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FACTORS INFLUENCING THE ADOPTION OF BIG DATA ANALYTICS IN SUPPLY CHAIN RISK MANAGEMENT: A CASE IN THE MANUFACTURING INDUSTRY

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A thesis submitted in fulfilment of the requirements for the Master's Degree in Information Management in the Economic and Management Sciences Facility of the University of the Western Cape

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Declaration

I declare that "**Factors influencing the adoption of Big Data Analytics in Supply Chain Risk Management: A Case in the Manufacturing industry*"*** is my own work, that it has not been submitted for any degree or examination in any other university, and that all the sources I have used or quoted have been indicated and acknowledged by complete references.

Mfundo Njabulo Zwane December 2022

Abstract

In Africa, supply chain processes are under pressure from political, economic and security risks that disrupt the free flow of goods. In South Africa, the manufacturing industry has high growth potential, however, the industry is bogged by supply chain risks that inhibit the flow of information, raw material or finished goods amongst supply chain partners. Supply Chain Risk Management has emerged as a process by which firms can identify, assess, and mitigate risks within their supply chains, enabling them to reduce uncertainties. Currently, SCRM continues to elude practitioners and scholars due to the shortage of skills, lack of experience, the absence of consensus on what SRCM is, and the lack of data analytics tools and platforms to process Big Data. Supply chain professionals have yet to adopt Big Data Analytics despite benefits such as improved risk evaluation, resilience planning, vulnerability reduction, increased robustness and resilience of the supply chain, and improved profitability and sustainability of the firm. In the context of this problem, this study sought to examine the factors that influence the adoption of Big Data Analytics in Supply Chain Risk Management. The researcher employed a case study method focused on depth rather than breadth by collecting qualitative data to determine the factors influencing the adoption of Big Data Analytics in Supply Chain Risk Management. Literature was systematically reviewed to understand the role of Big Data Analytics in Supply Chain Risk Management. The literature review was further reviewed to develop a conceptual framework. The study collected qualitative data from seven supply chain professionals using semi-structured interviews. The significant original contribution of this study is the refinement of a theoretical framework that identify factors that influence the adoption of Big Data Analytics in Supply Chain Risk Management by supply chain professionals in the manufacturing industry. This study found that factors related to Big Data management, organisational context, competitive pressures, and attitudes are the factors influencing the behavioural intention and usage of Big Data Analytics in Supply Chain Risk Magement. The study offers recommendations to practitioners and scholars on how the adoption of Big Data Analytics can be improved, including areas of future research.

KEYWORDS: Big Data Analytics, Big Data, Supply Chain Risk Management, Supply Chain Management, Big Data Adoption, UTAUT Framework, Manufacturing Industry

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Dedications

This mini dissertation is dedicated to Four Wom×n:

1. My Grand Mothers – Thank you for being faithful Ancestresses
2. My Mother – Thank you for your patience and love
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“Were I so tall to reach the pole, or grasp the ocean with my span. I must be measur’d by my soul. The mind’s the standard of the m×n”

~Isaac Watts (False Greatness, 1698)

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Terms and Definitions

Term	Definition	Source
Big Data	Datasets generated by heterogeneous data sources	Akter et al. (2016); Pandey & Ramesh (2015); Prabhu et al. (2019b)
Big Data Analytics	Techniques that encompass a variety of descriptive, exploratory, predictive and prescriptive methods that can be classified as machine learning, data mining, artificial intelligence, and audio-visual analytics	Fuller, Buote & Stanley (2017)
Supply Chain Management	Management activities associated with the design, planning, execution, controlling, and monitoring of global supply chains to unlock and preserve value through developing competitive infrastructure and performance monitoring	Bozarth, C. C. et al. (2019), Ivanov, D. (2019); Council of Supply Chain Management Professionals (2013); Oliver, R. K. et al. (1982)
Supply Chain Risk	Unpredictable triggering events that disrupt the flow of information, material and products in the supply chain	Milliken (1987); Heckmann, Comes & Nickel (2015); Peck (2006)

List of Acronyms

BDA – Big Data Analytics

IDT – Innovation Diffusion Theory

SCM – Supply Chain Management

SCRM – Supply Chain Risk Management

TAM – Technology Acceptance Model

TOE – Technology-Organization-Environment Framework

TPB – Theory of Planned Behaviour

UTAUT – Unified Theory of Acceptance and Use of Technology

Chapter 1 INTRODUCTION AND RATIONALE

1.1 Introduction and Background to the research problem

The manufacturing industry is crucial to the development of nations and is recognised as a potential driver of economic growth in Africa especially in the context of introduction of the African Continental Free Trade Area (AfCFTA) on 21 March 2018 (Balchin, N. et al., 2016; Signe, L. et al., 2018). However, Africa's supply chains are under pressure from political, economic and security risks that disrupt the free flow of goods and destroy logistic infrastructure, thus introducing risks and uncertainty in the manufacturing supply chain (Exx Africa, 2019). Locally, South Africa is beset with labour unrest and labour disputes that have led to disgruntled employees committing arson (Ibid) on corporate assets such as trucks which are essential in the logistics sector for the movement of goods on land, thus crippling logistics networks. Devastating civil unrest as a result of political and economic instability, such as the 2021 July protests in South Africa, exposed the vulnerability to cargo theft at the country's busiest port (Africa, S. S., Silumko; Gumbi, Mojankunyane, 2021; Blom, T. et al., 2022; Booth, I., 2021; Laney, D., 2001; Meyer, A. et al., 2019; Shezi, A., 2021; United Nations Office for the Coordination of Humanitarian Affairs, 2021; Vhumbunu, C. H., 2021).

Although no official statistics were released on the impact of this particular event on the manufacturing industry, it is worth noting that manufacturing output declined by 4.2% immediately after the civil unrest (Statistics South Africa, 2021). Furthermore, natural disasters such as the 2022 floods in Durban (Cele, S. T. et al., 2022; United Nations Office for the Coordination of Humanitarian Affairs, 2022); and information security events such as the cyber-attacks that disrupted port operations at South Africa's busiest port exposed firms to further supply chain risks (Anthoni Van, N., 2022; Claasen, J., 2021; Department of Public Enterprises, 2021; Meyer, A. et al., 2019; Njini, F. V., John, 2021; Transnet Soc, 2021). The above reveals that supply chain risks faced by developed countries are different to those in developing countries (Tukamuhabwa, B. et al., 2017).

A significant amount managers did not have formal processes for managing global supply chain risks, whilst one in every two supply chain professionals had little to no experience practising risk management as supply chain risk management (SCRM) is not standard practice, especially in developing countries such as South Africa where it has not yet fully matured (Apics, 2015:5; Christopher, M. et al., 2011; Harapko, S., 2021; Luke, R. et al., 2018). Ambiguous and vague definitions, inconsistencies in the literature and the lack of consensus on what constitutes Supply Chain Risk Management further exacerbate the deficiency in SCRM practices by supply chain professionals (Baryannis, G. et al., 2019; Heckmann, I. et al., 2015). Five out of every ten supply chain professionals had little to no experience practising risk management, even though six out of every ten respondents recognised the importance of supply chain risk management skills and experience (American Production and Inventory Control Society, 2015). An overwhelming six out of every ten supply chain professionals noted that the scarcity of data analytics platforms and tools could be one of the main challenges faced in integrating risk management into supply chain processes (American Production and Inventory Control Society, 2015). Luke, R. et al. (2018) identified a need to explore the reasons for the lacklustre levels of maturity of SCRM, especially within a developing country such as South Africa where there is a paucity of SCRM studies (Prakash, S. et al., 2017; Tukamuhabwa, B. et al., 2017).

Moreover, it is essential to consider how the corona virus ("COVID-19") accelerated the adoption of technologies (Kaushik, K., 2021; Mckinsey & Company, 2020; Trefcer, S., 2020), especially within the supply chain. Whilst considering that developing countries are lagging in information systems development projects (Kalema, B. M. et al., 2017). Developing countries face budgetary, data collection; data analysis; and data quality issues that further impact the adoption and utilisation of Big Data Analytics (Luna, D. R. et al., 2014; Rayed Assad, C. A., 2018). The limited storage infrastructure for big data processing, communication networks and the inability to integrate legacy systems with new systems further continue to hinder the adoption of Big Data Analytics in developing countries (Kshetri, N. et al., 2017; Luna, D. R. et al., 2014; Prasetyo, B. et al., 2019).

1.2 Identified Research Gaps

Awwad, M. et al. (2018); Nguyen, T. et al. (2018); Schoenherr, T. et al. (2015) postulate that lack of expertise and skills; the inability to identify useful data for data analytics, data security issues, the inability to clarify the business value of data analytics, waning top management support, and the absence of data policies and lack of data governance as factors impacting Big Data Analytics implementation. Awwad, M. et al. (2018) alluded to the organisational and technical factors that hinder the adoption of Big Data Analytics in the supply chain. This presents a need for understanding the individual factors that influence the adoption of Big Data Analytics in Supply Chain Risk Management, to improve the ability of supply chain professionals to adopt Big Data Analytics (Gain Group, 2020). Kshetri, N. et al. (2017) identified the need to explore the factors that influence the adoption of Big Data Analytics in developing countries. Alshamaileh, Y. et al. (2013) and Verma, S. et al. (2017) suggested that such a research gap can be filled by a qualitative study that explores the factors that influence the adoption of Big Data Analytics within different sectors and countries. Muposhi, A. et al. (2017) also suggest a technology adoption study be undertaken within the context of SCRM.

This study positions itself within this knowledge gap. This study also seeks to fill a gap identified by Alaskar, T. H. et al. (2021) by interviewing managers involved in supply chain management about their perceptions of the adoption of Big Data Analytics in SCRM. Additionally, it will contribute to Big Data Analytics adoption studies in South Africa by seeking to understand supply chain professionals' behavioural intentions to adopt Big Data Analytics in SCRM in South Africa. This study is propelled by the lack of adoption studies in developing countries (Alsqour, M. et al., 2015), the dearth of SCRM research originating from developing countries (Prakash, S. et al., 2017) and the scantiness of literature on the adoption of big data analytics in SCRM within a developing country context (Alaskar, T. H. et al., 2021; Kalema, B. M. et al., 2017).

1.3 Overview of the research problem

The limited adoption of Big Data Analytics by supply chain professionals in Supply Chain Risk Management has contributed to the lack of integration of risk management into supply chain processes in the manufacturing industry. Although various authors have analysed the lack of adoption of Big Data Analytics, there is limited research on the adoption of Big Data Analytics in Supply Chain Risk Management within the manufacturing industry, especially in the South African context. Despite the evidence in prior studies showcasing the benefits of adopting Big Data Analytics, there is a knowledge gap in understanding the perceptions of supply chain professionals and managers on adopting and using Big Data Analytics in Supply Chain Risk Management. Several studies such as that of Alshamaileh, Y. et al. (2013), Muposhi, A. et al. (2017), Verma, S. et al. (2017), Kshetri, N. et al. (2017), Alaskar, T. H. et al. (2021) Have mentioned this gap. This study, therefore, seeks to address this gap by investigating the factors that influence the adoption of Big Data Analytics in Supply Chain Risk Management by supply chain professionals in the manufacturing industry.

1.4 Aim of Study

This study aims to employ the UTUAT framework to explore the factors influencing the adoption of Big Data Analytics within a manufacturing firm.

1.5 Primary Research Question

The primary aim of this study is to answer the research question:

> What are the factors influencing the adoption of Big Data Analytics in support of Supply Chain Risk Management by supply chain professionals in the manufacturing industry in South Africa?

In pursuit of this aim, the study proposes the following research sub-questions to guide the study:

1. What is the role of Big Data Analytics in Supply Chain Risk Management?
2. What theoretical frameworks have been used to study the adoption of Big Data Analytics in Supply Chain Risk Management?
3. What conceptual model can be used to study the factors that influence the adoption of Big Data Analytics in Supply Chain Risk Management?
4. What are the factors influencing the adoption of Big Data Analytics in Supply Chain Risk Management?

1.6 Research Objectives

1. To review the adoption of Big Data Analytics in Supply Chain Risk Management.
2. To identify theoretical frameworks and models for understanding the adoption of Big Data Analytics in Supply Chain Risk Management.
3. To design a research protocol for investigating factors that influence the adoption of Big Data Analytics in Supply Chain Risk Management.
4. To determine the factors influencing the adoption of Big Data Analytics in Supply Chain Risk Management.

1.7 Alignment of Primary Research Question to Research Objective

Table 1: Alignment of Research Questions to Research Objectives

Research question: What are the factors influencing the adoption of Big Data Analytics in Supply Chain Risk Management by supply chain professionals in the manufacturing industry in South Africa?		
Research Sub-Questions	Method/s	Research objective
What is the role of Big Data Analytics in Supply Chain Risk Management?	Systematic Literature Review	To review the adoption of Big Data Analytics in Supply Chain Risk Management.
What theoretical frameworks have been used to study the adoption of Big Data Analytics in Supply Chain Risk Management?	Literature Review	To identify theoretical frameworks and models for understanding the adoption of Big Data Analytics in Supply Chain Risk Management.
What conceptual model can be used to study the factors that influence the adoption of Big Data Analytics in Supply Chain Risk Management?	Literature Review	To design a research protocol for investigating factors that influence the adoption of Big Data Analytics in Supply Chain Risk Management.
What are the factors influencing the adoption of Big Data Analytics in Supply Chain Risk Management?	Semi-structured interviews informed by literature.	To determine the factors influencing the adoption of Big Data Analytics in Supply Chain Risk Management

1.8 Research Design and Methodology

1.8.1 Research Design

The research project adopted a case study as part suitable research design to answer the research question. Yin, R. K. (2003:18) defines a Case Study as “an empirical inquiry that investigates a contemporary phenomenon within its real-life context, especially when the boundaries between phenomenon and context are not clearly evident”. A case can be understood as a unit of analysis such as a place, for example, a company or department, an event or activity, or a person (Bryman, A., 1989). By adopting a case study approach, the researcher seeks to study this case in its natural setting; however, case studies can be time-consuming, especially when the researcher has to negotiate access to the participants or the research setting (Oates, B. J., 2012). Issues around access to the research site are addressed in section 4.2.4.5 of Chapter 4.

1.8.2 Unit/s of analysis

Supply chain professionals within an organisation in the manufacturing industry in Cape Town are the unit of analysis. Supply chain professionals recognise the importance of supply chain risk management skills and experience and have highlighted concerns about the paucity of data analytics tools and platforms (Apics, 2015).

The interest, therefore, is in understanding what factors influence the adoption of Big Data Analytics by Supply Chain professionals.

1.8.3 Interview Guide

An interview guide was developed to facilitate the semi-structured interview by outlining the issues and themes to be probed, thus providing a structure for the interviewer to ask questions whilst maintaining flexibility (Harvard University, n.d.). Interview questions were developed based on the conceptual model using constructs that have been validated in previous studies, thus enforcing the requirements for content validity (Madhlangobe, W., 2018).

1.8.4 Data sources

According to statistical conventions, human respondents in a case study are considered a sample. The case is the population, as the research results will be limited to the studied case (Yin, R. K., 2018). The data sources were drawn from a population of supply chain professionals in a manufacturing organisation. The sample consists of Supply Chain Analysts, Supply Chain Data Analysts and Supply Chain Managers.

1.8.5 Data collection Techniques (Research Methods)

Data collection occurred via semi-structured interviews based on an interview guide that the researcher developed. The purpose of the semi-structured interviews is to refine the theoretical framework by exploring the factors that influence the adoption of Big Data Analytics in Supply Chain Risk Management. The interview guide assisted the researcher in posing questions to the participants based on the literature review and soliciting unstructured questions (Oates, B. J., 2006). The researcher, recognising their role in influencing the interview outcomes, adopted a traveller persona in that the researcher sought to reconstruct a picture of the adoption phenomenon through the participant's experiences (Buetow, S., 2013). In this regard, the researcher further acknowledged the possibility of an adverse effect of their presence on the participant and their response, which is addressed in further detail in Chapter 3.

1.8.6 Sampling method and strategy

Purposeful sampling was conducted where specific participants were sought out who were employed as supply chain professionals at Company X. The researcher implemented a selection criteria, which required that the potential participant to be an employee of Company X. The researcher invited potential participants via e-mail to participate in the study. The email contained an information note describing the research and an ethics approval letter. Furthermore, participants were informed that the employer had approved the research. The researcher further disclosed the existence of a Non-Disclosure Agreement to all research participants.

1.8.7 Data Analysis

Qualitative data analysis involves data reduction, visualisation, and drawing conclusions based on the analysis (Miles, M. B. et al., 1994). The researcher approached the data analysis unbiasedly by examining the data using the conceptual framework to discover implicit issues that could be included in the theoretical framework. The researcher relied on the thematic data analysis process proposed by (Braun, V. et al., 2006; Clarke, V. et al., 2018). The study utilised NVivo software to analyse the qualitative data contained in the interview transcripts. The transcripts were coded using NVivo nodes that are further developed into categories of the underlying qualitative data (Hwang, S., 2008). The categories were refined into themes that represent the factors influencing the adoption of Big Data Analytics in SCRM (Hwang, S., 2008).

1.9 Location of Study

The study is conducted among supply chain professionals in an organisation in the manufacturing industry in South Africa that is based in Cape Town.

1.10Ethical Considerations

Recognising that sensitive information could be collected from the respondents, the researcher ensured the security and the non-disclosure of responses. The researcher considered the rights of respondents not to participate in the research, the respondent's right to withdraw, the respondent's right to give informed consent, the respondent's right to anonymity, and the respondent's right to confidentiality (Oates, B. J., 2006). The researcher further considered internet-based research ethics that were included in the interview guide (Oates, B. J., 2006). This study obtained the approval of the organisation as well as approval from the interviewees. The research ensured ethical standards by obtaining ethical clearance from the University of the Western Cape to conduct the research. As such, consent forms were provided to all participants to obtain their consent. All information about their organisation remained confidential, and anonymity was provided. All research material, such as interview recordings, are securely stored for a minimum period of 5 years and destroyed after that.

1.11 The layout of the Mini Dissertation

The layout of the chapters of this study is depicted in Figure 1: Chapter Layout. Chapter 1 introduces the research problem in a practical context that requires intervention, such as the lacklustre adoption of Big Data Analytics by supply chain professionals in the manufacturing industry. Chapter 2 reviews the literature to understand what Big Data Analytics and Supply Chain Risk Management entail, including how Big Data Analytics can be utilised within a Supply Chain Risk Management context. The chapter then reviews previous studies on the adoption of Big Data Analytics by outlining seminal studies and the technology adoption models employed within those studies. Chapter 3 proposes the conceptual model employed by the researcher within the research study. Chapter 4 outlines the research process by considering the research questions, the appropriate design to answer these questions and justifying the methodology implemented to collect and analyse the data. The researcher also analyses issues related to the philosophical paradigm driving the research, the justification of the research methods, how the researcher could influence the participant’s responses, and the credibility of the research study. Chapter 5 presents the research study's findings to the reader. Finally, Chapter 6 discusses the results and briefly details the conclusions reached by the researcher and the recommendations to improve adoption in practice.

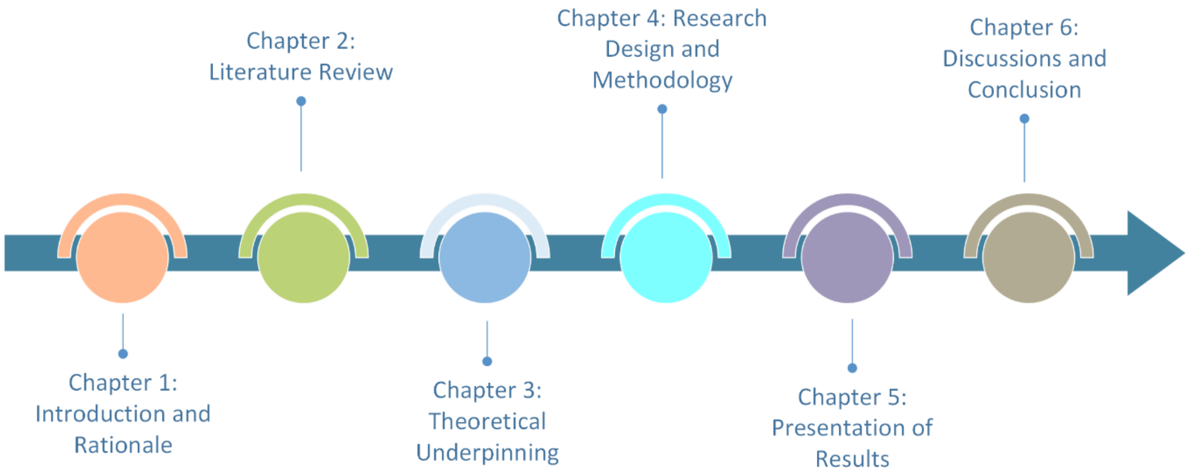


Figure 1: Chapter Layout

1.12 Chapter Summary

This chapter provided a background to the research problem, and identified the research gaps that this study seeks to fill. A nuanced and detailed discussion of the literature will be provided in Chapter 2. The chapter then proceeded with an overview of the research problem by outlining the aims of the study and the resultant research objectives. A brief description of the research design and methodology was given, which will be subsequently discussed In Chapter 4 of the study. The chapter identified the location of the study and addressed the ethical aspects of the research project. The chapter concluded with a layout of the thesis which indicated that the next chapter will conduct a review of the literature, Chapter 3 will present the theoretical framework, Chapter 4 will provide a detailed discussion of the research design and methodology that was outlined in section 1.8., whilst Chapter 5 will present the results and 6 and discuss and conclude on the findings of the research project.

Chapter 2 LITERATURE REVIEW

"Research is to see what everybody has seen and think what nobody has thought."

