data analytics identified by respondents is improved operational efficiency. Analytics help optimize production processes, reduce waste, and enhance productivity. This is supported by literature indicating that big data enables manufacturers to streamline operations and improve overall efficiency (Escobar et al., 2021; N. Kumar et al., 2021).

Predictive Maintenance - Respondents highlighted that predictive maintenance, facilitated by big data analytics, can significantly reduce unplanned downtime and maintenance costs. Real-time data analysis allows for the monitoring of equipment performance and the prediction of potential failures, thus optimizing maintenance schedules (N. Kumar et al., 2021; Lee et al., 2020).

Data-Driven Decision Making - The ability to make informed, data-driven decisions emerged as a major benefit. Respondents noted that big data analytics supports strategic decision-making and enhances competitive positioning. This is consistent with the literature, which emphasizes that data-driven strategies can improve efficiency, product quality, and profitability (Azeem et al., 2021; Ren et al., 2019).

Innovation and Strategic Advantage - Respondents also pointed out that big data analytics fosters innovation and provides a strategic advantage by offering insights that drive product development and market responsiveness. Literature supports this view, highlighting the role of data-driven insights in fostering innovation and maintaining competitive edge (Tao et al., 2018; B. Wang et al., 2021).

Research Question 2: What Are the Perceived Benefits of Adopting Big Data Analytics for Smart Manufacturers in South Africa?

Respondents consistently identified operational efficiency, predictive maintenance, and data-driven decision-making as primary benefits. These benefits align with the literature, which underscores the value of big data analytics

in optimizing processes, reducing costs, and enhancing strategic decision-making (Azeem et al., 2021; Escobar et al., 2021; Lee et al., 2020). However, challenges such as skills gaps and integration issues persist, reflecting the need for ongoing attention to address these barriers (Gumbi & Twinomurinzi, 2020; Maisiri & Van Dyk, 2021).

5.3 Implications

The primary objectives guiding the study was to uncover the barriers and challenges to adopting big data analytics and uncover the benefits thereof among smart manufacturing enterprises. The findings highlight a crucial factor: while there is acknowledgement of the benefits in employing big data analytics, most of their organizations have not fully embraced smart manufacturing practices, nor have they maximized their utilization of big data analytics capabilities.

Moreover, the study identified several barriers hindering the adoption of these technologies. Among these, the shortage of skilled personnel emerges as a predominant obstacle, alongside organizational culture, management buy-in, and financial constraints. The implications of these findings reverberate across various dimensions of organizational operations. The lack of skilled resources triggers a cascade of challenges, impacting everything from the adoption of new technologies to the formulation and execution of competitive strategies.

The implications of these findings for both theory and practice underscore the urgent need for enterprises to address several critical challenges. To fully harness the transformative potential of big data analytics in smart manufacturing, organizations must focus on mitigating skills shortages, cultivating a supportive organizational culture, and overcoming financial constraints. Neglecting these areas not only impedes technological advancement but also jeopardizes long-term competitiveness and sustainability in a rapidly evolving, data-driven landscape.

5.4 Recommendations

To build on the insights from this qualitative study and address its limitations, future quantitative research should focus on expanding the scope and generalizability of findings. This can be achieved by conducting studies with larger and more diverse samples of smart manufacturing firms across South Africa, incorporating various company sizes and regional differences. Additionally, employing survey-based analyses to quantify skills shortages and the effectiveness of training programs can provide valuable insights into their impact on technology adoption.

Assessing organizational culture and management buy-in through standardized measurement tools will help understand their influence on big data analytics initiatives. Financial constraints can be examined through cost-benefit analyses to provide empirical evidence on ROI and investment challenges. Longitudinal studies tracking infrastructure improvements and technological advancements will offer insights into the long-term effectiveness of big data investments.

Finally, quantitative risk assessments of cybersecurity measures and data management practices will contribute to understanding and mitigating data security risks. These approaches will enhance the generalizability and robustness of the research findings, offering actionable recommendations for the smart manufacturing sector.

5.5 Conclusion

In conclusion, this study aimed to identify the primary objectives guiding its inquiry: uncovering the barriers and challenges to adopting big data analytics and exploring the associated benefits for smart manufacturing enterprises. The findings reveal a critical nexus between these challenges and benefits, providing valuable insights for enterprises navigating the complexities of modern industrial landscapes. The study underscores the imperative of addressing skills shortages and cultivating a supportive organizational culture to fully harness the transformative potential of big data analytics in smart manufacturing.

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APPENDIX A. CONSENT FORM FOR PARTICIPATION

1. The research study was explained to me. I understand what this study is about.

	Tick
Yes	
No	

2. I agree to participate in the research study. I understand the purpose and nature of this study and I am participating voluntarily. I understand that I can withdraw from the study at any time, without any penalty or consequences.

	Tick
Yes	
No	

3. I grant permission for the data generated from this questionnaire to be used in the researcher's publications on this topic.