~ Albert Szent-Gyorgyi

2.1 Introduction

Researchers and practitioners have extensively studied the user acceptance of technology, and it is therefore considered a mature strand of research within the Information Systems discipline (Dwivedi, Y. K. et al., 2019; Hu, P. J. et al., 1999; Venkatesh, V. et al., 2003). Technology adoption within Supply Chain Management ("SCM") is another mature area of study, with more recent studies shifting towards understanding the adoption of emerging technologies such as cloud computing in SCM, mainly since cloud computing has supported the increased rate of data creation and its associated analysis through the use of Big Data Analytics. This chapter will, firstly, delineate the boundaries of the research by providing a concise account of what are supply chain risks and what is Supply Chain Risk Management ("SCRM"). Secondly, the researcher will review how past work has defined Big Data and Big Data Analytics ("BDA"). Thirdly, the researcher will then elucidate how BDA supports SCRM by reviewing how the literature has studied the adoption of BDA in SCRM. The chapter will proceed with a description of the various technology adoption models used in the study of technology adoption and use. Then, the researcher will present the proposed conceptual framework to be operationalised in the study, the variables and the relationship between the variables. Finally, the researcher will justify certain propositions in the conceptual framework, demonstrate how this chapter contributes to prior research, and highlight this chapter's practical and theoretical contributions to the current endeavour and future research.

2.2 Supply Chain Management and Supply Chain Risk Management

To gain insight into global supply chain risk management, it is necessary to understand what supply chain management is, including the emergent trends of digitalisation of Supply Chain Management.

2.2.1 Supply Chain Management

Supply chain management ("SCM"), during its infancy stages, was considered a trend, with academics and practitioners alike questioning its relevancy and the conceptual underpinning of SCM (Bechtel, C. et al., 1997; Mentzer, J. T. et al., 2001; Quinn, F. J., 1997). Mentzer, J. T. et al. (2001) argue that for SCM to be understood by academics and practitioners, the concept of SCM must be clearly defined and articulated, given the disputed definitions of what is understood to be SCM. For instance, Felea, M. et al. (2013) position two consultants, namely, Oliver, R. K. et al. (1982), as proponents of SCM definitions at a time when practitioners needed to manage their "supply chains" in the pursuit of improving organisational performance; gaining a competitive advantage; and optimising the performance of the supply chain (Lummus, R. R. et al., 1999).

SCM, which essentially began as an inventory management strategy within logistics (Cooper, M. C. et al., 1993), thus had no agreed-upon definition. When Oliver, R. K. et al. (1982) began engaging the concept of SCM, they sought to bridge this gap but undoubtedly sparked a debate amongst practitioners and academics on how best to define SCM. Historically, Oliver, R. K. et al. (1982), as cited in Felea, M. et al. (2013), described SCM as a "process of planning, implementing, and controlling the operations of supply chain with the purpose to satisfy customer requirements as efficiently as possible". From a practitioner's point of view, SCM, as defined by the Council of Supply Chain Management Professionals "encompasses the planning and management of all activities involved in sourcing and procurement, conversion, and all logistics management activities" (Council of Supply Chain Management Professionals, 2013).

From a scholarship viewpoint, one can conceive of SCM as "an integrating philosophy to manage the total flow of a distribution channel from supplier to the ultimate customer" (Ellram, L. M. et al., 1990). Bozarth, C. C. et al. (2019) define SCM as "the active management of supply chain activities and relationships in order to maximize customer value and achieve a sustainable competitive advantage". Ivanov, D. (2019) defines SCM as "cross-department and cross-enterprise integration and coordination of material, information, and financial flows to transform and use the SC resources in the most rational way along the entire value chain, from raw material suppliers to customers". In summary, the researcher defines SCM as the management activities associated with the design, planning, execution, controlling, and monitoring of global supply chains to unlock and preserve value through developing competitive infrastructure and performance monitoring Bozarth, C. C. et al. (2019), Ivanov, D. (2019); Council of Supply Chain Management Professionals (2013); Oliver, R. K. et al. (1982). This definition contextualises SCM with the emerging information technologies adopted in supply chains.

2.2.2 Defining Risk

Although the term risk is colloquially used in reference to personal circumstance, society and business (Borch, K., 1967; Spikin, I. C., 2013), its definition has always been contested (Fischhoff, B. et al., 1984), thus resulting in confusion. Issues such as subjectivity, the dimensions of risk, the quantification of risks via statistical measures, and the concerns of exposure to risk continue to cause controversy (Fischhoff, B. et al., 1984). In the literature, risk was first defined by Willett, A. H. (1901) as the "objectified uncertainty as to occurrence of an undesired event". One reads from this definition that risk is defined in the context of uncertainty, and thus one needs to understand the meaning of uncertainty to understand the concept of risk (Jedynak, P. et al., 2020).

Knights illuminates this argument further by distinguishing between risk and uncertainty, where risk is understood to be estimates that have priori probability that can be derived through deduction or empirically evaluated through observing frequencies. In contrast, uncertainty is when estimates have "no basis of classifying any kind of instances"(Knight, F. H., 1921:225). The presence of perfect information increases certainty, whilst the lack of information increases uncertainty (Outreville, J. F., 1988). Gough, J. D. (1988:9) states that risk exists where the "possible outcomes are well known and where a probability distribution for these outcomes can be agreed upon by a set of 'relevant experts'" whilst uncertainty is "when either the set of outcomes is unknown…

or where agreement as to a probability distribution cannot be reached". Thus we can infer from Gough, J. D. (1988); Knight, F. H. (1921) that risk is measurable while uncertainty cannot be measured through probabilistic means, and according to Outreville, J. F. (1988), perfect information reduces this uncertainty. These concepts of risk and uncertainty are what underpin the field of risk management.

2.2.3 Supply Chain Risk and Uncertainty

There is no consistent definition of risk within the context of SCM (Baryannis, G. et al., 2019; Heckmann, I. et al., 2015). March & Shapira (1987:1404) were the first scholars to conceptualise supply chain risk as the "variation in the distribution of possible supply chain outcomes, their likelihood, and their subjective values". Jüttner, U. et al. (2003) define supply chain risk as "any risks for the information, material and product flows from the original supplier to the delivery of the final product for the end user", with Peck (2006:132) concurring and conceptualising this risk as an " impediment or hazard". Heckmann, I. et al. (2015:130) state that "supply chain risk is the potential loss for a supply chain in terms of its target values of efficiency and effectiveness evoked by uncertain developments of supply chain characteristics whose changes were caused by the occurrence of triggering-events". Supply chain risks can thus be understood to be unpredictable (Milliken, F. J., 1987), triggering events (Heckmann, I. et al., 2015) that disrupt the flow of information, material and products (Peck, H., 2006) in the supply chain.

Heckmann, I. et al. (2015); Manuj, I. et al. (2008) acknowledge the existence of uncertainty in the supply chain environment due to supply chain risks. Uncertainty, which can be defined as the "perceived inability to predict something accurately" (Milliken, F. J., 1987:136), is a critical component of supply chain risk. Supply chain risks exist due to the uncertainty of the match between supply and demand (Jüttner, U. et al., 2003). Supply chain uncertainty can thus be understood to be "the perceived inability to predict the likelihood of a mismatch between supply and demand" (Heckmann, I. et al., 2015; Jüttner, U. et al., 2003; Manuj, I. et al., 2008; March, J. et al., 1987; Milliken, F. J., 1987). In essence, supply chain uncertainty exists when a probabilistic estimate or list of all possible alternative outcomes related to a decision or an event cannot be determined (Manuj, I. et al., 2008). Once a supply chain risk has manifested upon the occurrence of a disruptive or triggering event, this supply chain risk will transform into a supply chain vulnerability (Jüttner, U. et al., 2011). Jüttner, U. et al. (2003:9) defines supply chain vulnerabilities as "the propensity of risk sources and risk drivers to outweigh risk-mitigating strategies, thus causing adverse supply chain consequences".

2.2.4 Mitigating Supply Chain Risks

SCRM is a contested and complex phenomenon. Jüttner, U. et al. (2003) define SCRM as "the identification and management of risks for the supply chain, through a coordinated approach amongst supply chain members, to reduce supply chain vulnerability as a whole". This definition by Jüttner, U. (2005); Jüttner, U. et al. (2003) appreciates the central importance of the risk concept in managing supply chain risks by extending SCRM beyond the focal organisation to its supply chain members. Baryannis, G. et al. (2019) state that "SCRM encompasses the collaborative and coordinated efforts of all parties involved in a supply chain to identify, assess, mitigate and monitor risks with the aim to reduce vulnerability and increase robustness and resilience of the supply chain, ensuring profitability and continuity". SCRM mitigates supply chain risks and optimises supply chain objectives (Baryannis, G. et al., 2019). Manuj, I. et al. (2008) outline a process to identify, assess and mitigate global supply chain risks, which is showcased in **Error! Reference source not found.**Figure **2** below, which is adopted by this research study as being the model suitable framework to study SCRM in a globalised society like ours. The process begins with identifying risks arising from the domestic and global environment that could disrupt normal operations of the supply chain. The firm will consider risks arising from its relationships with suppliers. They may also consider risks which arise from the firm's operations and which expose the supply chain to further vulnerabilities. Demand risks are another consideration as these have a ripple effect on supplies. The organisation will then conduct a risk assessment and evaluate its risk exposure with the primary intent of developing risk mitigation strategies. The organisation will then implement these risk mitigation strategies supported by a suitable information system (Manuj, I. et al., 2008). The organisation's supply chain strategy informs the supply chain risk mitigation strategy. The organisation can either respond by avoiding, controlling, cooperating or introducing flexibility, amongst other things. Avoidance may involve dropping a specific product, control may involve vertical integration, cooperation could entail the development of joint partnerships for information sharing, and flexibility may result in multiple or local sourcing strategies Jüttner, U. et al. (2003).

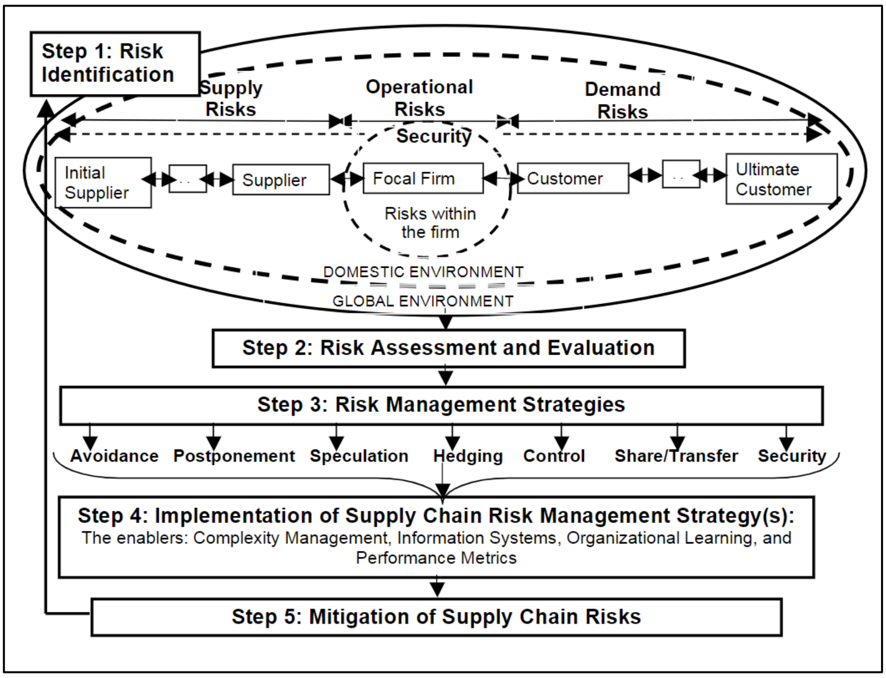


Figure 2: Global Supply Chain Risk Management (Manuj & Mentzer, 2008)

2.3 Big Data and Big Data Analytics

2.3.1 Defining Big Data

Big Data, as a concept, founds its origins within the Physical Sciences, where Astronomers and Physicists plied their craft to develop analytical techniques to process large amounts of data generated from devices such as the

Square Kilometre Array (Japec, L. et al., 2015). There are contested meanings and definitions of Big Data (Al-Mekhlal, M. et al., 2019; Signorelli, S. et al., 2018). Debates around the definition of Big Data have centred around the characteristic features of Big Data (Myburgh, S., 2015) which are volume, velocity and variety, as identified by Laney, D. (2001). The literature is replete with arguments and discussions from various authors on what characteristics should be used to define Big Data. Authors such as Davis, C. K. (2014); Mcafee, A. et al. (2012); Sun, E. W. et al. (2015) emphasise volume, velocity, and variety - commonly referred to as the three V's - as being characteristics of Big Data. Jain, A. (2016) expanded the three V's by including veracity and value. Japec, L. et al. (2015) have added complexity as a further characteristic of Big Data. Kumar, Y. et al. (2020) alluded to an additional 5 V's, which include Variability, Validity, Vulnerability, Volatility and Visualisation. Definitions of Big Data are contested, and consensus has not been reached except to the extent of recognising that Big Data arises from non-traditional data sources (Signorelli, S. et al., 2018).

To perceive Big Data purely along its dimensional aspects would be a travesty for this research project, as there is evidence that Big Data is being conceptualised based on its data sources. Technological advancements have led to documents that form a crucial component of supply chain information flows being replaced by structured and unstructured data from more than 52 data sources (Awwad, M. et al., 2018). These data sources generate more than 2.5 quintillion bytes of data generated daily, with 95% of this data being unstructured (Dobre, C. et al., 2014; Rawat, R. et al., 2021). Practitioners have realised the economic and scientific value of this Big Data (Fan, J. et al., 2014) from data sources such as phone and server logs (Rawat, R. et al., 2021), healthcare data sources (Kumar, Y. et al., 2020), social media networks (Dobre, C. et al., 2014), sensor networks (Sivarajah, U. et al., 2017), and radio frequency identifier (RFID) scanners (Awwad, M. et al., 2018).

The importance of collecting and managing such data gained traction in light of Akter, S. et al. (2016), who conceptualise Big Data as valuable, high-quality datasets generated and collected at unprecedented velocity from heterogeneous data sources in large quantities. Traditional data processing and storage technologies cannot handle Big Data (Pandey, A. et al., 2015); however, advancements in technologies such as distributed computing, parallel processing and distributed file systems over the past decade have catapulted Big Data into the spotlight and enabled the emergence of Big Data Analytics (Prabhu, C. S. R. et al., 2019a).

2.3.2 Defining Big Data Analytics

The need to analyse voluminous data as it is generated via streams in an unstructured form has necessitated the development of Big Data Analytics (Rawat, R. et al., 2021). Big Data Analytics transforms raw data into information suitable for decision-making purposes (Prabhu, C. S. R. et al., 2019b) by implementing advanced analytical methods to generate insights from structured and unstructured datasets (Nguyen, T. et al., 2018). Big Data Analytics is concerned with the real-time processing and distributed aggregations of large volumes of various types of data (Nuaimi, E. et al., 2015; Xu, Z. et al., 2016).

According to Ramasamy, R. (2016:212), Big Data Analytics is the provision of “seamless and real-time business intelligence, culled from the integration of backend operation systems such as Enterprise Resource Planning, Customer Relationship Management and Supply Chain Management with internal employee administrative records and external records outside the organisation”. Dinov, I. D. et al. (2016:2-3) present Big Data Analytics as “algorithms, systems and tools that use Big Data to extract information, generate maps, prognosticate trends, and identify patterns in a variety of past, present or future settings”. Big Data Analytics are the techniques used to analyse Big Data, including machine learning, data mining, artificial intelligence, image analytics, video analytics and audio analytics (Fuller, D. et al., 2017). Big Data Analytics is a method to gain an in-depth understanding of the data to develop rich foresight into the future or enhance hindsight into patterns in historical data (Goyal, S. et al., 2018).

Big Data Analytics involve methods and techniques used to analyse Big Data. Big Data methods encompass descriptive, exploratory, predictive and prescriptive methods, whilst machine learning, stochastic models, and mathematical visualisations are understood to be Big Data Analytics techniques (Husamaldin, L. et al., 2019). Rehman, M. H. U. et al. (2016) outlined various Big Data Analytics techniques, classified as Descriptive, Predictive and Prescriptive Analytics. Descriptive Analytics encompass statistical methods such as descriptive and inferential statistics (Rehman, M. H. U. et al., 2016). Predictive Analytics concerns itself with Data Mining methods such as classification, association rule mining and regression analysis (Rehman, M. H. U. et al., 2016). Prescriptive Analytics involves using supervised, unsupervised and deep learning (Rehman, M. H. U. et al., 2016). These techniques and methods have different roles and outcomes (Awwad, M. et al., 2018) and may also involve the use of innovations in machine learning (Prabhu, C. S. R. et al., 2019b); deep learning (Al-Mekhlal, M. et al., 2019); natural language processing and artificial intelligence (Rawat, R. et al., 2021). Table 2 below summarises the methods used to analyse Big Data (Rehman et al., 2016).

Table 2: Data Analysis Methods for Big Data (Rehman et al., 2016)

Type	Methods	Description
Machine Learning	Supervised Learning	Supervised learning methods predict future events from learning models that are trained using labelled data points. These models are tested with leave-one-out, cross-validation, and 5-fold validation methods. Supervised learning models are widely used for data classification and clustering. However, supervised learning algorithms may not be able to handle information shifts in big data.
	Unsupervised Learning	Unsupervised learning models are trained using unlabelled data points to predict future events.

		Unsupervised learning models are mainly used for data clustering.
	Semi-Supervised Learning	The semi-supervised learning models are initially developed from labelled data points and continuously updated on the feedback from positively predicted events. The adaptive behaviour of semi-supervised learning models enables these models to handle information shifts.
	Deep Learning	The deep learning models are a hierarchical representation of supervised and unsupervised learning models. Deep learning models are best suitED for large-scale high-dimensional data and are a good choice when analysing big data.
Data Mining	Classification	Classifiers are built with or without learning models and are used to predict the object class of nominal data points.
	Association Rule Mining	Association rule mining methods work in two steps. First, the frequent item sets are outlined by setting a minimum support threshold value and then the association between item sets is established by giving a minimum confidence threshold.
	Regression Analysis	Regression analysis methods are based on statistical theories and are used to establish a relationship between given data points.
Statistical Methods	Descriptive Statistics	Descriptive statistical methods are used to produce summary statistics using basic statistical operations over whole input data.
	Inferential Statistics	Inferential statistical methods are used to make inferences on the behaviour of a population using a representative sample.

Big Data Analytics can also be conceptualised as a process. Gandomi, A. et al. (2015:140) define “Big data analytics are efficient processes to turn high volumes of fast-moving and diverse data into meaningful insights”. Akter, Shahriar et al. (2016:178) take this further by viewing Big Data Analytics as a “holistic process that involves the collection, analysis, use and interpretation of data for various functional divisions with a view to gaining actionable insights, creating business value, and establishing competitive advantage”.

In summary, Big Data are datasets generated by heterogeneous data sources. Big Data Analytics techniques encompass a variety of descriptive, exploratory, predictive, and prescriptive methods that can be classified as machine learning, data mining, artificial intelligence, and audio-visual analytics. Regardless of the chosen technique, the objective is to develop insights and foresight by examining Big Data in real-time and in hindsight.

2.4 Big Data Analytics and Supply Chain Risk Management

Supply Chain Management occurs within an environment where business processes and decision-making are characterised by risk and uncertainty (Heckmann, I. et al., 2015). Manuj, I. et al. (2008) suggest that historical data can be used to model the probability within the context of SCRM. Quantifying and modelling supply chain risk remains a considerable challenge facing the SCM community (Heckmann, I. et al., 2015). Big Data Analytics presents supply chain managers with the opportunity to improve supply chain risk management processes (Baryannis, G. et al., 2019; Schoenherr, T. et al., 2015; Truong, H. Q. et al., 2018).

For organisations in manufacturing, Big Data Analytics can enable the continuous probing of supply chain risk (Engelseth, P. et al., 2018), reduce demand uncertainty and transport-related risks (Baryannis, G. et al., 2019), risk assessments and resilience planning (Awwad, M. et al., 2018). The adoption of Big Data Analytics to support Supply Chain Risk Management by manufacturing companies is still in its infancy (American Production and Inventory Control Society, 2015; Baryannis, G. et al., 2019), given the disruptive nature of Big Data Analytics (Madhlangobe, W., 2018). However, supply chain managers have also recognised the invaluable contributions of Big Data to improve their decision-making, managing supply chain risks and solving supply chain challenges (Christopher, M. et al., 2011).

Emerging technologies, such as Big Data Analytics, can improve the management of risk within the supply chain. Big Data Analytics can enhance the collection and analysis of Big Data for purposes of managing risk and uncertainty in the supply chain (Fan, Y. et al., 2015; Sheng, J. et al., 2021), given that disruptive events render traditional forecasting systems ineffective as they do not provide supply chain visibility capabilities beyond an organisation's direct suppliers (Aggarwal, R. et al., 2011; Schuster, R. et al., 2021; Sharma, A. et al., 2020; Zimmerman, N. et al., 2021). Big Data Analytics can enable the continuous probing of supply chain risk, reduce demand uncertainty and transport-related risks, risk assessments and resilience planning for manufacturing organisations (Awwad, M. et al., 2018; Baryannis, G. et al., 2019; Engelseth, P. et al., 2018). A study by Singh, N. et al. (2019) reveals that adopting Big Data Analytics can improve an organisation's risk mitigation measures by effectively utilising organisational knowledge of previous responses to disruptive events. Big Data Analytics is an "information opportunity" for Supply Chain Management in general and Supply Chain Risk Management in particular (Baryannis, G. et al., 2019; Schoenherr, T. et al., 2015; Truong, H. Q. et al., 2018).

2.5 Chapter Summary

This chapter reviewed the concepts of Big Data, Big Data Analytics, and Supply Chain Risk Management, which have gripped the attention of researchers in recent years. Although no consensus has been reached on their definitions, the importance of these concepts cannot be underscored. The researcher provided a background into the technology adoption models used to study Big Data Analytics. The researcher will present their proposed conceptual framework in Chapter 3 that will guide the interpretation of findings in Chapter 5. The literature reviewed in this chapter is further supplemented by a systematic literature review conducted by the researcher as described in section 4.3.2 of Chapter 4, whose findings are presented in section 5.2 of Chapter 5 and discussed in section **Error! Reference source not found.** of Chapter 6.

Chapter 3 Theoretical Underpinning

3.1 Introduction

This section of the dissertation will discuss the proposed conceptual model for this research project. The literature review analysed the major technology adoption theories and found that theories such as the Technology Adoption Model, Theory of Planned Behaviour and Unified Theory of Acceptance and Use of Technology all study the adoption of technology at the individual level (Oliveira, T. et al., 2011b). The UTAUT model, through its synthesis of the eight adoption models, provides a unified view of user acceptance of technology. The UTAUT model hypothesises that the adoption of technology is influenced by the user's behavioural intention to use the technology. The UTAUT model seeks to predict the behavioural intention and actual use of technology by considering various factors that influence the behaviour intention. This study section will explain how the chosen theoretical framework will be implemented.

3.2 Technology Adoption Models and Theories

3.2.1 History of Theories and Models of Technology Adoption or Acceptance

Information Systems scholars have, since the 1970s, developed theories and models for understanding the reasons for the acceptance or rejection of technology by users as this determines the exploitation of I.T. (Momani, A. M. et al., 2017). According to Momani, A. M. et al. (2017), these “theories and models aim to convey the concept of how users may understand and accept the new technology and how they may use it”. However, there are several widely accepted and used technology acceptance models (Momani, A. M. et al., 2017). The technology acceptance models use various constructs to measure the “degree of acceptance and satisfaction to the individuals against any technology or information system” (Momani, A. M. et al., 2017). Different authors have developed technology acceptance theories as either new theories or extensions of existing ones (Momani, A. M. et al., 2017). The Innovations Diffusion Theory (IDT) and Technology-Organisation-Environment (TOE) are at the firm level, and the Technology Adoption Model (TAM), Theory of Planned Behavior (TPB) and Unified Theory of the Acceptance and Use of Technology (UTAUT) are at the individual level (Oliveira, T. et al., 2011a).

3.2.2 Innovations Diffusion Theory (IDT)

The Innovations Diffusion Theory was developed in 1963 by Rogers to study innovation (Momani, A. M. et al., 2017), including the adoption, evaluation and implementation of technology (Fichman, R. G., 1992). Rogers (Rogers, E. M., 2003:12) defines innovation as “innovation is an idea, practice, or object that is perceived as new by an individual or other unit of adoption”. Moreover, diffusion is defined as the “process in which an innovation is communicated through certain channels over time among the members of a social system” (Rogers, E. M., 2003:5). Communication is defined as the “process in which participants create and share information with one another in order to reach a mutual understanding” (Rogers, E. M., 2003:5). Diffusion is the communication of innovations via communication channels between individuals. Rogers recognises the social aspect of diffusion as one that is enforced by “interpersonal communication relationships” (Rogers, E. M., 2003:19). Rogers, E. M.

(2003:172), argues that the innovation-decision process as "an information-seeking and information-processing activity, where an individual is motivated to reduce uncertainty about the advantages and disadvantages of an innovation". According to Rogers, E. M. (2003), the innovation-decision process involves five steps: knowledge, persuasion, decision, implementation, and confirmation. A recent study aimed to explore the determinants or consequences of adopting Big Data Analytics by small and medium enterprises using the IDT (Maroufkhani, P. et al., 2020).

3.2.3 Technology-Organisation-Environment Context Framework (TOE)

Tornatzky, L. G. et al. (1990) developed the Technology-Organisation-Environment (TOE) framework. According to the TOE framework, the technology, organisation and environment context influence the adoption and implementation of technology in a firm (Tornatzky, L. G. et al., 1990). The technology context refers to the internal and external technologies that may be relevant to the firm. The organisational context describes the firm's scope, size and managerial structure. Environmental context is the external environment in which the firm operates, and this construct includes industry characteristics and market structure, technology support infrastructure, and government regulation (Tornatzky, L. G. et al., 1990). The organisational constructs are formal and informal linking structures, communication processes, size and slack. The technology constructs are availability and characteristics (Oliveira, T. et al., 2011a).

Several studies used TOE to study BDA adoption; one such study is that of Lai, Y. et al. (2018), whose objective was to explore the factors influencing the firm's intention to adopt Big Data Analytics in their daily operations. Another study by Walker, R. S. et al. (2019), in a South African context, aimed to explore the factors influencing the BDA adoption process in a telecommunication organisation. A subsequent study sought to explore the factors influencing Small and Medium Enterprises (SMEs) to adopt Big Data Analytics and determine whether Big Data Analytics enhances their performance (Maroufkhani, Parisa et al., 2020).

Youssef, M. a. E.-A. et al. (2022) were interested in identifying factors influencing the adoption of Big Data Analytics within the retail industry of three countries. Another study's objective was to understand the organisational variables that influence the intention of supply chain professionals in Saudi to adopt Big Data Analytics in SCRM (Mezghani, K. et al., 2021).

3.2.4 Technology Acceptance Model

The Technology Acceptance Model (TAM) is an extension of the Theory of Reasoned Action (TRA) by Davis, F. D. (1986). It is one of the earliest theories that modelled technology acceptance by users (Momani, A. M. et al., 2017). TRA has a social psychology basis (Davis, F. D. et al., 1989:983), given that technology is inherently social (Martin, B., 2008). Even though TAM is an evolution of TRA, it excludes the subjective norm construct of TRA (Bradley, J., 2012). TAM is arguably the most applied theory for understanding technology adoption by users and was further developed into TAM2 and TAM3 (Bradley, J., 2012). TAM is premised on perceived usefulness and perceived ease of use (Bradley, J., 2012). TAM2 by Venkatesh & Davis (2000) included seven new variables (Bradley, J., 2012) that further explain the perceived usefulness (Venkatesh, V. et al., 2000), whilst TAM3 introduces three theoretical extensions (Venkatesh, V. et al., 2008). TAM could be useful for this study by explaining user behavioural intentions to adopt and use technology. For instance, Shahbaz, M. et al. (2019) explored the adoption of Big Data Analytics in a healthcare organisation, whilst (Alyoussef and Al-Rahmi 2022) determined the factors that influence the adoption of Big Data Analytics by students in Higher Education. (Verma, S. et al., 2018) focused their study on the effects of system characteristics on the attitude of managers towards the usage of Big Data Analytics systems.

3.2.5 Theory of Planned Behaviour

The Theory of Planned Behaviour (TPB) was extended from the TRA by Ajzen (1985) as cited by Ajzen, I. (1991); Momani, A. M. et al. (2017). TPB included perceived behaviour control as a new construct to TRA, and this theory posits that perceived behaviour control, attitude toward behaviour and subjective norm are moderators (Momani, A. M. et al., 2017). TPB has been integrated with other Information Systems, such as TAM and Diffusion of Innovation, to predict technology acceptance, adoption, and use (Al-Lozi, E. et al., 2012).

TPB is concerned with explaining the intentions of individuals in adopting technology, including understanding what may influence their behaviour or affect their attitudes towards the adoption of the technology (Al-Lozi, E. et al., 2012). The TPB is another useful model that provides the researcher with more information that explains the intention of users to perform behaviours (Al-Lozi, E. et al., 2012), such as adopting a technology. A case in point is a study by Zaman, U. et al. (2021) exploring the antecedents of using Big Data Analytics technologies for disaster management.

3.2.6 Unified Theory of Acceptance and Use of Technology

The Unified Theory of Acceptance and Use of Technology (UTAUT) was developed by Venkatesh, et al. (2003) as a unified model of the Theory of Reasoned Action, the Technology Acceptance Model, the Motivational Model, the Theory of Planned Behaviour, the Model of PC Utilisation, the Innovation Diffusion Theory and the Social Cognitive Theory. This model enhances the ability to predict user acceptance by consolidating the different constructs of the eight competing models (Bradley, J., 2012), and according to Marchewka, J. T. et al. (2007:95), UTAUT considers how "individual differences influence technology use". Using previous studies, UTAUT incorporates the constructs of performance expectancy, effort expectancy, social influence and facilitating conditions (Bradley, J., 2012). UTAUT is a valuable model in this study as it combines many constructs of existing theories, thus enabling the researcher to gain a deeper understanding of various issues in technology adoption. UTAUT highlights individual factors that could influence the adoption and use of technology (Marchewka, J. T. et al., 2007).

The UTAUT framework has been implemented by Queiroz, M. M. et al. (2019) to evaluate the variables that influence the intention of Brazilian SCM professionals to adopt big data. Cabrera-Sánchez, J.-P. et al. (2019) sought to implement UTAUT to explore companies' adoption and use of Big Data Analytics and to understand implementation challenges to offer recommendations to practitioners. Another study by Aghimien, D. O. et al.

(2021) identified the factors influencing the intention to adopt Big Data Analytics in Supply Chain Risk Management by analysing the role of competitive pressure as a moderator variable. The objective of a study by Alharbi, S. T. (2014) is to revise and extend the UTAUT model for studying the adoption of cloud computing by considering trust as the central construct.

3.2.7 Technology Adoption Models for Big Data Analytics in Supply Chain Risk Management

Lutfi, A. et al. (2022) examined the drivers of Big Data Analytics and the impact of adopting Big Data Analytics in the Retail industry. Madhlangobe, W. (2018) sought to study the relationship between trust-in-technology and intent to use Big Data Analytics in an organisation and whether both perceived risk and perceived usefulness mediate this. Marchena Sekli, G. F. et al. (2021) were concerned with the factors influencing the adoption of big data and whether it affects performance and knowledge management in the organisation. The objective of Verma, S. (2017) and Verma, S. et al. (2017) was to investigate the factors influencing the adoption of Big Data Analytics in a manufacturing firm within an emerging economy. Wamba, S. F. et al. (2017) examined the impact of Big Data Analytics capability on improving firm performance. Sejahtera, F. et al. (2018) identified significant enablers and inhibitors of the effective use of big data.

3.3 Overview of Proposed Theoretical Framework

Several studies, such as that of Lutfi, A. et al. (2022); Walker, R. S. et al. (2019); Youssef, Eid and Agag (2022); Maroufkhani, et al. (2020); Lai, Sun and Ren (2018); Maroufkhani, Parisa et al. (2020); Alaskar, T. H. et al. (2021) have utilised the TOE model in studying the factors that influence the adoption of big data analytics. This research project seeks to depart from this tradition and align itself with another strand of researchers who see the value of UTAUT in understanding and predicting the acceptance and usage of technology. The researcher adapted the UTAUT model proposed by Venkatesh, et al. (2003), as illustrated in **Error! Reference source not found.** below, which explains 70 per cent of the variance in behavioural intention (Venkatesh, V. et al., 2003). The UTAUT model considers individual factors that influence technology adoption by considering the four variables of performance expectancy, effort expectancy, social influence, facilitating conditions, and the moderators of crucial behaviours, gender, age, experience, and voluntariness (Bradley, J., 2012).

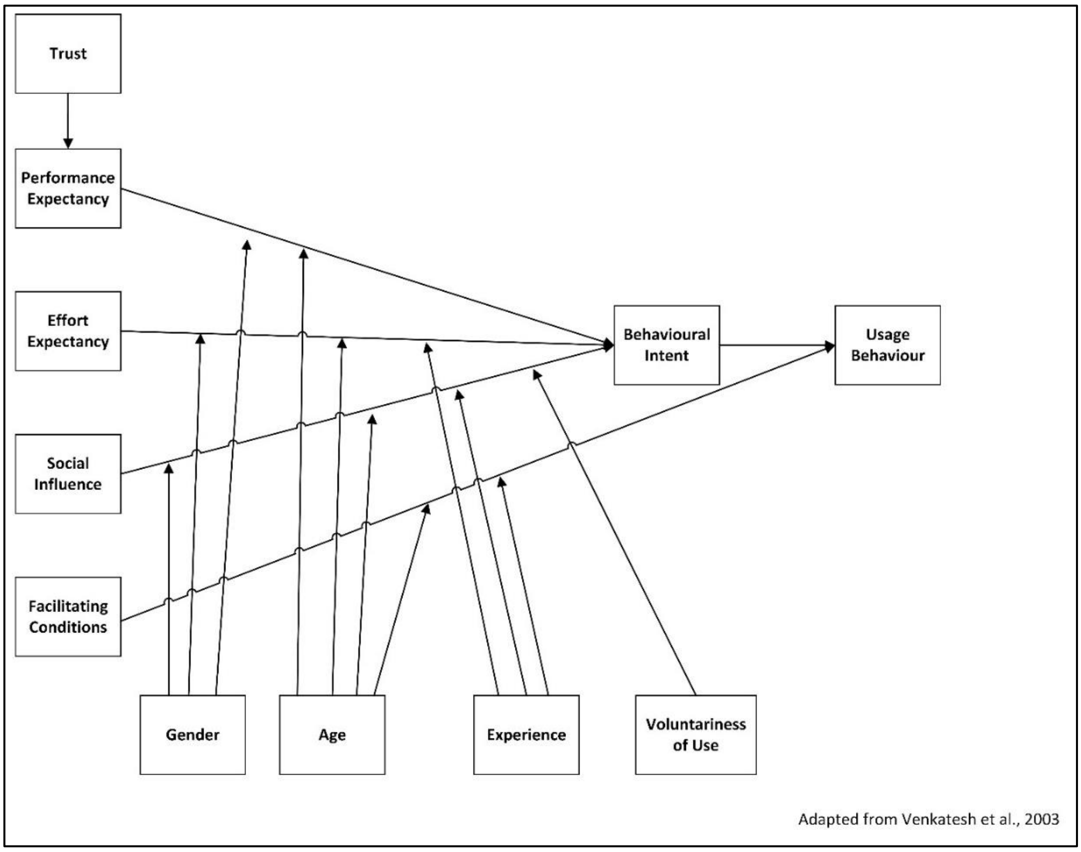


Figure 3: Proposed Conceptual Framework

3.3.1 Performance Expectancy

Performance Expectancy is "the degree to which an individual believes that using the system will help him or her to attain gains in job performance" (Venkatesh, V. et al., 2003:447). Performance Expectancy is the strongest predictor of the behavioural intention to adopt technology (Venkatesh, V. et al., 2003). This construct relates to how users perceive that adopting technology will enhance their job performance. The construct also considers the perceived usefulness of the system in achieving performance gains, whether the features of the technology improve their performance at work, and whether motivation, such as rewards or promotions, influence user acceptance and usage behaviour (Venkatesh, V. et al., 2003).

3.3.2 Effort Expectancy

Effort Expectancy is "the degree of ease associated with the use of the system" (Venkatesh, V. et al., 2003:450) This construct concerns itself with how much effort would be required from the users to adopt the technology. This construct relates to how easy and complex an information system is. According to Batucan, G. B. et al. (2022), "the more effort it takes to use technology, the less useful it is perceived to be".

3.3.3 Social Influence

Social Influence is "the degree to which an individual perceives that important others believe he or she should use the new system" (Venkatesh, V. et al., 2003:451). This construct pertains to the social environment under which the user adopts technology. This social environment has been found to influence the behavioural intention to adopt and use technology.

3.3.4 Facilitating Conditions

Facilitating Conditions is “the degree to which an individual believes that an organisational and technical infrastructure exists to support use of the system” (Venkatesh, V. et al., 2003:453). Queiroz, M. M. et al. (2019) identified Facilitating Conditions as a good predictor of the behavioural intention to use Big Data in SCM. The researcher thus ensured that the interview protocol focused on understanding this factor in depth, as recommended by Queiroz, M. M. et al. (2019).

3.3.5 Behavioural Intention

Behavioural Intention is “one’s intention to perform a specific behaviour” (Fishbein, M. et al., 1975). According to Fishbein & Ajzen (Fishbein, M. et al., 1975), behavioural intention is a “special case of beliefs” (Fishbein, M. et al., 1975) Within user technology acceptance research, Behavioural intention can be determined by the user’s subjective probability that they will accept the technology (Fishbein, M. et al., 1975).

3.3.6 Trust

Trust has emerged as a vital issue when studying the adoption of Big Data and Big Data Analytics (Madhlangobe, W., 2018; Shahbaz, M. et al., 2019). The researcher sought to extend Venkatesh, V. et al. (2003) UTAUT model by including Trust as a factor. The researcher found solace in a prior study by Alharbi, S. T. (2014) and Cabrera-Sánchez, J.-P. et al. (2020), who revised the UTAUT model for a cloud computing context. The researcher is cognisant that BDA is optimally implemented via cloud computing (Potter, G. J., 2015), thus presupposing that those adopting BDA are aware of the cloud computing element. Sahid, N. Z. et al. (2021), who, within a public sector context, sought to understand whether trust influences the behavioural intention to adopt Big Data, concluded that it is not the case. While the researcher notes this conclusion, considering how possible challenges such as data quality (Lai, Y. et al., 2018; Walker, R. S. et al., 2019) impact behavioural intention would be valuable. Manrai, R. et al. (2020) found that users are more inclined to adopt an innovation if they can trust that the innovation is secure and has enhanced privacy. Trust is also a good predictor of performance expectancy (Queiroz, M. M. et al., 2019). The researcher intends to determine whether the participants trust Big Data Analytics and whether this influences Performance Expectancy and the behavioural intention to adopt BDA in SCRM.

3.4 Chapter Summary

The first two chapters provided a broad overview of the research problem and the literature that underpins the research problem. This chapter began with a brief outline of the history of technology adoption models, within the Information Systems domain. It then proceeded with discussing six of the most used technology adoption models and how previous studies have implemented the models. The chapter then proceeded with outlining the how technology adoption have been previously used to study Big Data Analytics, laying the foundation for the current study. The chapter then gave an overview of the proposed theoretical framework to be used in this study, and the concepts that accompany this theoretical framework. The researcher then concluded with how these concepts will be operationalised in the study including a brief description of the role of the concept in the current study. The next chapter will outline the research design and methodology, and the last two chapters will present the result and discuss these results and the conclusions that can be inferred from the studys findings.

Chapter 4 RESEARCH DESIGN AND METHODOLOGY

4.1 Introduction

The preceding chapter outlined the theoretical lens used in Chapter 5 to discuss and interpret the results. The researcher provides a rich account of the results in Chapter 4. This chapter of the dissertation seeks to substantiate the data collection and analysis methods utilised in this research project. More specifically, the researcher will outline the data collection method and the advantages and disadvantages of the method employed. Thereafter justifications for the chosen methodology, including a detailed discussion about the study design will be presented. The chapter will also detail the ethical guidelines of this study and demonstrate how the researcher prepared for data collection and execution of the data collection process. Furthermore, a description of the thematic data analysis is provided. Finally, the researcher briefly reflects on the transcription process contributing to reflexivity in qualitative research.

4.2 Research Design and Methodology

A valuable point of departure for designing a study would be a well-versed understanding of the importance of following a scientific method or a research methodology when undertaking research. According to Crotty, M. (1998:3), research methodology is " the strategy, plan of action, process or design lying the choice and use of particular methods and linking the choice and use of methods to desired outcomes". In simple terms, the research methodology outlines the data collection and analysis strategy as informed by the nature of the research problem, research objectives, the research paradigm and resource availability (Abeysekera, R., 2019; Al Kilani, M. et al., 2016; Creswell, J. et al., 2019).

According to Creswell, J. (2009), the research design is part of the planning process for a research project as it involves proposing the research to be conducted. The research design should address the philosophical worldviews that underlie the study (epistemology and ontology); the strategy of inquiry (research methodology) that is informed by these philosophical worldviews; and the research methods that will operationalise the research design (Creswell, J., 2009; Salmons, J., 2016). The strategy of inquiry becomes the framework through which the research question will be answered (Creswell, J. W., 2003) and thus, sound decisions made by the researcher during the research design results in a credible research project where data is collected systematically to address research questions (Yin, R. K., 2016).

4.2.1 Research Process

The planning of the research commenced by delineating the field of study to identify the objectives of the study. Thereafter, the research methodology was outlined to attain each of these objectives. Considerations such as the research paradigm, ontology and epistemology were explored before adopting a research strategy. The researcher then identified the research site to be utilised. A review of the literature resulted in the development of a research instrument. Access to the research site was then gained by concluding a Non-Disclosure Agreement with the Legal Department of the research site.

Table 3: Research Process

Research Phase	Research Step
Planning	1) Define Research Objectives 2) Select Research Methodology 3) Operationalise Research Strategy
	4) Develop Research Instrument 5) Access Research Site 6) Conclude Non-Disclosure Agreements
	7) Delineate the Unit of Analysis 8) Execute Snowball Sampling
Data Collection	9) Setup ICT Platforms 10) Request Signed Digital Consent Forms
	11) Online Interviews Process 12) Obtain Verbal Consent
	13) De-neutralize Transcription 14) Member Checking Transcription
Data Analysis	15) Thematic Analysis of Transcripts
Results Presentation	16) Write-Up 17) Reflections

4.2.2 Overview of Research Methodology

A researcher may choose to utilise quantitative or qualitative research methods as qualitative methods are similar to quantitative methods, except for the data collection and analysis procedures (Creswell, J., 2009). Anderson, C. (2010) argues that if a researcher is looking for an in-depth understanding of a particular phenomenon, then qualitative methods will suffice; however, if the researcher seeks to observe differences or make comparisons, then a quantitative approach would be appropriate. Qualitative methods collect, analyse and interpret non-numerical data such as audio, video, images, documents, press releases, videos and even observation or case study notes taken during the research process (Anderson, C., 2010).

Neuman, W. L. (1997:17), compared the quantitative and qualitative research approaches as illustrated in Table 4 below and identified key differences between these two approaches. Quantitative research seeks to utilise variables to measure specific factors without bias and make general findings based on statistical analysis that can be applied in any context. In contrast, qualitative research involves the researcher co-constructing a contextual reality to reveal contextual issues through thematic data analysis (Neuman, W. L., 1997).

Table 4: Differences between Qualitative and Quantitative Research Approaches (Neuman, 1997)

Quantitative Approach	Qualitative Approach
Measures objective facts	Construct social reality, and cultural meaning
Focus on variables	Focus on interactive processes, events
Reliability is the key factor	Authenticity is the key factor
Value free	Value present and explicit
Separate theory and data	Theory and data fused
Independent of context	Situationally constrained
Many cases, subjects	Few cases, subjects
Statistical Analysis	Thematic Analysis
Research detached	Researcher involved

Irani, Z. et al. (1999) have critiqued qualitative research as being time-consuming and further argued that qualitative research does not infuse theory. Qualitative research is also well-known for its limited external validity. Qualitative research is further impaired by the need to restrict the unauthorised disclosure of confidential information and maintain the participants' anonymity (Anderson, C., 2010). Qualitative data is notoriously difficult to analyse and visualise and is also prone to bias, given the reliance on the researcher as the research instrument (Al Kilani, M. et al., 2016; Anderson, C., 2010). In light of Anderson, C. (2010), who argued that the researcher could also influence the response of respondents during the data collection process and that rigour encumbers qualitative research (Anderson, C., 2010), the researcher has sought to address both these issues in sections 4.11 and 4.9, respectively.