	Tick
Yes	
No	

4. I grant permission for the questionnaire responses to be recorded and saved for purpose of review by the researcher. [If others (such as research assistants, dissertation supervisor) will view the recording then note here.]

	Tick
Yes	
No	

…… (signature)

…… (name of participant)

…… (date)

APPENDIX B. QUESTIONNAIRE

Section A: Demographic Information

Q1. What is your current role?

Q1.1

Role	**Tick**
Engineer	
Analyst	
Consultant	
Manager	

Other

Q1.2

Seniority	**Tick**
Junior/Associate	
Intermediate	
Senior/Lead	
Principal	
Chief	
Executive	
Director	

Q1.3

Speciality	**Tick**
Data	
Electrical	
Mechanical	
Industrial	
Quality	
Operations	
Supply Chain	
Projects	
IT	

Q2. How many years of work experience do you have?

Tick			
Experience	0-4 years	5-10 years	>10 years

Q3. What is the size of your organization (number of employees)?

Tick					
Experience	<100	100-399	400-599	600-799	>800

Q4. How would you rate the level of adoption of smart manufacturing capabilities in your organization?

	Tick
Not adopted	
Initial stages of adoption	
Partial adoption	
Advanced adoption	
Fully adopted	

Q5. In your opinion, to what extent does your organization use big data analytics?

	Tick
Not utilised	
Partially utilised	
Fully utilised	

Section B: Main study questions

Q6. Do you believe that the integration of big data analytics capabilities is necessary for smart manufacturing practices to result in a competitive advantage? Please explain your answer.

Q7. What are the key organizational challenges or barriers to effectively utilizing big data analytics capabilities?

Q8. Have you observed any positive changes in your organization's competitive position since adopting big data analytics capabilities? If yes, please describe those changes.

Q9. How do you perceive the role of big data analytics capabilities in shaping the future competitiveness for manufacturing enterprises?

Q10. Are there any challenges or barriers that your organization has faced in implementing and utilizing big data analytics capabilities? If yes, please describe those challenges.

APPENDIX C. Interview guide Semi-structured

Date:	Interviewer:	Archival
Start Time:		End Time

Introduction

Greetings

- The researcher introduces himself (name and background).
- An explanation of the purpose of the research aims to understand the barriers and associated benefits of adopting big data analytics within a South African context.
- Explain to the participant that the information shall be kept confidential; all information relating to their identity will be reduced or excluded as it is not the focus of the study.

Interview Questions

1. Can you please describe your role in the company and detail your experience in smart manufacturing?
2. Does your organization use big data analytics in its smart manufacturing operations?
3. From your perspective, what led your organization to look into adopting big data analytics?
4. Can you walk me through the challenges you've faced while integrating big data analytics into your manufacturing operations?
5. What internal organizational challenges have you faced?
6. Which of the challenges and barriers experienced would you attribute to be a South African challenge?
7. How would you characterize the impact of big data analytics on your manufacturing operations post-adoption?
8. Tell me about the positive outcomes you've observed as a result of utilizing big data analytics in your manufacturing operations.
9. Do you believe that the use of big data analytics has made your organization more competitive?
10. Looking ahead, what future trends or advancements in big data analytics do you anticipate will further transform manufacturing operations, and how do you plan to adapt to these change

APPENDIX D. ETHICAL CLEARANCE

Graduate School of Business Administration
University of the Witwatersrand, Johannesburg

Wits Business School Ethics Committee
Constituted under the University Human Research Ethics Committee (Non-Medical)

Ethics Clearance Certificate

Ethics protocol number: WBS/BA458057/685
This certificate is only valid with a legitimate ethics protocol number and signed by the Researcher (below).

Project title	The impact of big data analytics on the competitiveness of South African smart manufacturing enterprises
Investigator / Researcher	Mr Nyiko Mavodze
Nature of Project	MBA (Research Article)
Decision of the Committee	Approved, provided stakeholders and participants are guaranteed confidentialty.
Issue Date of Certificate	9/4/2023
Expiry date	Date of submission of the project / research report
Chairperson	Dr Pius Oba ☎ +27 11 717 3976 +27 82 733 6587 pius.oba@wits.ac.za

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Declaration by Researcher

One copy must be signed by the Researcher and returned to the Chairperson of the Wits Business School Ethics Committee.

I fully understand the conditions under which I am authorized to carry out the abovementioned research and I guarantee to ensure compliance with these conditions. Should any departure to be contemplated from the research procedure as approved I undertake to resubmit the protocol to the Committee.

Signature

04/09/2023
Date:

APPENDIX E. SURVEY RESULTS

https://docs.google.com/spreadsheets/d/17Z_CZkQJyoeG6hBr3AboCDwPxDGASv3xzO2N0c6l1Sg/edit?usp=sharing

APPENDIX F. INTERVIEW TRANSCRIPTS

https://drive.google.com/drive/folders/1RifVkk9ARIY5G-rHJrs_ecwOoqvfYulD?usp=drive_link