4.2.3 The rationale for Qualitative Research Methodology

A qualitative research methodology was adopted to gather evidence to make findings and reach conclusions on the research question posed for this study. However, the suitability of a qualitative research methodology needs to be justified beyond the requirement of a deeper understanding of the adoption of Big Data Analytics in Supply Chain Risk Management. Research is implicitly shaped by philosophical worldviews based on a particular ontological and epistemological understanding (Hassan, N. R. et al., 2018; Niehaves, B. et al., 2006). According to Hiller, J. (2016:100), a “researcher’s beliefs about what can be known (ontology) and how to approach coming to know it (epistemology)” profoundly influences their theoretical standpoint, research methodology and research methods.

4.2.4 Research Paradigm

The importance of a research philosophy cannot be over emphasised (Bahari, S. F., 2010), given its influence on the research methodology. Philosophy can be defined as the “love of wisdom or knowledge” (Hassan, N. R. et al., 2018:263). The research philosophy underpins the research design (Bahari, S. F., 2010). Research philosophy is concerned with the nature of knowledge and how knowledge is developed (Guba, E. G. et al., 1994). Research philosophy examines the nature of reality (ontology), the theory of knowledge (epistemology) and how knowledge is developed (methodology) (Tuli, F., 2010).

4.2.4.1 Ontology

Ontology concerns itself with "what kind of world we are investigating, with the nature of existence, with the structure of reality as such"(Ahmed, A., 2008:2). The assumptions underlying the ontological belief system influence the "types of questions a researcher might pursue about how the world works or how people act or interact" (Hiller, J., 2016:99). There are two juxtaposing positions on ontologies: critical realist and relativist ontologies (Levers, M.-J. D., 2013). Relativists assume that each participant has their view of reality constructed through "thoughts and ideas" (Hiller, J., 2016:99). For a Relativist, the reality is subjective when there are multiple observers of that reality, thus giving rise to multiple realities (Abeysekera, R., 2019; Creswell, J. W. et al., 2017). In contrast, critical realists view reality as objective and existing independently of the observer (Levers, M.-J. D., 2013).

4.2.4.2 Epistemology

Epistemology positions the researcher in the context of the studied phenomena (Kivunja, C. et al., 2017). Epistemology is described as the "theory of knowledge embedded in the theoretical perspective and thereby in the methodology"(Crotty, M., 1998:3). The epistemological assumptions inform what can be or not be considered as knowledge (Bahari, S. F., 2010). Hiller, J. (2016:99) describes epistemology as "how valid knowledge is produced".

4.2.4.3 Interpretivist Philosophy

The research question that guides this study is epistemological as it seeks to understand phenomena, thus leaning towards an interpretivist paradigm. The Interpretivist paradigm argues that there is "no single objective truth to be discovered about the social world" (Takahashi, A. R. W. et al., 2020:104); thus, interpretivists understand the world from the participant's point of view, which is subjective, as opposed to that of an objective observer (Ponelis, S. R., 2015). Interpretivists view the social world as a complex structure and cannot be reduced to definitive laws and generalisations, such as those in Physical Sciences (Al-Ababneh, M. M., 2020).

The Interpretivist research philosophy aims to develop rich insights into contemporary phenomena by describing and understanding the participant's views of their multiple realities (Goldkuhl, G., 2012; Oates, B. J., 2006; Runeson, P. et al., 2008) . The interpretivist philosophy is a fully established paradigm within the Information Systems discipline with an equally long history (Klein, H. K. et al., 1999; Walsham, G., 2006). The researcher decided to lean on the interpretivist research paradigm as a philosophical guide for this study as this project's goal is to understand the acceptance and use of information systems from the participant's perspective (Klein, H. K. et al., 1999; Oates, B. J., 2006). By aligning this research project with the interpretivist paradigm, the assumptions of the chosen paradigm will guide the study at hand and which includes its philosophical worldviews (Kivunja, C. et al., 2017; Ponelis, S. R., 2015).

4.2.4.4 Axiology

Given this study's phenomenological nature, this research project requires brief reflections. Sutton, J. et al. (2015) argue the importance of the researcher reflecting before beginning with their analysis as personal history "forms the filter through which the data will be examined" (Sutton, J. et al., 2015:227). The research study should state, acknowledge (Sutton, J. et al., 2015) and describe these "filters" to provide context to the study at hand (Sutton, J. et al., 2015).

4.2.4.5 Positioning the Researcher as a Research Instrument

Qualitative research is interpretive as it engages the participants during the research process. The researcher is positioned as the primary research instrument, thus necessitating the need for the researcher to reflect on their position with the research (Walsham, G., 1995). Therefore, there is a need to address ethical concerns, especially when gaining access to the research site (Creswell, J., 2009). Online interviews provide privacy (Roberts, J. K. et al., 2021) which may result in an over-disclosure of sensitive information (Novick, G., 2008). The researcher focused on executing ethical internet-based research (Oates, B. J., 2006) that combatted the challenges of over-disclosure in internet-based interviews. The researcher informed the participants that Company X and the researcher have signed a Non-Disclosure Agreement that will enable the participants full participation in the research project.

4.3 Research Methods

4.3.1 Case Study

Qualitative research methods include (a) basic qualitative research; (b) phenomenology; (c) ethnography; (d) grounded theory; (e) narrative inquiry; and (f) qualitative case studies (Merriam, S. B. et al., 2016). A Case Study is equivalent to "natural science experiments" (Tsang, E. W. K., 2014:174). The use of case study methods in Information Systems is mature, valid and widely accepted (Klein, H. K. et al., 1999; Runeson, P. et al., 2008). Case studies offer academics and practitioners a rich description of the case in single settings (Eisenhardt, K. M., 1989; Merriam, S. B. et al., 2016). Case studies are an exploratory research method that can be used for theory generation (Eisenhardt, K. M., 1989). Case studies enable the researcher to gain rich data from participants for theory testing (Carrim, N. M. H., 2012; Irani, Z. et al., 1999; Oates, B. J., 2012). Case studies can be used to explore research issues that have not been previously investigated (Bryman, A., 1989). Case studies further allow the confirmation of previous studies' findings (Bryman, A., 1989).

The main argument for rejecting case study research is that it leads to poor generalisations given the lack of rigour, thus presenting the main argument for rejecting case study approaches (Bryman, A., 1989; Oates, B. J., 2012; Rollanda, K. H. et al., 2000). Bryman (Bryman, A., 1989:142) states that "a major reason for the loss of faith in case studies was a prevailing view that it was not possible to generalize the results of research deriving from just one or two cases". Generalisations, defined as "inferring from the observation of the particular to a general statement or proposition"(Tsang, E. W. K., 2014:178), are dealt with differently under the Interpretivist Paradigm. Authors such as Walsham, G. (1995) argued that case studies could lead to the development of concepts, the generation of knowledge, the drawing of specific implications, and the contribution of rich insight. Van Wynsberghe, R. et al. (2007) state that generalisations, like predictions, are contextual and these are updated as the context changes. What can be understood from the above is that generalisations are possible with case studies, primarily where the context is appropriately understood and the generalisations are justified in the context of the research question.

For this research participants were interviewed using a digital meeting platform called Microsoft Teams. The use of the digital meeting platform was mainly a result of the COVID-19 pandemic requiring social distancing. Using a digital platform to conduct the interview is more cost-effective than a face-to-face interview and efficient in recording and transcribing the interview. However, issues such as lack of trust, the inability to establish an interpersonal relationship with the interviewee, and cultural divides may negatively impact this strategy (Oates, B. J., 2006).

This study utilised a semi-structured interview approach with a structured set of issues and themes to be discussed. Still, it allowed for flexibility as the interviewer may re-arrange questions as the interview progresses. This flexibility in the interview process enables the use of unstructured follow-up questions that may arise depending on the response received from the interviewee (Oates, B. J., 2006). Oates, B. J. (2006:188) states that in a semi-structured interview, "the interviewees are able to speak with more detail on the issues you raise, and introduce issues of their own that they think relevant to your themes". Through an interview, the researcher gains insight from research participants, who are the primary source of data (Manrai, R. et al., 2020). In an interview setting, the researcher becomes the research instrument through which data is collected from the data source (Pezalla, A. et al., 2012). The research instrument is the researcher who conducted one-on-one interviews between selected cases (Oates, B. J., 2006).

The interview followed a semi-structured approach that the interviewer controls in an open manner for purposes of probing specific issues and topics of particular interest to the researcher (Oates, B. J., 2006). The goal of the interviews was to refine the theoretical framework. Interviews are common in Information Systems research and have been utilised as a data generation method in adoption studies (Oates, B. J., 2006). Interviews enable the interviewer to gain in-depth insights into complex issues with the appropriate interviewee who has information on the topics of interest to the interviewer (Oates, B. J., 2006). Interviews enable a much more flexible approach to gather data by allowing the interviewee to speak freely about their thoughts and ideas to a non-critical lister as the conversation flows between the interviewer and interviewee (Oates, B. J., 2006). Oates, B. J. (2006) states that there are shortcomings to interviews which include the amount of time required for the study, reliability and generalisability of the study, and the skills set of the researcher.

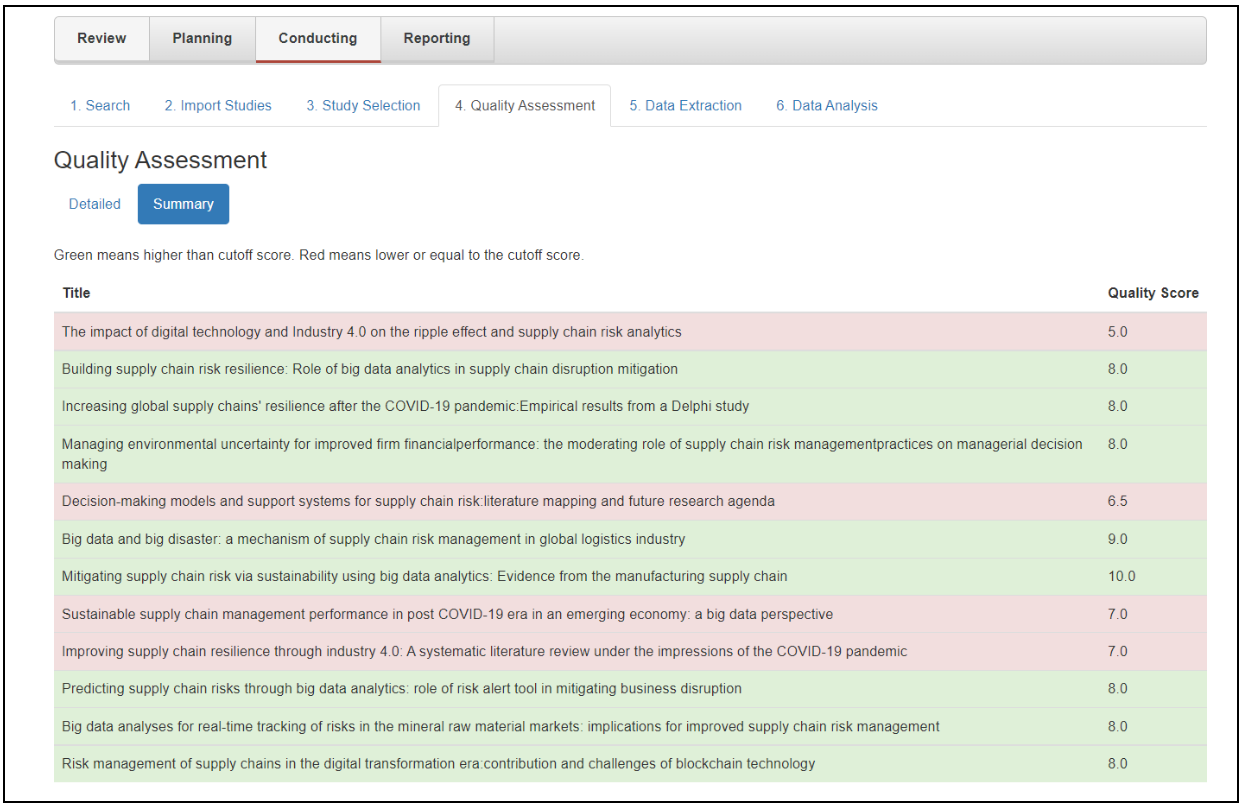
4.3.2 Systematic Literature Review

A systematic literature review method was employed to collect data to answer the research question: "What is the role of Big Data Analytics in Supply Chain Risk Management?". The review explored the adoption of Big Data

Analytics in a Supply Chain Risk Management context. The research project adopted a systematic literature review approach described by Okoli, C. et al. (2010); (Zheng, T. et al., 2021). The researcher queried the TITLE-ABS-KEY fields Web of Science and Scopus databases using the following query:

*((**Big Data Analytics**" OR "**BDA**") AND ("**Supply Chain Risk Management**" OR "**SCRM**"))*

The query sought to retrieve any document referring to Big Data Analytics and Supply Chain Risk Management or their abbreviation of BDA or SCRM, respectively. Standard database filters were used to retrieve the records, and a total of 38 records, 19 from each data source, were found. The 38 papers were then downloaded from the respective records from their databases in Bibtex format. The researcher uploaded the 38 articles to Parsif.al, a platform used to design, conduct and report systematic literature reviews. A screenshot of the Parsif.al platform is depicted in Figure 4 below.


Review Planning Conducting Reporting
1. Search 2. Import Studies 3. Study Selection 4. Quality Assessment 5. Data Extraction 6. Data Analysis
Quality Assessment
Detailed Summary
Green means higher than cutoff score. Red means lower or equal to the cutoff score.

Title	Quality Score
The impact of digital technology and Industry 4.0 on the ripple effect and supply chain risk analytics	5.0
Building supply chain risk resilience: Role of big data analytics in supply chain disruption mitigation	8.0
Increasing global supply chains' resilience after the COVID-19 pandemic:Empirical results from a Delphi study	8.0
Managing environmental uncertainty for improved firm financialperformance: the moderating role of supply chain risk managementpractices on managerial decision making	8.0
Decision-making models and support systems for supply chain risk:literature mapping and future research agenda	6.5
Big data and big disaster: a mechanism of supply chain risk management in global logistics industry	9.0
Mitigating supply chain risk via sustainability using big data analytics: Evidence from the manufacturing supply chain	10.0
Sustainable supply chain management performance in post COVID-19 era in an emerging economy: a big data perspective	7.0
Improving supply chain resilience through industry 4.0: A systematic literature review under the impressions of the COVID-19 pandemic	7.0
Predicting supply chain risks through big data analytics: role of risk alert tool in mitigating business disruption	8.0
Big data analyses for real-time tracking of risks in the mineral raw material markets: implications for improved supply chain risk management	8.0
Risk management of supply chains in the digital transformation era:contribution and challenges of blockchain technology	8.0

Figure 4: Quality Assessment of Articles (Source: Parsif.al, 2022)

The screening phase involved the application of exclusion criteria to reject any conference reviews, conference articles, and book chapters. This amounted to 13 records being rejected. The researcher identified 13 duplicate records. Duplicates were then identified, and if duplicates were found, the Web of Science version of the record was marked as a duplicate, and a Scopus version of the record was retained. The justification is that Scopus is a citation database covering all scientific fields, although Web of Science is the defacto database used by most authors (Cantú-Ortiz, F. J., 2017). Twelve records were accepted to proceed to the first selection process, where the researcher proceeded to quality assure the accepted articles using criteria developed by Dybå, T. et al. (2008), where the researcher extended the answers to 3-scale options of "Yes", "Partially", and "No" to each of these questions. Each paper was scored and assigned a score out of 11, and four articles failed, as depicted in

Figure 4. The documents that made it to the final review were retrieved and catalogued in EndNote. Data were extracted from each article based on data extraction criteria as documented in the SLR Protocol attached as Appendix C. The full Systematic Literature Review process is presented in **Error! Reference source not found.** below.

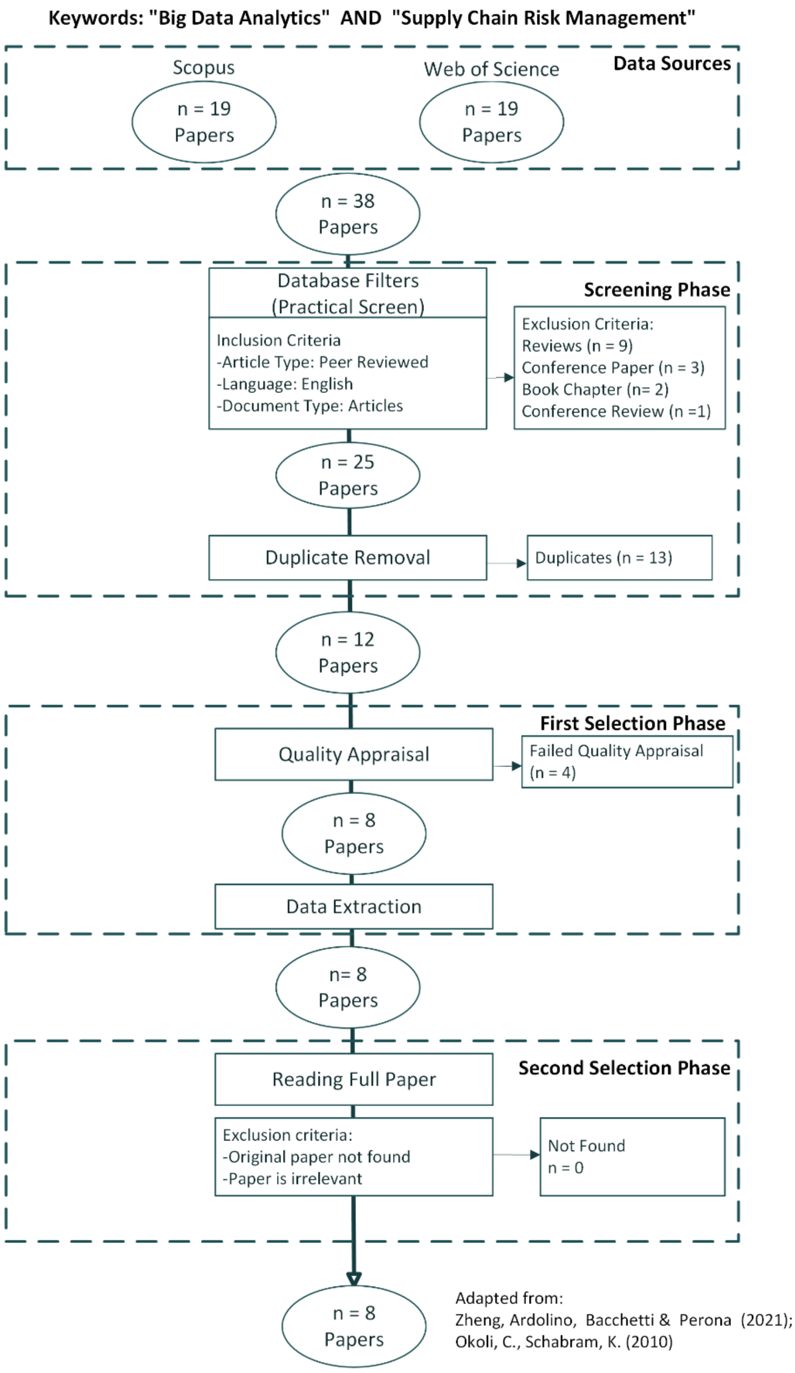


Figure 5: Systematic Literature Review

4.4 Research Setting

The researcher believes a description of the research setting will be valuable (Creswell, J. et al., 2019). The case study is an organisation in the manufacturing industry. The organisation processes large amounts of data daily, with data for inventory stock exceeding more than 20 million records daily.

4.5 Research Protocol

Quality control of the research instrument and the study will be enforced using three criteria: (a) internal validity, (b) external validity, and (c) reliability (Yin, R. K., 2018).

4.5.1 Developing the Systematic Literature Review Protocol

The systematic literature review was developed based on the guidance of Okoli, C. et al. (2010). Eleven Quality Appraisal criteria were adapted from Dybå, T. et al. (2008). The researcher assigned 1.0 point to “yes”, 0.5 points to “partially”, and 0.0 points to “no”. The researcher also placed a benchmark of 7.0 points for further review; if an article received 7.0 or more points, it would be included, and anything below that would be excluded. The researcher then read the titles and abstracts of the records.

4.5.2 Developing the Semi-Structured Interview Guide

For this study, the researcher used theory to develop constructs, thus enabling the researcher to provide insights into the more significant phenomena being studied by deploying a theoretical framework. Walsham, G. (1995:76) states that utilising theory in the early stages of a research project “can provide a valuable initial guide” that incorporates previous studies. There have been critiques against the use of theory during the initial phases of the research project as the research could find itself limited to the theory at hand. However, Walsham, G. (1995:77) argues that a researcher could conduct research without being “trapped in the view that it represents final truth in that area”.

The theory finds use in the data collection and analysis phases and can even be constructed as a final product of the research project (Walsham, G., 1995). The researcher utilised the theory to obtain valid constructs that would form part of the conceptual model that was eventually implemented in the form of an interview guide. The interview guide was initially evaluated by the researcher based on the guidelines outlined by Oates, B. J. (2006:199). The initial evaluation focused on construct validity (Yin, R. K., 2018). The University of the Western Cape’s Research and Ethics Committee further evaluated the interview guide. The researcher further validated the interview guide through the pilot interview the researcher conducted.

4.6 Recruiting the Participants

4.6.1 Unit of analysis

The unit of analysis within the context of a case study is referred to as a “case” (Merriam, S. B. et al., 2016). Given that a case study is “an in-depth description and analysis of a bounded system” (Merriam, S. B. et al., 2016). Supply chain professionals within an organisation in the manufacturing industry in Cape Town are the unit of analysis. Supply chain professionals recognise the importance of supply chain risk management skills and experience, noting their concerns about the paucity of data analytics tools and platforms (American Production and Inventory Control Society, 2015). The interest, therefore, is in understanding what factors influence the adoption of Big Data Analytics by Supply Chain professionals.

4.6.2 Sampling of Interviewees

According to statistical conventions, human respondents in a case study are considered a sample, and the case is the population, as the results of the research will be limited to the case being studied (Yin, 2018). The study utilised a non-probabilistic sampling method to select respondents for the case; in particular, it employed a purposive sampling strategy. Purposive sampling involves the "deliberate seeking out of participants with particular characteristics" (Morse, J. M., 2004:884). Daniel, J. (2012) outlines purposive sampling procedures as (a) defining the target population, (b) specifying inclusion and exclusion criteria, (c) devising a recruitment plan, (d) determining the sample size, and (d) selecting the targeted number of population elements. The selection criteria for this study is specialized knowledge; that is, the study intends to select participants based on their expertise as Supply Chain Analysts, Supply Chain Officers and Supply Chain Managers (Daniel, J., 2012).

The sampled participants by implementing a snowball or nominated sampling strategy where participants recruited earlier into the study refer to other potential participants (Ellis, P., 2021; Morse, J. M., 2004:885). The study recruited more respondents based on nominations or recommendations from the original participants upon completion of the interviews (Morse, J. M., 2004). The researcher found this to be the most effective sampling strategy for recruitment. The researcher found that this sampling strategy is "useful when groups are hard to identify or may not volunteer or respond to a notice advertising for participants", especially in instances "when locating participants who would otherwise be hard to locate" (Morse, J. M., 2004:885). Participants were recruited via an e-mail invitation. The e-mail contained a technical information sheet, a short description of the study and a copy of the research ethics approval letter. Further, before each interview, the participants were informed about their employer's approval for the study to be conducted and for their participation in the study see Figure 6.

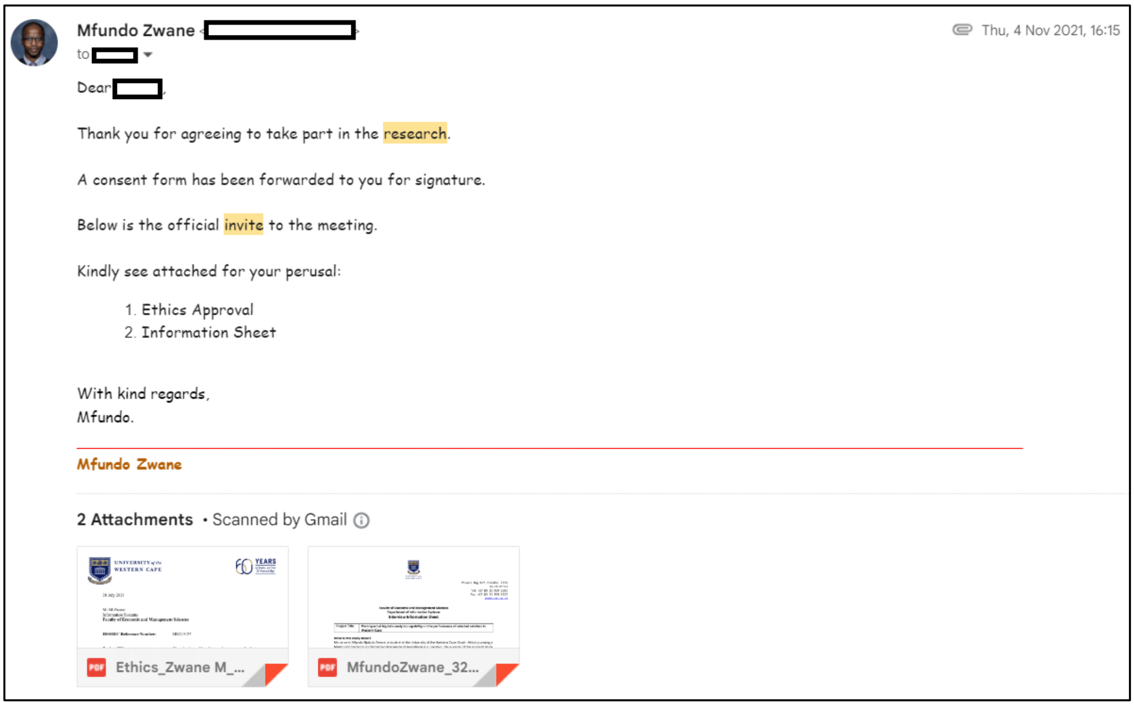


Figure 6: Research Invite

The snowballing strategy facilitated the recruitment of participants until data saturation was reached (Naderifar, M. et al., 2017), that is when "no new analytical information arises anymore, and the study provides maximum information on the phenomenon" (Moser, A. et al., 2018). Although there are no guidelines on sample sizes in qualitative research, the sample size will rarely exceed 200 cases (Emmel, N., 2013). Instead, qualitative research utilises theoretical saturation to determine the sample size. Mason, M. (2010:15) cautions that it is "rather difficult to identify" the saturation point. This study purposively sampled 7 participants, supported by Moser, A. et al. (2018), who suggested that 7 - 12 participants are sufficient for interviews. The researcher also stopped collecting the data as soon as no participants were available, and this was indeed the case after the sixth interview.

4.6.3 Ethical Issues during Data Collection

The research participants were made aware of a Non-Disclosure Agreement that was entered between their employer and the researcher. Participants were furnished with a consent form signed electronically via Adobe e-Sign as depicted in. Those participants who had not submitted the form decided to give their verbal consent and sign it.

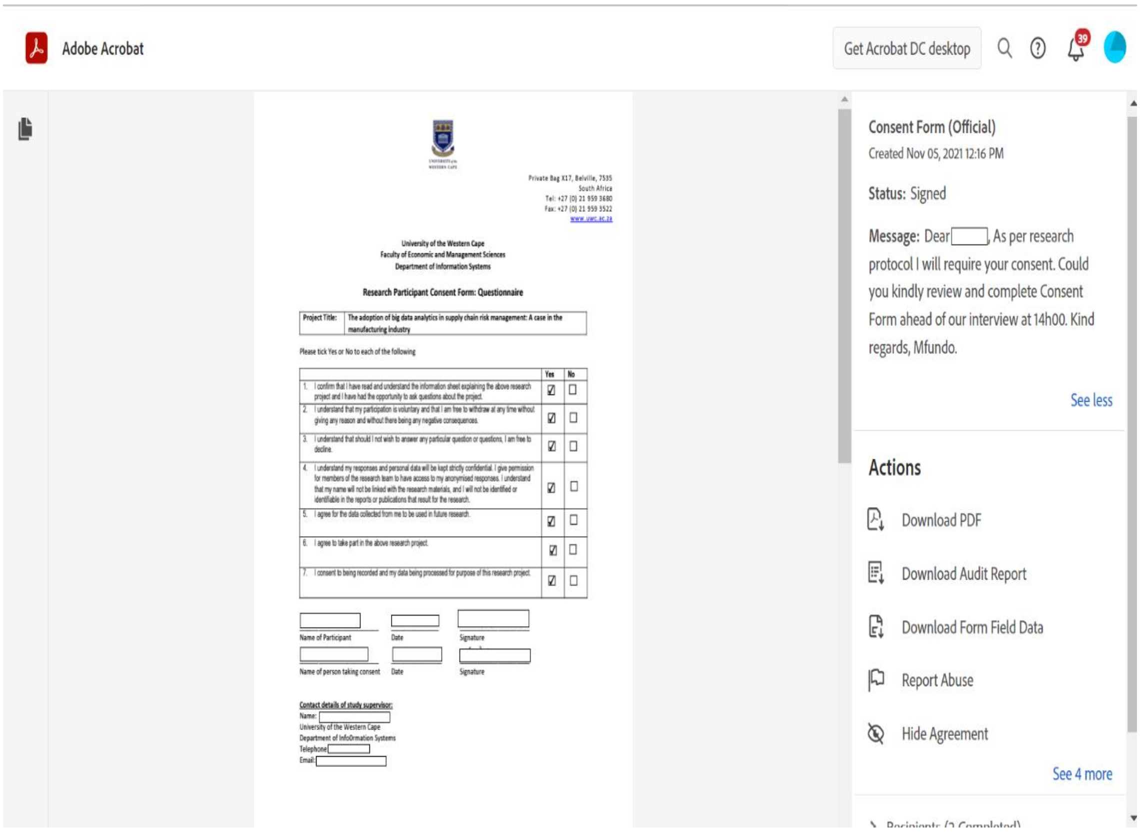


Figure 7: Example of Completed Adobe Consent e-Form

4.7 Collecting the Data

The interviews were held over four weeks, from 03 November 2021 to 01 December 2021 A Microsoft Teams license was procured, and participants were added to a private channel accessible only by the researcher and participant, thus ensuring that the participant's identity was not exposed and the ethical requirements for confidentiality and privacy were supported.

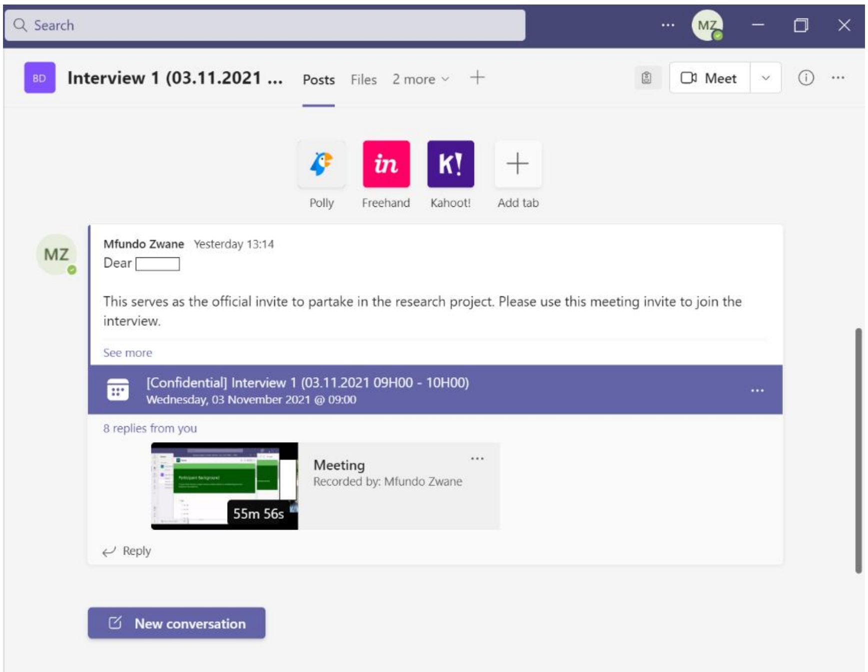


Figure 8: Microsoft Teams Online Interview Channel

4.7.1 Pilot Study

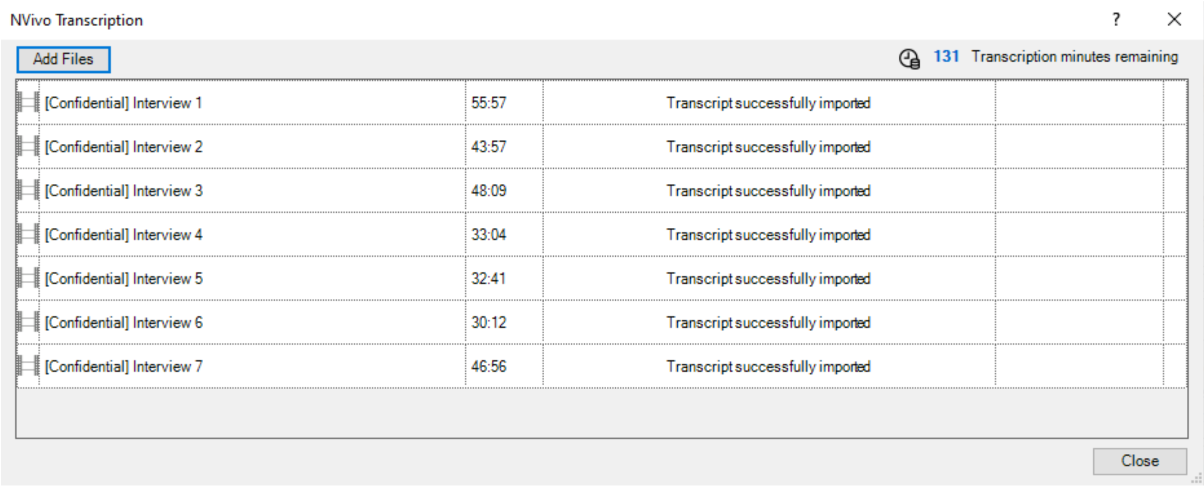
A pilot study was conducted to validate the interview guide and a list of additional questions. The researcher included additional questions and interview questions in a randomised form during the pilot study. The pilot participant was informed of the pilot study, and consent was obtained. The pilot study revealed that the additional questions were unnecessary, and the interview guide was adopted without these additional questions. The questions that have been excluded are listed in *Appendix B: Questions Excluded from Final Interview Protocol*.

4.7.2 Point of Saturation

Saturation is reached when no new information could be obtained from interviews (Saunders, B. et al., 2018). In the current study, saturation was reached in the seventh interview. The researcher did not find this alarming as Interpretivist studies such as the present study may have fewer than ten interviews (Moser, A. et al., 2018).

4.7.3 Transcription

Researchers have neglected the role of transcription in research methodology (Lapadat, J. C. et al., 1999) even though it is a crucial part of data management in qualitative research projects (Matheson, J., 2015). Transcription has been relegated to a mechanical (Tilley, S. A. et al., 2002) back-end (Oliver, D. G. et al., 2005) and thus do not adequately describe the transcription process (Lapadat, J. C. et al., 1999). Transcripts form part of the data collection phase (Oliver, D. G. et al., 2005). The transcription process is tedious (Mcmullin, C., 2021) and laborious (Brinkmann, S. K., Steinar, 2018). The transcriber is faced with many subjective decisions (Lapadat, J. C. et al., 1999; Mcmullin, C., 2021) that could impact the outcome of the research project. For this project, a decision was made to upload the video recordings to a secure cloud platform on NVivo, where they were converted into transcripts by NVivo. These transcripts were initially edited on NVivo online. Subsequently, the transcripts were retrieved from NVivo Transcription and linked to the video file; see Figure 9 below. A denaturalised transcription approach was adopted. Reflections on this decision are outlined in section 4.11 below.

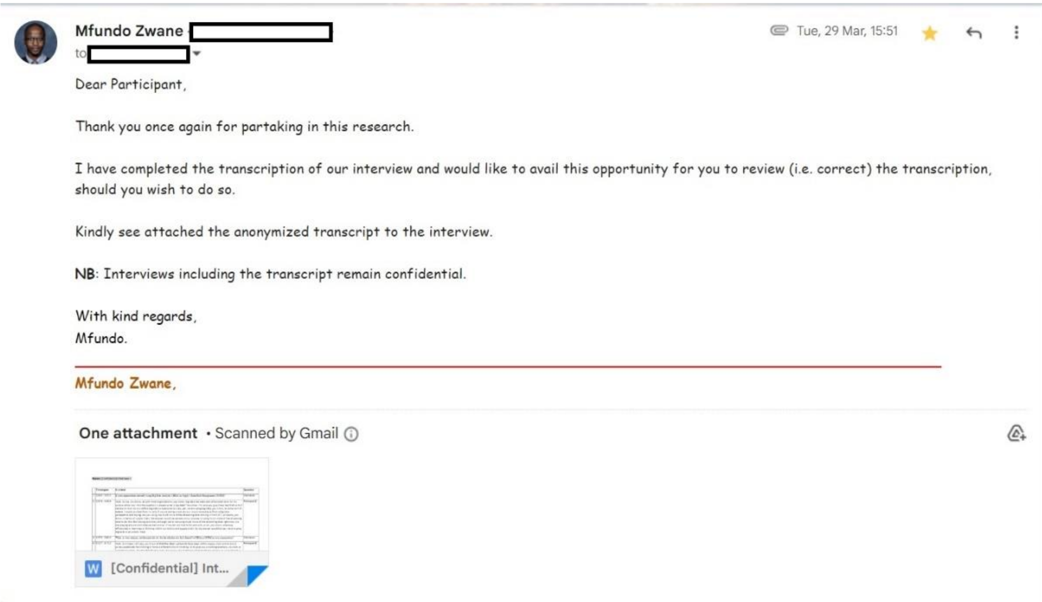


[Confidential] Interview 1	55:57	Transcript successfully imported
[Confidential] Interview 2	43:57	Transcript successfully imported
[Confidential] Interview 3	48:09	Transcript successfully imported
[Confidential] Interview 4	33:04	Transcript successfully imported
[Confidential] Interview 5	32:41	Transcript successfully imported
[Confidential] Interview 6	30:12	Transcript successfully imported
[Confidential] Interview 7	46:56	Transcript successfully imported

Figure 9: Interview Transcripts

4.7.4 Data Validity (Member Checking)

The researcher also presented participants with an opportunity to correct the transcripts as part of the interviewee transcript review (Hagens, V. et al., 2009). Participants were allowed to indicate if the transcript represented their perceptions fairly, as shown in Figure 10 below.


Mfundo Zwane [redacted]
to [redacted]
Tue, 29 Mar, 15:51

Dear Participant,

Thank you once again for partaking in this research.

I have completed the transcription of our interview and would like to avail this opportunity for you to review (i.e. correct) the transcription, should you wish to do so.

Kindly see attached the anonymized transcript to the interview.

NB: Interviews including the transcript remain confidential.

With kind regards,
Mfundo.

Mfundo Zwane,

One attachment • Scanned by Gmail

[Confidential] Int...

Figure 10: Transcript Validation

4.8 Analysing the Data and Reporting

The data analysis process must engender a sense of trustworthiness, dependability, confirmability and credibility (Bloomberg, L. D. et al., 2018). Given the contextual nature of qualitative research, the researcher must describe and justify their analytical approach in the context of the research question, including how the themes and concepts were derived from the data to detail how the findings were arrived at **(Anderson, C., 2010)**. In light of this, the researcher seeks to provide a transparent account of how they approached the qualitative data analysis process rather than viewing data analysis as the "black hole" qualitative researcher where data goes in, and code are generated in an indecipherable manner (St. Pierre, E. A. et al., 2014). In this regard, thematic data analysis was found to be a much more appropriate method of analysing the data as the researcher seeks not to confirm what was already in the literature but rather to guide their thinking using literature (St. Pierre, E. A. et al., 2014). The researcher leaned on the guidance of Braun, V. et al. (2006); Clarke, V. et al. (2018) for the qualitative data analysis, as depicted in Figure 11.

Phase 1 – Familiarisation

The researcher digitised and revisited the field notes taken down during the online interviews to identify the key issues discussed by each participant during the interview. The researcher re-watched each video and compared the field notes to what was recorded to gain a deeper contextual understanding. The researcher noted further thoughts in their research diary about emerging issues or emerging topics that were not recorded in the field notes. Armed with this, the researcher proceeded to transcribe each recording.

Phase 2 – Generating Initial Codes and Creating Categories

The participants validated the transcripts through a member check to ensure that their views and perceptions were correctly recorded. The researcher approached the coding process according to the (Saldana, 2009) guidance by coding one question at a time for each participant. The transcripts were coded by appending nodes in NVivo, representing a code on the validated transcript. These nodes are descriptive and seek to capture the sentiments and perceptions of the participants. The researcher then proceeded with generating initial codes from the transcribed interviews coding using the UTAUT framework as a basis, as suggested by Adu, P. (2019). The researcher sought to employ the UTAUT framework as an apriori framework to generate the initial codes that revealed the initial insights in the data (Adu, P., 2019; Grimm, P. et al., 2021). The researcher then proceeded with placing codes into categories based on the similarity of the code, based on an observation by (Saldana, 2009:8) that "codes are essence-capturing and essential elements of the research story that, when clustered together according to similarity and regularity – a pattern – they actively facilitate the development of categories and thus the analysis of their connections".

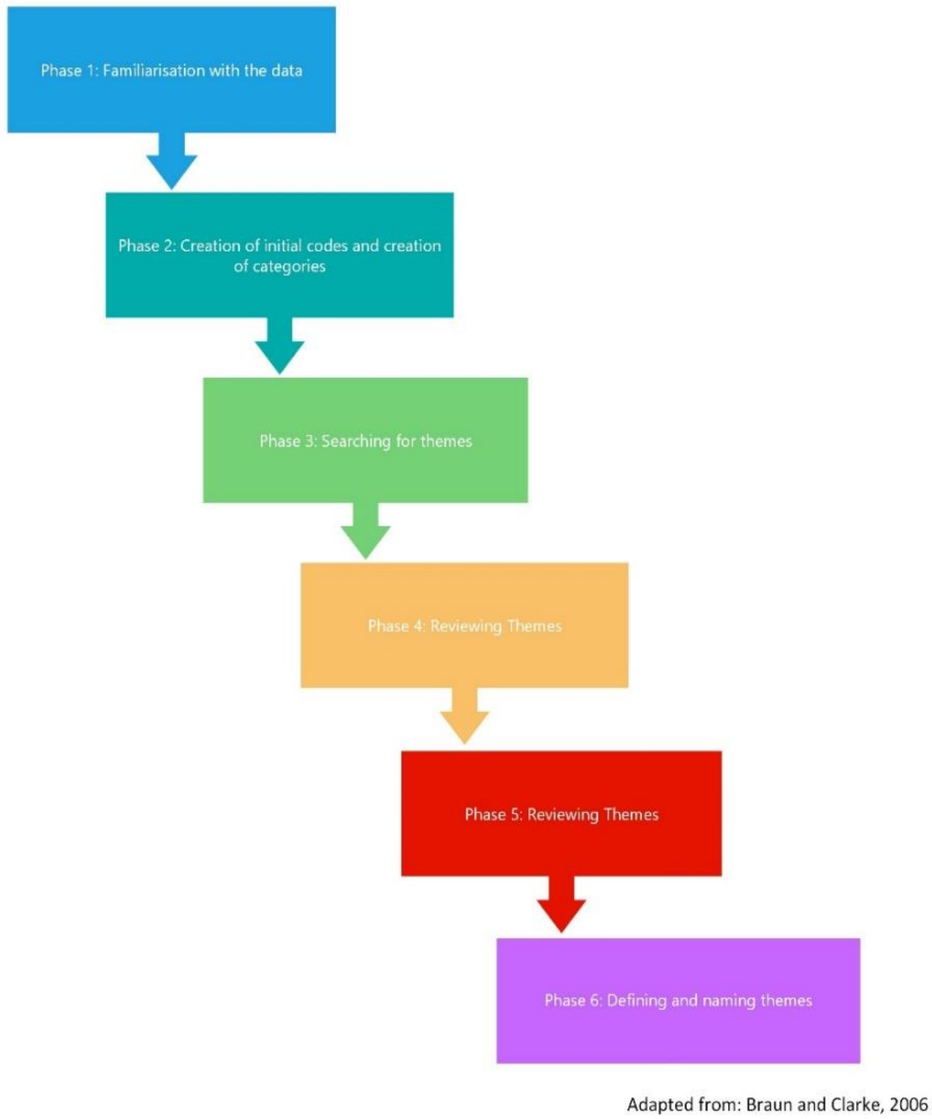


Figure 11: Thematic Data Analysis Process

Phase 3 – Generating Themes

The researcher then proceeded to search for themes within the categories seeking themes that "represent the collective meaning of the codes and categories that underpin them" (Saldana, 2009:90). The researcher ensured that a collection of categories is associated with commonly held perceptions represented by codes. Through this deductive approach to the data analysis, the researcher began searching, reviewing, defining and naming the themes.

Phase 4 – Reviewing Potential Themes

Categories were developed during the first phase to find common and uncommon types to make decisions such as whether a category should stay a category, or be a theme, whether the potential theme helps answer the research question and whether there is enough data to support the theme. The relationships between the codes were subsequently reviewed and nodes were re-organised into relevant categories which would act as sub-themes. The researcher created new codes as they became apparent to enrich the data.

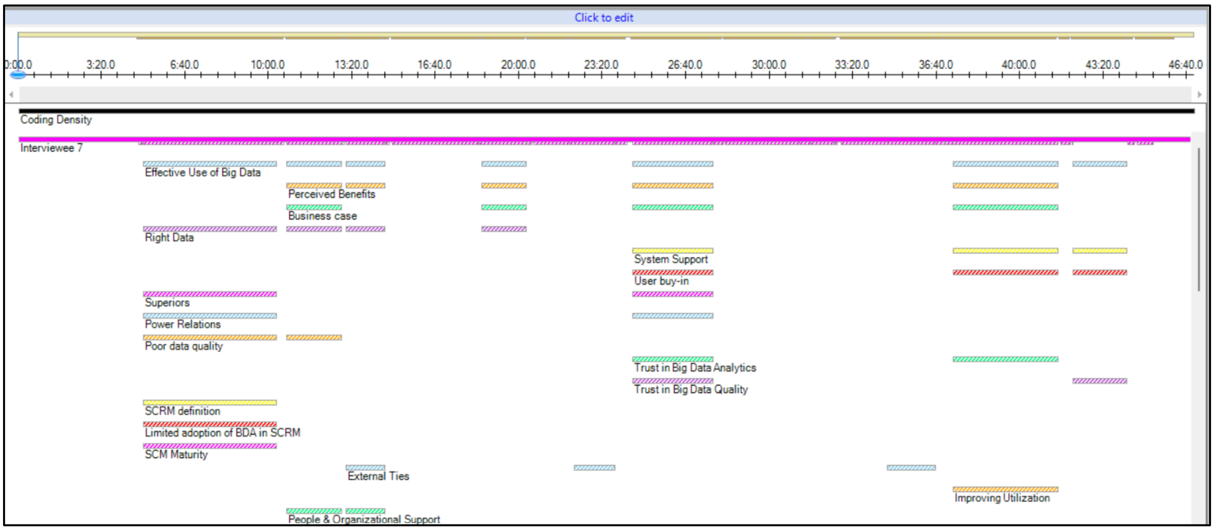


Figure 12: Example of Codes Generated from Interview with Participant A

Phase 5 – Defining and Naming Themes

Similar sub-themes were then grouped to create an overall theme representing the data and enabling informed interpretation. Each theme was mapped to a construct in the conceptual framework to provide a coherent and congruent account of the data. The researcher defined and named the theme through a comparative analysis of the underlying codes and categories. Definitions ensure that specific themes have an associated meaning shared across the sub-themes.

Phase 6 – Reporting

The researcher then related the identified themes to each other and selected certain extracts that supported either the underlying theme or sub-theme. The subject's complexity was recognized to seek excerpts that captured the essence of what was communicated narratively. The findings were analysed in the context of the literature and subsequently presented following the guidance given by Anderson, C. (2010) on the presentation of qualitative research.

4.9 Criteria for Evaluating this Study

Finally, to enable the reader to evaluate the quality of Interpretivist research, the researcher below has addressed issues related to trustworthiness, confirmability and transferability (Oates, B. J., 2006). These issues are addressed by keeping an Audit Trail throughout the research process (Oates, B. J., 2006). The researcher provides a detailed account, in section 4.10, of an Audit Trail that forms part of the Case Study database for this research project.

4.9.1 Trustworthiness

Trustworthiness concerns "how much trust we can place in the research"(Oates, B. J., 2012:294). The focus on trustworthiness convinces readers that the research was done systematically. Trustworthiness should be embedded in the decisions taken throughout the qualitative research process (Carcary, M., 2020). Research audit trails have been identified as a critical strategy for establishing trustworthiness (Carcary, M., 2020). The researcher has developed an audit trail for the reader to gain insight into the research process, as described in section 4.10.

4.9.2 Confirmability

Confirmability is when the researcher lays out the decision-making process for the reader (Bloomberg, L. D. et al., 2018:86). Further to this, a discussion of the research paradigm, the outlining of the research strategy and research methods, and through rich and detailed reflections the researcher accounts to the reader as to why certain decisions were made. The researcher has traversed this terrain extensively in the preceding sections, 4.2.4; 4.3; and 4.11, respectively.

4.9.3 Transferability

Transferability is the "ways in which the reader determines whether and to what extent this particular phenomenon in this particular context can transfer to another particular context" (Bloomberg, L. D. et al., 2018:87). The researcher has documented all their evidence in a systematic manner such that it enables the reader to confirm whether the findings the researcher puts forward are based on evidence (Ponelis, S. R., 2015). The researcher has kept an Audit Trails, which is discussed further in section 4.10. The codes and themes are systematically documented in reflexive journals, interview notes such as Figure 13 below, and memos. The researchers' conclusions are further informed by the evidence collected during the systematic literature review. Thus the researcher has ensured that the findings are dependable (Bloomberg, L. D. et al., 2018).

4.10 Audit Trails

Given the flexible nature of qualitative research, a researcher must keep an audit trail of decisions taken, reviewed documents, comments, and field notes, amongst other things. These artefacts enable the reader to understand how certain conclusions were arrived at through what scientific method if any. The Audit Trail provides a unique opportunity to inform the reader how quality was assured throughout the research project (Carcary, M., 2020). At the beginning of this study, a proposal detailing the research methodology was developed along with a research instrument for submission to the University of the Western Cape's Research and Ethics Committee. The research instrument is attached in Appendix A and the ethical clearance from the Research and Ethics Committee is attached in Appendix C as further evidence that the research methodology and research instrument were feasible and ethical. A Systematic Literature Review Protocol was also developed, attached as Appendix C, to guide the systematic literature review and to reveal how and why an article was excluded. Before commencing with the data collection, the researcher informed the potential participants about the research project and the ethical clearance and addressed technical and privacy concerns of the online interview platform. This information was provided in the interview invite attached as Appendix D. During the semi-structured interviews, the researcher compiled field notes which guided the development of the initial codes. Some of these were digitised as memos in NVivo. All audio-visual interview recordings are stored safely on a secure cloud computing platform. A reflexive journal was maintained throughout the research project that guided thinking and decision-making. During the data analysis process, a codebook was developed as part of the thematic analysis, which is attached as Appendix G.

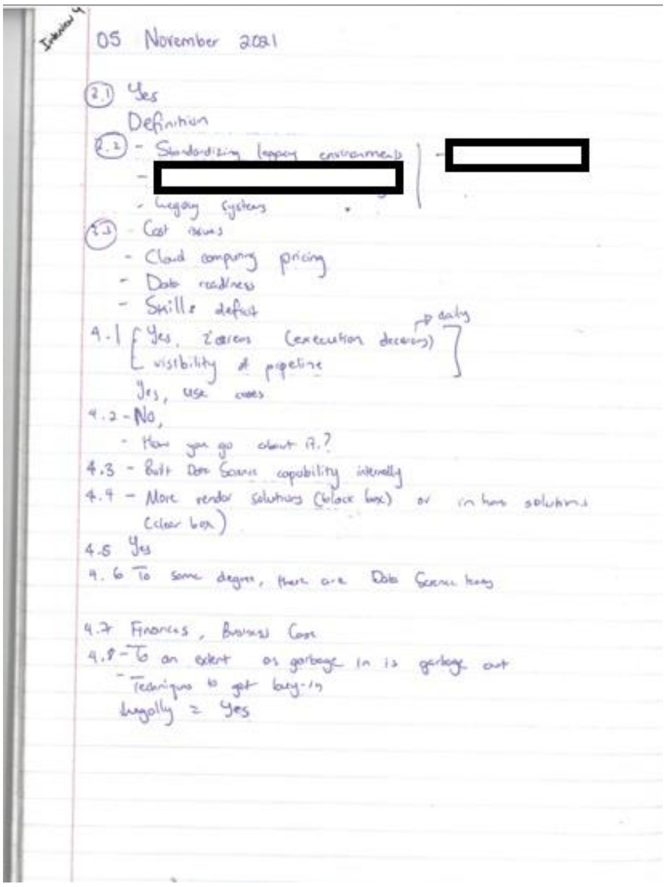

Interview 4
05 November 2021
2.1 Yes
Definition
2.2 - Standardizing (legacy environment) - [redacted]
- [redacted]
- Legacy Systems
2.3 - Cost issues
- Cloud computing pricing
- Data readiness
- Skills deficit
4.1 Yes, [illegible] (execution decisions) daily
visibility of pipeline
Yes, use cases
4.2 - No,
- How you go about it?
4.3 - Built Data Science capability internally
4.4 - More vendor solutions (black box) or in house solutions (clear box)
4.5 Yes
4.6 To some degree, there are Data Science teams
4.7 Finances, Business Case
4.8 - To an extent as garbage in is garbage out
- Techniques to get buy-in
[illegible] = Yes

Figure 13: Interview Journal

4.11 Reflections

The researcher's background, which includes their knowledge of the subject, experience, age, and social standing, will invariably influence the research approach, methods, findings and conclusions (Malterud, K., 2001). Malterud, K. (2001:358) states that “reflexivity starts by identifying preconceptions brought into the project by the researcher, representing previous personal and professional experiences, pre-study beliefs about how things are and what is to be investigated, motivation and qualifications for exploration of the field, and perspectives and theoretical foundations related to education and interests”. The researcher employed a denaturalised method for the transcription (Oliver, D. G. et al., 2005). The denaturalised method was viewed as the most suitable given that the researcher suffers disfluency and may influence the interviewee and the transcript. Denaturalised transcription processes accommodate speech disfluency as it attempts to remove “idiosyncratic elements of speech (e.g., stutters, pauses, nonverbals, involuntary vocalisations)” (Oliver, D. G. et al., 2005:1273). Grounded Theorists have also used denaturalised transcription. The researcher seeks to elevate the transcription process at the same level as the data collection process. This stance is informed by Nascimento,

L. et al. (2019); (Oliver, D. G. et al., 2005), who argued for researchers to report how they transcribed their data within the methodology section.

4.12 Chapter Summary

This chapter began with an overview of the research design and methodology, where a justification for qualitative research methods and the paradigm were presented. The researcher described the research method and the research strategy. A detailed account of the data collection and analysis process is provided, including ethical issues impacting these processes. A very brief reflection is also provided about the transcription. The upcoming chapter will present the results, which will be discussed and interpreted along with the conclusions that arose from the research findings in Chapter 6.

Chapter 5 PRESENTATION OF RESULTS

5.1 Introduction

The previous chapters highlighted the need to understand the factors influencing the adoption of Big Data Analytics in Supply Chain Risk Management by supply chain professionals in the manufacturing industry by presenting a review of the literature. The research methodology and design was presented. This chapter will describe the participants and their demographic characteristics. The chapter will further summarise the qualitative data collected from the semi-structured interviews. In presenting the findings, pseudonyms are used to enforce anonymity to facilitate the disclosure of information with the sensitivity required. For instance, a participant may mention a project their organisation is undertaking but may mention confidential information such as the systems, methods and techniques utilised to develop the Information System. For this reason, the researcher has redacted the names of organisations, people, technologies, systems, and any other information not publicly disclosed. This redaction is also according to a Non-Disclosure Agreement the researcher has signed to gain access to the research site and the participants, which seeks to protect the participants from over-disclosure and enable the participants to partake freely in the research project.

5.2 Part A: Systematic Literature Review

What is the role of Big Data Analytics in Supply Chain Risk Management?

As shown in Figure 14, most records were rejected as they did not conform to the Quality Assessment criteria. Based on Figure 15, the first article to be published was in 2017, a possible indication that this research area is nascent. However, this could also be due to the exclusion of other publications such as conference papers, book chapters and conference reviews. Figure 16 also revealed that articles published in the past two years had received lower citations than older ones, possibly indicating the seminal nature of these publications. As per Figure 15, the data also revealed that Dynamic Capabilities were the most employed theoretical framework. However, the Knowledge-Based View framework was the most consumed by researchers based on citations. It also seems to be the case that mixed methods were the most utilised research method for researchers, with mixed methods receiving more citations than quantitative methods, as shown in Figure 17.

As shown in Table 5 and Figure 16, many studies did not report any use case or application of BDA in SCRM. All of these studies utilised a survey research method. Singh, N. et al. (2019), who surveyed 297 respondents with a 16.05% response rate, found that adopting BDA capabilities facilitates knowledge management, including developing SCRM capacity. The author found that BDA augments existing IT capabilities. At the same time, another study by Gebhardt, M. et al. (2022) utilised the Resource Dependency Theory as part of a projection to understand how companies will adapt their global supply chains by 2025 to increase SCRES post-COVID-19. Surveying 94 supply chain professionals and academics, Gebhardt, M. et al. (2022) found that the participants shunned the use of safety stocks and competition. Instead, there is a tendency towards collaboration, mapping out the supply chain and increasing the risk criteria during the supplier selection (Gebhardt, M. et al., 2022).

These findings are similar to those of Singh, N. P. (2020), who also found that organisations that adopt SCRM practices are able to mitigate environmental risks that have a negative financial impact. The author found that Entrepreneurial Managerial Capitalism is a mediator and can improve decision-making. Although these studies do not explore applications of BDA in SCRM, they do enable practitioners and researchers to understand how managerial decision-making is made under conditions of environmental uncertainty, how firms have adopted their global supply chains in response to COVID-19 and how SCRM capabilities can be developed by adoption BDA in SCRM.

Mani, V. et al. (2017) developed a survey instrument based on a panel discussion with three academics and six senior executives. Mani, V. et al. (2017), surveying 54 supply chain professionals, found that Big Data Analytics can improve the firm's sustainability by reducing social and environmental risks. By utilising Internet-of-Things sensors for fleet management and vehicle tracking, the author found that Big Data Analytics can assist in predicting workforce safety, fuel consumption monitoring, workforce health, security, the physical condition of vehicles, unethical behaviour, and theft. The author concluded that information management actions could mitigate social risks. Other authors, Li, L. et al. (2022), also investigated the relationship between BDA and supply chain integration, especially in the context of Disaster Management. By employing a Hierarchy Model of Capabilities, the authors found that capabilities such as proactiveness, reactiveness, and resource reconfiguration are developed through BDA capabilities. These authors found that BDA capabilities and supply chain integration help build an organisation's immunity to disaster.

A few studies explored modern technologies such as risk alerts, real-time tracking and blockchain technologies. Park, M. et al. (2022) found that an organisation's BDA capability influences risk alert tools. The author suggested that IT infrastructure augmented by a BDA capability are critical for developing effective risk management tool. Rauniyar, K. et al. (2022), as part of a review article, interviewed 26 supply chain professionals to understand how organisations adopt blockchain technologies to reduce their supply chain risks. The author found that blockchain can decrease some supply chain risks. Finally, Buchholz, P. et al. (2022) utilised Data Mining methods to demonstrate the real-time tracking of risks in mineral raw markets using satellite data and web scraping. The author showcased BDA as an effective tool to extract data from various data sources that enable a firm to react timely to disruptions. More specifically, the author concludes that only supervised models are most effective for risk monitoring, especially in mineral raw material markets.

Figure 14 below presents the number of articles retrieved from the databases and which were subsequently accepted. In Table 5 below, the role of Big Data Analytics in Supply Chain Risk Management is presented by reviewing the research method, the industry and the theoretical framework adopted for the accepted articles. These articles are further analysed in Figure 15 that shows the number of articles published across years and followed by Figure 16 that provides insight into the research impact of the articles by analysing citations. Figure 17 presents the distribution of research methodologies used by various studies that were accepted. Figure 18 juxtaposes the identified research methodologies against the theoretical employed adopted for these studies.

Finally, Figure 19 presents the use cases identified in the accepted study including the most cited use case and the research design of that study.

Table 5: Literature on Big Data Analytics in Supply Chain Risk Management

Bibliographic reference	Research Method	Industry	Theoretical Framework
Mani, V. et al. (2017)	Survey	Logistics	Knowledge-Based View
Singh, N. P. et al. (2019)	Survey	IT software products, IT services, health care, manufacturing	Institutional Theory, Dynamic Capabilities
Li, L. et al. (2022)	Survey	Logistics	Hierarchy model of capabilities
(Park, M. et al., 2022)	Survey	IT software products, IT services, health care, manufacturing	Dynamic Capability
Buchholz, P. et al. (2022)	Data Mining	Raw Mineral Market	None
Gebhardt, M. et al. (2022)	Survey	None	Resource Dependence Theory
Rauniyar, K. et al. (2022)	Survey	None	None
Singh, N. P. (2020)	Survey	General Manufacturing, Logistics, Services, Food Manufacturing	Entrepreneurial Managerial Capitalism

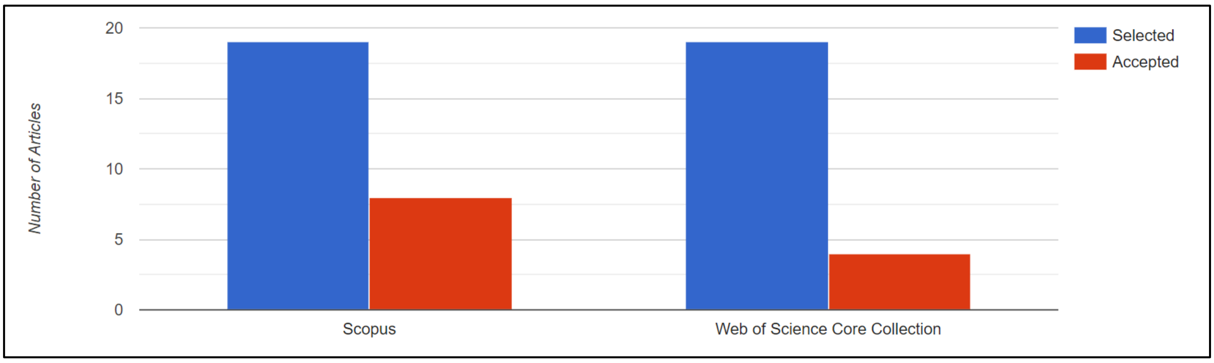


Figure 14: Number of Articles Accepted

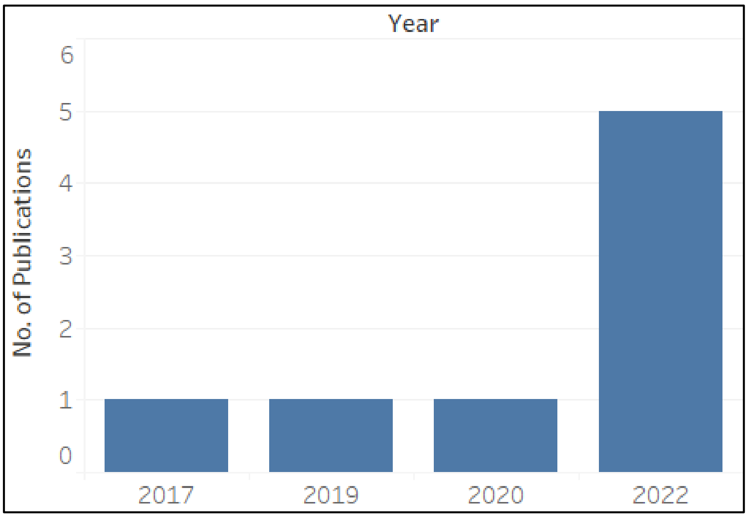


Figure 15: Number of Articles Published per Annum

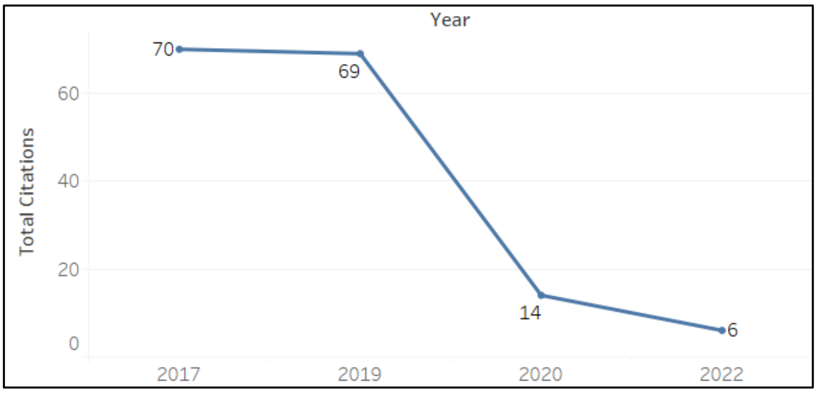


Figure 16: Total Number of Citations by Publication Year

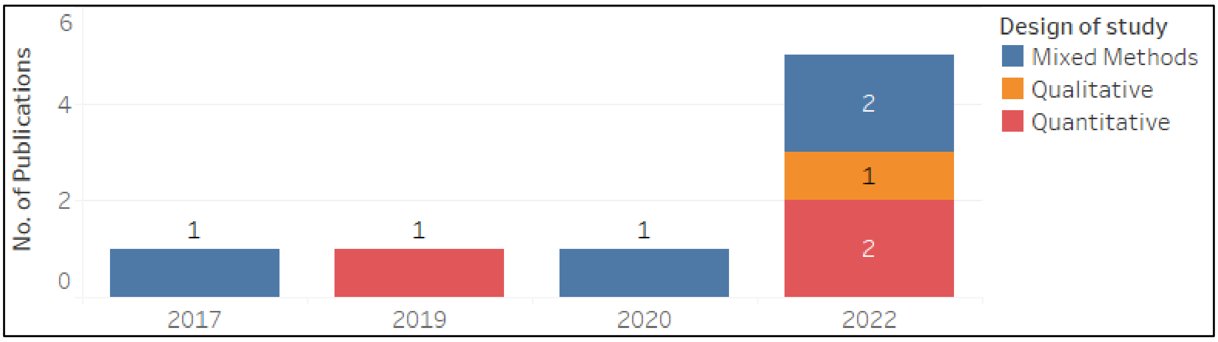


Figure 17: Distribution of Research Methodology by Publication Year

	Design of study		
Theoretical Framework	Mixed Methods	Qualitative	Quantitative
Dynamic Capability			1
Entrepreneurial Managerial Capitalism	14		
Hierarchy model of capabilities	0		
Institutional Theory, Dynamic Capabilities			69
Knowledge-Based View	70		
None		1	0
Resource Dependence Theory	4		

Figure 18: Research Methodology by Theoretical Framework Employed

	Research Method	
Use Case/Application	Data Mining	Survey
Block Chain		1
Disaster Management		0
IoT Sensors for Fleet Management and Vehicle Tracking		70
None		87
Real-time tracking of risks in mineral raw markets using satellite data and web scraping	0	
Risk Alert Tool to predict Disruptive Events		1

Figure 19: Big Data Analytics Use Case by Number of Citations

5.3 Part B: Semi-Structured Interviews

What are the factors influencing the adoption of Big Data Analytics in Supply Chain Risk Management?

5.3.1 Demographic Analysis

Most participants were males who held at least a degree, except for one male participant. Female participants were in the minority, but all held a postgraduate degree. Most participants were supply chain professionals, while some were supply chain managers and one is a supply chain data analyst. The majority of the supply chain managers held a Masters degree. The participants also had a wide range of years of experience. Most supply chain professionals had less than 15 years of experience compared to the more than 15 years held by most supply chain managers. This wide range of years of experience allows the researcher to gain nuanced perspectives, given that none participant was older than 49 years old.

Table 6: Participants' Demographics

Participant	Interview No.	Age	Gender	Education	Experience	Role
A	7	30-39	Male	Masters	10-15 years	Executive/Manager
B	3	30-39	Male	Bachelors	5-10 years	Supply Chain Analyst
C	4	40-49	Male	Bachelors	15+ years	Executive/Manager
D	5	30-39	Male	Grade 12	10-15 years	Supply Chain Analyst
E	1	40-49	Male	Masters	15+ years	Executive/Manager
F	2	30-39	Female	Honours	15+ years	Supply Chain Analyst
G	6	18-29	Female	Honours	3-5 years	Supply Chain Data Analyst

5.3.2 Definitions and Summary of the Themes

5.3.2.1 Organisational Context

This theme encapsulates the participants perceptions about the organisation that could be influencing the supply chain professionals to adopt Big Data Analytics in Supply Chain Risk Management. This theme explicates the important of understanding the role the organisation in socially influencing and also as a facilitating the conditions for behavioural intention and usage of Big Data Analytics in Supply Chain Risk Management.

5.3.2.2 Support Context

The theme Support Context revolves around the support structures that should be in place for supply chain professionals to adopt Big Data Analytics in Supply Chain Risk Management. Support within and outside the organisation is a necessary facilitating condition that could ease the effort required to adopt Big Data Analytics in Supply Chain Risk Management.

5.3.2.3 Big Data Management

The Big Data Management theme reflects the participants perceptions and views about certain aspects of the infrastructure, security and trust that would have to be in place for the participants to successfully adopt Big Data Analytics in Supply Chain Risk Management. This theme captures the importance of an organisation Big Data Management capability as a facilitating condition that could enhance the trust of Big Data Analytics by supply chain professionals, which subsequently positively influences the usage of Big Data Analytics in Supply Chain Risk Management.

5.3.2.4 Attitudes

This theme encapsulates the attitudes within the organization that contribute to supply chain professionals adopting Big Data Analytics in Supply Chain Risk Management. In summary, supply chain professionals attitudes towards Big Data Analytics tends to influence the behavioural intention and usage of Big Data Analytics in Supply Chain Risk Management. Thus, for supply chain professionals to adopt Big Data Analytics in Supply Chain Risk Management, it is important for their attitudes towards Big Data Analytics be clearly understood by the organisation.

5.3.2.5 Competitive Pressures

The Competitive Pressures encapsulates the participants perceptions about how the competitive environment within Supply Chain Management is influencing the adoption of Big Data Analytics in Supply Chain Risk Management by supply chain professionals. Competitive pressures, which are external to the organisation tend to influence usage of Big Data Analytics in Supply Chain Risk Management, as supply chain professionals seek to improve their performance with Big Data Analytics.

5.3.3 Theme 1: Organisational Context

The participants were questioned about whether their organisation had adopted Big Data Analytics in Supply Chain Risk Management. All the participants responded in the affirmative, with most participants indicating that the adoption of Big Data Analytics is being adopted in phases. It tends to begin in certain areas and then become more widely adopted. See their responses below:

> *"Yeah, I think we are adopting it, but I don't think it is at the level that we should be adopting it. I do believe that we are." (Participant F, Supply Chain Analyst)*

> *"There's far more of a focus at the moment on trying to get data made more available, to get data into a data lake, all of those sort of things which once those are in place and then it's going to make it obviously a lot more powerful and useful for supply chain professionals to then leverage that data for those purposes." (Participant C, Executive/Manager)*

> *"Some of the more customer-related analytics areas are typically a starting point for Analytics in a lot of companies. So they start there, and then eventually they realise: 'Oh*

wow, the merchandising, the supply chain, a lot more of the other service functions could also benefit from it."(Participant A, Executive/Manager)

5.3.3.1 Drivers

Participants spoke to the drivers of the adoption of BDA in SCRM, with a majority of those who held this view identifying the need for visibility of supply chain risks and the increased availability of data along with the increased focus on supply chain management by business as having been the factors driving behind the adoption. For instance, one participant remarked that Big Data is already penetrating their industry. The participant further noted the potential benefits were driving their acceptance of Big Data Analytics. Another participant confirmed this and took it further by stating that the business strategy has become data-driven, with various use-case areas being identified and prioritised.

"Look, this is where the world is going. Big data is where the world is going, and if you want to compete in the retail environment, you have foresight or insight as to how other operations operate basically." (Participant B, Supply Chain Analyst)

"I think what counts in everyone's favour is that data is becoming more available." (Participant A, Executive/Manager)

5.3.3.2 Business Strategy

Participants highlighted the importance of a sound business strategy when adopting BDA in SCRM. Participants mentioned challenges related to operational structure and the ability to scale adoption. They noted that the business strategy drives the business case, which facilitates the adoption of BDA in SCRM. What the participants made clear is that there also needs to be a shift in the paradigms of thinking within the organisation as seen in the extracts below.

"It's so much easier to track inventory with sensors, and there are so many different ways you can get better data. I think it's maybe business strategy." (Participant A, Executive/Manager)

"Is your organisation correctly structured to take advantage of whatever it is that your big data is showing you?" (Participant E, Executive/Manager)

"I also just think you've got to be careful to use a term like just adopt big data analytics; that's a big word that doesn't mean much unless you've got a specific use case. Ultimately, I think it's about using big data techniques, possibly for some very specific, well, clearly articulated use cases. I think that's also what organisations struggle with, and they struggle to have clarity around what it is that they would like to measure and manage." (Participant C, Executive/Manager)

"I think maybe people don't understand the value in it yet. If you can show what the value is in that and what are your potential scenarios, and how you could mitigate risk using big data. If you can show people the value in that, then I think people are more likely to look at it." (Participant G, Supply Chain Data Analyst)

"I think it's changing because now they can see the importance of the supply chain." (Participant F, Supply Chain Analyst)

5.3.3.3 Costs

Participants were asked the reasons that other organisations are not adopting Big Data Analytics in Supply Chain Risk Management despite the benefits raised by participants of doing so. Participants highlighted concerns related to the costs of adopting Big Data Analytics, perceiving it as a key barrier to adopting Big Data Analytics in Supply Chain Risk Management, especially in a developing country such as South Africa. They raised concerns about the cost of adopting Big Data Analytics and implementing a Supply Chain Risk Management programme as seen from their responses.

"I think from a South African perspective, to be honest, the cost is a bit of an inhibitor. It's a lot more expensive than people realize. Cloud computing is not cheap, and obviously A.I./M.L. computational stuff, it gets very expensive." (Participant C, Executive/Manager)

"I think one of the things with risk management is that it actually costs you to manage your risks, and normally people try and want the cheapest option generally." (Participant G, Supply Chain Data Analyst)

5.3.3.4 Contestations

The interviews revealed that contestations have spilt over from the research discipline to the field of practice, specifically to the managers. These contestations were a common theme from participants who classified themselves as supply chain managers. Participants questioned what constituted Big Data and Big Data Analytics in practice. It seems that supply chain managers were not only concerned about the contestations around Big Data and Big Data Analytics. They were also dissenting in their views on what constitutes Supply Chain Management and Supply Chain Risk Management.

"And the question is always, what is big data?" (Participant E, Executive/Manager)

"I guess the big question is what big data analytics, right?" (Participant C, Executive/Manager)

"Well, I would say maybe we can just quickly talk about what falls under supply chain. So I think in a lot of organisations, especially in retail, when they think supply chain, they normally just talk about logistics and transport. Whereas other organisations, maybe a bit more internationally, when they think supply chain, it covers more of it end-to-end from the

demand planning to a lot more of the inventory management as well. Instead of the actual transport and movement of goods.” (Participant A, Executive/Manager)

“When you talk about the risk, I suppose I think bigger beans to the sustainability of the company. Use the example of looting or burning down or whatever. You know, those are catastrophic risks as opposed to is this shipment going to be delayed by a week?” (Participant C, Executive/Manager)

5.3.4 Theme 2: Support Systems

The participants were questioned about how their organisation supported the adoption of Big Data Analytics in Supply Chain Risk Management. Amongst other things, the participants revealed that the organisation has put in place various support systems to facilitate the adoption of Big Data Analytics. The researcher found that the organisation has set up a dedicated Business Unit to drive the adoption across the firm. The Business Unit plays a support role for supply chain professionals and gives the supply chain professionals access to technical expertise that would be out of reach. What is revealed from the above is that the supply chain professionals are not expected to have the entire skillset required to adopt Big Data Analytics. The supply chain professionals are also aware of this. A case in point is that the supply chain professionals were asked if they believed that their colleagues could assist them in adopting Big Data Analytics. A significant number of participants indicated that they could get access to internal colleagues to assist them when they faced any difficulties.

“So I mean, the way which we have gone and looked at this is not so much that each of our supply chain professionals need to have an understanding of BDA. It's, rather, set up a centre of excellence - a centralized unit - which has got a highly specialized skill. The rest of the supply chain professionals and other people within the supply chain, what they will do is be able to get views of their output and be able to slice and dice their output. But we're not expecting specialised sort of thinking, data pipeline building, actual model building, statistics and stuff like that as this is a fairly niche skill.” (Participant E, Executive/Manager)

“But I think with the new system, there's a different focus and there's an entire team dedicated to it.” (Participant B, Supply Chain Analyst)

“I do have some colleagues that I can ask, and we have brought in a consultant, for example, with supply chain analytics just to assist and make sure that we're on the right path.” (Participant G, Supply Chain Data Analyst)

5.3.4.1 External Consultants

The participants were further asked whether they would require an external consultant to assist them in adopting Big Data Analytics in Supply Chain Risk Management. Some participants indicated that they would require a consultant, but the majority did not hold this view. These contrasting views result from the organisation's phased approach to adopting Big Data Analytics. Another participant also stated that they would require a consultant to facilitate this whilst they recognised that their organisation would still be primarily involved in the adoption process. The participant believed that consultants are essential sources of new information. The participants did not perceive consultants as replacing their organisation's technical implementation team; instead, the consultant is viewed as complementary to this team. More specifically, consultants were considered sources of industry best practices and rich information.

Some participants stressed that consultants have to be managed effectively for one to receive benefits from them. Thus, consultants are not brought in to solve the organisation's "universe" of problems. The consultant is seen as a complimentary team member whose output is also reviewed to ensure conformance with the organisation's standards. Consultants thus provide the organisation with the industry standards incorporated into the organisation's standards to avoid issues such as biased algorithms that would end up in production. Consultants are peer-reviewed as the adoption process unfolds.

> *"I do think that often it is good to get an external view from a consultant. Company X, as a company, likes to do things internally because it's also more sustainable to keep those processes going, but it's important to get new information from consulting firms as well." (Participant G, Supply Chain Data Analyst)*

> *"Obviously, if you work with consultants and you pay them to do a job for you or build a model for you, I think it would be part of their list of things to check. We would also make sure when we sit with them, and we review models, we review approaches, we would try and make sure that all our concerns are taken care of things that we typically see take place historically when we try to do things, you know. I think there is there is support for that." (Participant A, Executive/Manager)*

5.3.4.2 Skills Availability

The participants were asked whether they foresee difficulties in adopting Big Data Analytics in Supply Chain Risk Management. A majority of the participants indicated that they did not foresee any problems as they believed it was not difficult to find skills within their organisation to assist them with adopting Big Data Analytics. Some supply chain professionals even revealed that it would not be difficult to acquire the necessary skills in Big Data Analytics within Supply Chain Risk Management as long as other supply chain professionals were interested in this initiative.

Participants believed that the organisation should be utilising a cohort of supply chain professionals who already have the requisite skills to facilitate the adoption of Big Data Analytics within Supply Chain Risk management. Several participants dissented and argued that they encountered difficulties accessing the skills required to facilitate the adoption of Big Data Analytics in Supply Chain Risk Management. The main concern for the participants was the talent shortage. The shortage of talent on the market to facilitate the adoption of Big Data Analytics is exacerbated by a concern raised by participants that there is a lack of business knowledge among candidates. The participants lamented this as they perceived that it was challenging to adopt Big Data Analytics within Supply Chain Risk Management as candidates were technically skilled to utilise Big Data Analytics but lacked an understanding of the business elements of Supply Chain Risk Management that would enable them to add value. Participants mentioned the lack of supply chain knowledge as they tend to find technically competent professionals who lack an understanding of supply chain management.

> *"I think, you know, anything can be taught if the want is there and if you are passionate about something. If you are interested in it. And I think it's an interesting subject, and it can be very much achievable." (Participant F, Supply Chain Analyst)*

> *"I don't think it's going to be difficult. I mean, I think it's there. I think it's just utilising them, utilising the skills." (Participant B, Supply Chain Analyst)*

> *"I think it is a bit difficult to find. It's quite difficult to find candidates. We have had struggles before to find candidates both within supply chain and that can work with data very well. I think it is difficult to find the right talent in that area." (Participant G, Supply Chain Data Analyst)*

> *"It's not that easy. If you want someone who's really good with data and is a real Data Scientist, they typically have more experience in financial services companies. They don't necessarily have a lot of supply chain knowledge or retail knowledge even. I think that is sometimes a big hindrance. Also finding supply chain or industrial engineering talent, is also not that easy. It's not." (Participant A, Executive/Manager)*

> *"The first challenge is always going to be skills set because as much as we can talk big data you need guys who've got the technical know-how, but you also need to kind of understand the tech and business. How do you rightly frame the business questions, and what business questions are worth going after?" (Participant E, Executive/Manager)*

5.3.4.3 Training

Almost all the participants registered the need for training interventions. Some participants stated this clearly, whilst others provided the practical implications of not providing training. Whilst another participant suggested that the organisation should consider setting up a learning and development unit focused on assisting supply chain professionals with gaining the skills required to facilitate the adoption of Big Data Analytics in Supply Chain Risk Management. Although the importance of training was recognised, there were also contestations on the type of training and the modes of training. Participants noted that training should be purposeful and primarily seek to solve business problems.

> *"I think one of the important things is also to provide training for adoption to the new systems." (Participant G, Supply Chain Data Analyst)*

"Think of it this way, you've got people who've probably been working on-premise for all their careers, and suddenly, there's stuff which is going to move to the cloud. People become very unsettled unless you take them on the journey and your best bet is to take those people who've been doing your on-premise on a very rapid, accelerated cloud training because the advantage you get is they understand this solution in depth." (Participant E, Executive/Manager)

"We've got people in planning, buying, data analytics or whatever that are good at what they've done that do and been there for a long time. So why not create an academy that offers the newcomers and whoever is interested in custom sessions kind of thing, you know?" (Participant B, Supply Chain Analyst)

"What you're going to look at it from is that no business guys out there and says 'Hi guys, we want to adopt big data analytics. Please go forth and get it trained, and we're going to support you to get trained'. Get trained in what? The broad topic? You've got to solve business problems." (Participant C, Executive/Manager)

5.3.4.4 Technical Support

Some participants indicated that because an internal team facilitated the adoption of Big Data Analytics, they believed their organisation had the necessary technical skills should they encounter any difficulties. Participants viewed the internal technical support team as supportive throughout the adoption process. The team has been supportive and continues to be supportive. Some participants believed obtaining user buy-in was the ideal method for facilitating adoption within their organisation and generating support from supply chain professionals. Techniques such as user acceptance testing and A/B testing were regularly implemented to understand if the proposed solutions meet the user's requirements and, at the same time, generate engagement.

"Getting an external company up to speed would be kind of the same as getting someone internal up to speed. So I don't necessarily think that would be a necessity, but we do need a kind of better system in place that isn't or that only a few people know how to use it." (Participant G, Supply Chain Data Analyst)

"Through this journey, they've held our hands through it, they've listened, they've delivered. So we're really turning the wheel. The wheel is turning. I'm excited about it. It's exciting to work with something so advanced." (Participant F, Supply Chain Analyst)

"The first key thing is to make sure you've done your A/B testing properly and make sure that you've got buy-in from everyone." (Participant E, Executive/Manager)

"What the company does around that is it utilizes teams like ours to work with them and do some tests. Show them that they could actually get better results if they use analytics. If

they trust the use of data to make decisions and not just trust their gut feel." (Participant A, Executive/Manager)

However, no system implementation is free of incidents. Even in these circumstances, participants asserted that their colleagues who are part of the technical implementation team have been supportive and provided them with further technical support should it be required.

"If there's any areas of concern or something that we don't understand or we need enhancements on, we go back to the I.T. team." (Participant B, Supply Chain Analyst)

5.3.5 Theme 3: Big Data Management

5.3.5.1 Information Management

Participants were asked if they would require changes to their information technology infrastructure to adopt Big Data Analytics in Supply Chain Risk Management. Most participants indicated that they would not require any new hardware as they have existing cloud computing capabilities. However, they did identify the possibility of needing new software. Participants emphasised the importance of understanding how best to deliver Big Data Analytics, including how users can interact with Big Data Analytics. This can impact the solution the organisation invests in.

Some participants mentioned concerns about legacy systems and the challenge of maintaining these legacy systems. Participants were concerned about the compatibility of these systems. Participants alluded to the need for a clear understanding of the capabilities to manage Big Data, including aligning Big Data Analytics capabilities with their existing infrastructure. Some participants were of the view that there need to be significant investments in modalities of deploying Big Data Analytics into production.

The majority of participants believed that their current cloud infrastructure would serve them well as they would not require investments in hardware. Some of these participants intimated that their concerns relate to ensuring that the Big Data Analytics systems are operationally ready and can provide value to the supply chain professionals. For instance, one participant stated the following:

"One of the problems that we've always had is the systems that we use is a legacy thing." (Participant G, Supply Chain Data Analyst)

"At the end of the day again, depends on how you go about implementing it. Are you going to go out there and find a vendor that's got a solution that already leverages big data that is tied to your use case and all you need to do is stream data into that solution? That's an easier thing to make happen because I need to understand the mechanics and the dynamics of big data and machine learning and all of that. If I want to build those models and create those models myself, it becomes another complicated situation." (Participant C, Executive/Manager)

“I mean, our structure won't change a lot because we're using cloud infrastructure. All you need to do is ensure your integration and that the data you want to send up is going through.” (Participant E, Executive/Manager)

5.3.5.2 Trust in Big Data Analytics

Participants were asked whether they could trust Big Data Analytics. A number of the participants noted that trust influences their decision to adopt BDA in SCRM. Participants expressed their confidence in Big Data Analytics, although it was with varying degrees. Some participants viewed Big Data Analytics as a starting point for their decision-making as they relied on their intuition even when Big Data Analytics does exist. Participants mentioned that data quality is another concern that influences their trust in Big Data Analytics. The participants viewed Big Data Quality as instrumental see explanations provided.

“Yes, I definitely trust BDA to an extent, but you could also look at your intuition. You know you got to have some kind of intuition as well.” (Participant B, Supply Chain Analyst)

“No doubt in my mind. I'm an engineer. I think with a mathematical brain that there is no doubt that algorithms if implemented correctly and designed correctly, can probably make better decisions than humans can.” (Participant C, Executive/Manager)

“In general, as a Data Analyst, I do rely more on data than on subjective views. However, if the data is not good, your decision isn't going to be good.” Participant G, Supply Chain Data Analyst)

“For me, the integrity of the data is an important factor but I don't look [for] 100 per cent accuracy. If it's telling 98% accuracy and if what it's telling you what is there, and it does not change the message, then it's not an issue for me.” (Participant F, Supply Chain Analyst)

5.3.5.3 Information Security

The participants were asked if there were legal and technological means to ensure their security, and several responded in the affirmative. The participants noted that almost all technology projects, including a project that would entail adopting Big Data Analytics in Supply Chain Risk Management, thus preventing adoption. Participants also mentioned how information security and legal protection mechanisms are essential for the adoption of BDA in SCRM. The participants mentioned that there were data security and data anonymisation techniques in place.

“Yes, it does exist. An example, we were starting a new project, and we had to obviously speak to our lawyers before we go ahead because of the theft of information.” (Participant D, Supply Chain Analyst)

"On the legal side, the data which people generally see is anonymised, so they've got no ability to actually get to the individual level and understand it. That's all taken care of upstream." (Participant E, Executive/Manager)

"Yes, we have very stringent policies and rules around POPI, and now we need to deal with and manage data." (Participant C, Executive/Manager)

5.3.6 Theme 4: Attitudes

5.3.6.1 Adoption Willingness

Participants were asked if they were willing to adopt Big Data Analytics in Supply Chain Risk Management. Many participants were willing to adopt Big Data Analytics in Supply Chain Risk Management. They were also questioned about their willingness to recommend the adoption of Big Data Analytics in Supply Chain Risk Management to other supply chain professionals, and an overwhelming number of participants indicated that they would recommend the adoption of Big Data Analytics in Supply Chain Risk Management. However, participants noted that the adoption of Big Data Analytics in Supply Chain Risk Management must informed by specific objectives that address a business problem.

"You know, if we met six months ago and you asked me this question, you would have gotten a very negative answer from me... I'm excited about it. It's exciting to work with something so advanced." (Participant F, Supply Chain Analyst)

"So within Company X, it means from an SCRM perspective we have got a start-up culture which is growing, which is basically saying that there are no holds barred: Bring in the best talent which we can find around the country and let's operate very quickly and then scale this thing." (Participant E, Executive/Manager)

"Well, that's great, but if you're not clear about what outcome you want to achieve with it. You can't define the problem, and therefore you can't then configure the solution." (Participant C, Executive/Manager)

5.3.6.2 Involuntary Usage

What also emerged from the interviews was the influence of superiors, such as line managers, on adopting BDA in SCRM. Leaders sought to optimise the utilisation of the BDA within SCRM for decision-making, thus possibly driving involuntary usage. Managers perceived the low utilisation as an obstacle to solving the organisation's problems. It is worth noting that managers are aware of their employee's resistance to change, and hence they see their role as facilitating the adoption process. The manager will facilitate this process by developing a business case encompassing a use case that proves the solution's business value. Managers also explored incentivisation schemes such as gamification to drive utilisation.

> *"They are resistant to change in a way, and they want to have absolute control about what decisions are made about their products. What the company does around that is it utilises teams like ours to work with them and do some tests. Show them that they could actually get better results if they use analytics." (Participant A, Executive/Manager)*

> *"In my team, I have a small team of data scientists. I have some data science capability, and they work with the business around trying to solve certain business problems." (Participant C, Executive/Manager).*

> *"It's amazing how with incentivising, all you do is on a weekly basis you actually publish engagement statistics and which of your staff, etcetera, have made use of the tools." (Participant E, Executive/Manager)*

5.3.7 Theme 5: Competitive Pressures

The impact of competitors on the behavioural intention to adopt Big Data Analytics in Supply Chain Risk Management is underscored by several participants, which is further supported by another participant who compares their former organisation with the current organisation, thus influencing their behavioural intention. The participant is convinced that when compared with their competitors, it seems to be that their current organisation is well ahead of the curve and has reinforced their intent to adopt Big Data Analytics in Supply Chain Risk Management.

> *"A business, like Company X, has if you compare us to someone like Company W, Company W is an absolute supply chain. It's sort of like in their blood the way they operate. Or if you think of something like Company V, which is now consumer goods, but that's just always been their strength." (Participant A, Executive/Manager)*

> *"In our case, we learned a lot from Company T and Company U on where the mistakes are, and we learn from that. The only way you can learn from that if they have big data is for you to enter into that sphere as well." (Participant D, Supply Chain Analyst)*

> *"I used to work at Company Y, and before I started at Company X. In terms of comparing the technology, Company Y was far ahead at that time. The frustration around our systems and what we had available was definitely there. But now, with this new platform, I think we're going to bang it out." (Participant F, Supply Chain Analyst)*

5.3.7.1 Competitive Advantage

When asked whether adopting Big Data Analytics in Supply Chain Risk Management would give their organisation a competitive advantage, an overwhelming number of participants revealed that they expect to gain a competitive advantage with the introduction of Big Data Analytics in their Supply Chain Risk Management process. The participants seemed to have clear expectations on how the competitive advantage would be achieved and what would be required to attain this mooted competitive advantage. They perceived Big Data Analytics as assisting the organisation in being proactive, and it is through these proactive actions that a competitive advantage is gained over their competitors. The participants noted that Big Data Analytics can also help them gain insights into their competitive operations, thus informing their actions. Participants recognised the role of operational readiness that enables a firm to progress rapidly toward the attainment of competitive advantage.

> *"Yes, I do think so. Definitely. I think it could help a lot to understand your risks." (Participant G, Supply Chain Data Analyst)*

> *"There is a competitive advantage when you know what your risks are, and you know how to attend to that proactively and allow yourself to be exposed to that risk. You learn." (Participant D, Supply Chain Analyst)*

> *"You actually have the ability to wait and have more data and more information about the season you're in before you have to place the order." (Participant A, Executive/Manager)*

> *"I think it does grant you the competitive advantage. But my viewpoint in terms of that is without your operations or your organisation being operationally ready to work any of that output and everything else; it remains pointless because then you're doing stuff for the sake of doing it. You're actually getting nowhere." (Participant E, Executive/Manager)*

5.3.7.2 Improved Decision-Making

Many participants expected Big Data Analytics to improve their decision-making within the Supply Chain Risk Management process. Participants noted that Big Data Analytics plays a role in facilitating decision-making through advanced data analytics methods; however, these benefits will not be accrued without the uptake. There is a recognition that the decision-making of supply chain professionals can only be improved if they willingly adopt Big Data Analytics in Supply Chain Risk Management. Participants recognised the importance of utilising decision-making to reduce transport-related risks.

> *"You are in a very volatile environment, so you need to take decisions, informed decisions. I mean, for instance, if a shipping line changes the routine, you want to know at the tip of your fingers." (Participant G, Supply Chain Data Analyst)*

> *"We need to have a forward view of what's happening in the supply chain. " (Participant B, Supply Chain Analyst)*

> *"I think they are very used to how they do things, make decisions, use the data - working spreadsheet all the time." (Participant A, Executive/Manager)*

5.3.7.3 Supply Chain Visibility

Four out of the seven participants anticipated Big Data Analytics to improve the visibility of the supply chain in general and supply chain risks in particular. The participants were convinced that Big Data Analytics could not only enable them to see the supply chain transparently, but they viewed that Big Data Analytics could improve their supply chain operations. Several use cases were provided by the participants related to supply chain visibility, such as network planning, demand planning, and inventory management. For instance, some participants mentioned the use of Advanced Analytics to gain an end-to-end view of the supply chain, the ability to use data as part of production planning, and the strategic capability of informing design decisions through data collected from retail stores.

> *"Within a retailer as it's critically important for us to obviously get stock to stores on time. To manage that pipeline, to have visibility of that pipeline and all of that sort of thing." (Participant E, Executive/Manager)*

> *"What is not available in every business, is a proper view of an end-to-end supply chain pipeline from production to the factory right until it gets into store. We would want to see a glass pipeline." (Participant B, Supply Chain Analyst)*

5.4 Chapter Summary

This chapter aimed to answer two questions: (a) What is the role of Big Data Analytics in Supply Chain Risk Management; and (b) What are the factors influencing the adoption of Big Data Analytics in Supply Chain Risk Management? The Research methods, designs, use cases, and research impact of a number of articles was systematic literature reviewed. Supply chain professionals were interviewed, and five themes were developed through thematic data analysis of the interview transcripts. These themes are representative of the factors influencing supply chain professionals to adopt Big Data Analytics. Supply chain professionals consider the organisational context, support systems, Big Data management capabilities, competitive pressures, and attitudes. In the organisational context, contestations and costs negatively influence adoption, whilst a clear business strategy is crucial. External consultants and internal technical support are critical components of the support system, with training interventions addressing any skills deficiencies. The willingness to adopt and voluntariness of usage also influence the attitude of supply chain professionals towards adoption. Nonetheless, competitive pressures such as the pursuit of competitive advantage, the need for improved decision-making and requirements for supply chain visibility continue to drive the adoption of Big Data Analytics in Supply Chain Risk Management by supply chain professionals. This chapter presented the findings, whilst the next chapter will discuss these findings in the context of the literature reviewed. The researcher will discuss these overall findings, including the study's limitations and highlight any possibilities for future research.

Chapter 6 DISCUSSIONS, INTERPRETATION AND CONCLUSIONS

> "Any fool can know. The point is to understand."
>
> ~ Albert Einstein

6.1 Introduction

This chapter will begin by answering the main research and then go into a detailed discussion of each research objective. This chapter discusses the main trends, patterns and connections developed through the thematic data analysis. The chapter will summarise and discuss salient participants, including anomalies, surprise findings, deviations, and the underlying reasons for this. The chapter will also outline the relevance of the study in so far as its significant contribution to knowledge, and the implications of the research findings on research and practice.

6.2 Discussion of the main Research Question

The project identified seven theoretical frameworks that can be used to explore the factors that influence the adoption of Big Data Analytics in Supply Chain Risk Management by supply chain professionals. The researcher adopted the UTAUE framework as the theoretical framework that will be used to guide the development of a research protocol that was implemented during the semi-structured interviews. The findings revealed that the organisational and support context, the attitudes of supply chain professionals along with support systems and big data management capabilities influence supply chain professionals to adopt Big Data Analytics in Supply Chain Risk Management. In short, for supply chain professionals to successfully adopt and use Big Data Analytics in Supply Chain Risk Management, it is important to solicit the attitudes of supply chain professionals towards Big Data Analytics, that will enable the organisation to develop the support systems and Big Data management capabilities that are responsive to competitive pressures within the organisational context.

6.3 Discussion and Interpretation per Research Objective

6.3.1 Objective 1: To review the adoption of Big Data Analytics in Supply Chain Risk Management

The literature review revealed that Big Data, Big Data Analytics and Supply Chain Risk Management are contested concepts, and different researchers have sought to quell these contestations. The researcher found in the literature that Big Data Analytics has an essential role in improving the flow of information in the supply chain, thus integrating Supply Chain Risk Management practises into Supply Chain Management. In the manufacturing industry, Big Data Analytics finds application in supply chain network design and optimisation; strategic source; demand planning; transportation and distribution. Big Data Analytics can improve the reactive and proactive management of supply chain risks. Big Data Analytics enhances the identification and evaluation of supply chain risks, facilitates resilience planning, and reduces demand uncertainty.

During the fieldwork, it was found that supply chain professionals apply Big Data Analytics to gain visibility into their supply chain to anticipate potential risks better. Further, that participants utilised Big Data Analytics to enhance the decision-making process. Big Data Analytics was perceived as providing the organisation with the competitive advantage of the improved flow of information required for decision-makers. Supply chain professionals frequently apply Big Data Analytics to optimise supply chain execution by reducing demand uncertainty, confirming the findings of Baryannis, G. et al. (2019). As part of supply chain planning, supply chain professionals view Big Data Analytics as essential to supply chain network and demand planning. This finding is supported by Baryannis, G. et al. (2019); Engelseth, P. et al. (2018). Supply chain professionals also employ Big Data Analytics to continuously probe transport-related risks, a finding in line with the results of Engelseth, P. et al. (2018).

6.3.2 Objective 2: To identify theoretical frameworks and models for understanding the adoption of Big Data Analytics in Supply Chain Risk Management.

Several models are appropriate for the study of the adoption of Big Data Analytics that have been employed in the literature. Seminal studies revealed the UTAUT, TOE framework, Trust-In-Technology (TT), Diffusion of Innovation, Decomposed Theory of Planned Behaviour, Technology Adoption Model, and Technology Task Fit (TTF) were the most common technology adoption models to study BDA adoption. Surprisingly, these models have combined another theoretical model known as the Resource-Based View. The integration of the Resource-Based View with technology adoption models reveals that Big Data Analytics is being viewed as an organisational resource that must be managed efficiently and effectively.

Table 7: Theoretical Models to study adoption of Big Data Analytics

Model	**Author**
UTAUT	Queiroz and Pereira (2019); Cabrera-Sánchez and Villarejo-Ramos (2019); Aghimien et al. (2021); Alharbi, S. T. (2014)
TOE	Walker, R. S. et al. (2019); Youssef, Eid and Agag (2022); Maroufkhani, et al. (2020); Lai, Sun and Ren (2018); Maroufkhani, Parisa et al. (2020); Maroufkhani, P. et al. (2020); Alaskar, T. H. et al. (2021)
Trust-In-Technology (TT)	Madhlangobe, W. (2018);
Resource-Based View (RBV)	Maroufkhani, Parisa et al. (2020); Wamba, S. F. et al. (2017)
Diffusion of Innovation (DOI)	Maroufkhani, P. et al. (2020)
Decomposed Theory of Planned Behaviour	Zaman, U. et al. (2021)
TAM	Shahbaz, M. et al. (2019); Verma, S. et al. (2018); Ibrahim Youssef, A. et al. (2022)
Technology Task Fit (TTF)	Shahbaz, M. et al. (2019)

6.3.3 Objective 3: To design a research protocol for investigating factors that influence the adoption of Big Data Analytics in Supply Chain Risk Management.

The conceptual framework adopted in this study is depicted in Figure 3, in section 3.3 of Chapter 3. This conceptual model assumes that Trust is a predictor of Performance Expectancy, whilst Performance Expectancy, Effort Expectancy and Social Influence the behavioural intent. Facilitating Conditions along with behavioural intent influence usage behaviour. Age, gender, experience, and voluntariness of usage impact the predictor variable.

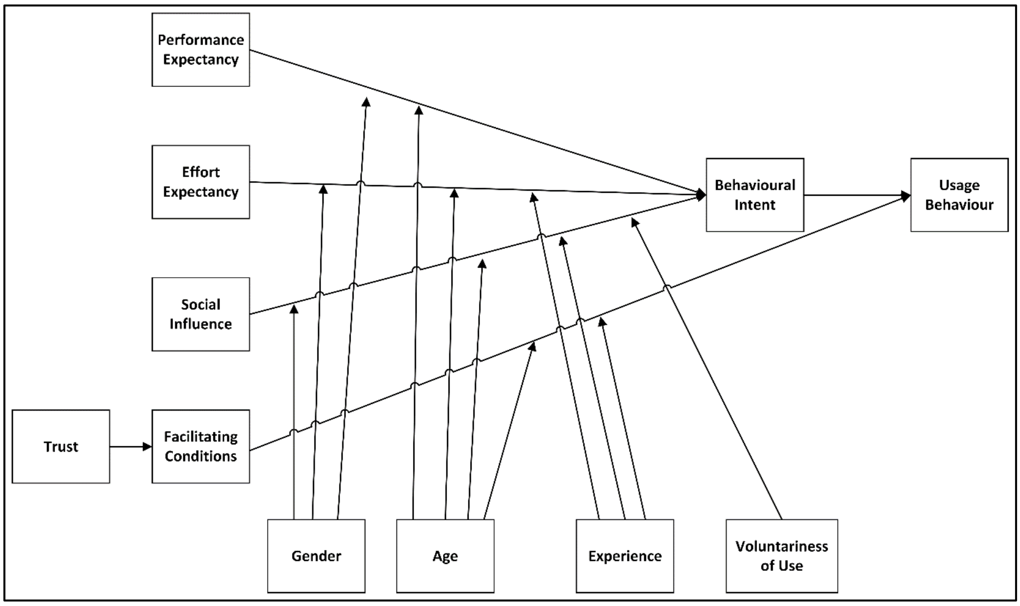


Figure 20: Revised UTAUT Framework

6.3.4 Objective 4: To determine the factors influencing the adoption of Big Data Analytics in Supply Chain Risk Management.

The conceptual model discussed above was employed as part of the data collection and thematic data analysis process. The themes were mapped onto this conceptual framework, as depicted in Table 8 below.

Table 8: Alignment of Themes and Conceptual Framework

Theme	**Performance Expectancy**	**Effort Expectancy**	**Social Influence**	**Facilitating Conditions**	**Trust**	**Behavioural Intention**	**Usage**
Organisational Context			X	X		X	X
Support Context		X		X			
Big Data Management				X	X		X
Attitudes						X	X

Competitive Pressures	X						X

6.3.4.1 Organisational Context

The researcher found that the adoption of BDA in SCRM is limited, confirming the results of Shahbaz, M. et al. (2019), who found that BDA is still in the initial stages. There is evidence that budgetary constraints tend to influence the behavioural intention to adopt BDA in SCRM. This finding is similar to that of Verma, S. (2017); Verma, S. et al. (2018). The fieldwork further confirmed that supply chain managers are also contesting terms such as Big Data and Big Data Analytics. The researcher found that these contestations are influencing the adoption of BDA in SCRM and that for professionals to adopt BDA in SCRM, these concepts must be clearly defined within the organisation. This finding supports Verma, S. et al. (2017), who found that the organisational data environment influences BDA adoption.

6.3.4.2 Support Systems

The research confirmed during the fieldwork that the role of Big Data Analytics in Supply Chain Risk Management is still largely dependent on a skilled, experienced and innovative supply chain professional cohort capable of leveraging Big Data Analytics. Although skills availability influences behavioural intention, participants did not perceive this as a hindrance to adopting BDA in SCRM. This finding is contrary to the findings by Verma, S. (2017); however, the results of Cabrera-Sánchez, J.-P. et al. (2020) reaffirm the researcher's findings that effort expectancy is not that significantly influential on behavioural intention to adopt Big Data Analytics in Supply Chain Risk Management. The researcher also found that using consultants as part of an external support system was supported by the literature, particularly by Marchena Sekli, G. F. et al. (2021).

6.3.4.3 Big Data Management

The researcher found that participants trusted Big Data Analytics, and these findings are supported by Sun, S. et al. (2020). Supply chain professionals asserted that trust in Big Data, Big Data Analytics and Big Data Quality influences their behavioural intention to adopt BDA in SCRM, a finding in concurrence with the results of Lai, Y. et al. (2018); Walker, R. S. et al. (2019). Findings support those of Shahbaz, M. et al. (2019), who found that trust is a significant predictor of behavioural intention. Furthermore, it was confirmed that trust within this context is directly linked to how the organisation manages its information technology infrastructure, leading the researcher to conclude that trust may be a crucial facilitating condition. This contradicts the findings of Queiroz, M. M. et al. (2019), who concluded that trust is a predictor of performance expectancy.

The study also found that participants are willing to trust Big Data Quality. These findings align with those of Verma, S. (2017); Walker, R. S. et al. (2019). Findings confirm that management's focus on improving the data quality for purposes of enabling adoption is supported by the work of (Verma, S. et al., 2018), who found that managers who focused on information quality and systems quality had a higher behavioural intention to adopt Big Data Analytics.

6.3.4.4 Attitudes

The researcher found that top management of Company X, influences the adoption of BDA in SCRM, and these findings contradict those of Marchena Sekli, G. F. et al. (2021); Queiroz, M. M. et al. (2019) but align with the findings of Alsaad, A. et al. (2019); Chen, D. Q. et al. (2015); Sun, S. et al. (2020). This study found that top management is driving the adoption and utilisation of BDA in SCRM. These findings support that of Bremser, C. (2018), who found that financially ready organisations with an innovation-driven business strategy tend to adopt a Business First approach. However, supply chain professionals could also interpret these findings as involuntary usage of BDA.

6.3.4.5 Competitive Pressures

Further findings support prior research by Alaskar, T. H. et al. (2021); (Chen, D. Q. et al., 2015; Sun, S. et al., 2020; Walker, R. S. et al., 2019) that competitive pressures do influence the adoption of Big Data Analytics as competitors tend to reinforce the behavioural intention to adopt innovative technologies. The researcher found that the attainment of competitive advantage is an essential factor influencing the adoption of BDA in SCRM. These findings tend to contradict the findings by Queiroz and Pereira (2019). Barratt, M. et al. (2007) argued that real-time data exchange, such as point of sales data for demand information, significantly can assist in gaining supply chain visibility, thus improving performance that would result in a sustainable competitive advantage for retailers.

6.4 Significance of Findings

This research study's significant original contribution to research is a theoretical framework that lists the factors that influence supply chain professionals in the manufacturing industry to adopt Big Data Analytics in Supply Chain Risk Management within a developing country such as South Africa. This study identified the organisational context, support systems, Big Data management practises and competitive pressures influencing the adoption of Big Data Analytics in Supply Chain Risk Management by supply chain professionals in the manufacturing industry. The findings arrived at are significant in both research and practice. This research study's original contribution is exploring the factors that influence supply chain professionals in the manufacturing industry to adopt Big Data Analytics in Supply Chain Risk Management within a developing country such as South Africa. These insights can assist scholars and practitioners in understanding what hinders the integration of Supply Chain Risk Management in Supply Chain Management. Given that firms in developing countries are not immune to global supply chain risks, and firms in South Africa are not exempt from global competition, the adoption of Big Data Analytics is worth considering as there is a paucity of literature and insufficient studies within developing countries. This research study expanded the body of knowledge by exploring the concept of Big Data Analytics as an information management tool within a manufacturing firm in a developing country. Finally, this research study also identified different theoretical models that can be utilised in future studies looking into adopting Big Data Analytics.

6.5 Assumptions and Limitations

The study is limited to understanding the phenomenon in a single case and may not represent the whole target population, thus impacting generalisability. The primary assumption is that the interview request and invitations will receive a reasonable response rate. The other main limitation is the time and labour required, including developing interview guides, conducting the interview, transcribing the interview and coding the transcript. These limitations are further impacted by whether the respondents are given an accurate and honest recollection of their experiences and thoughts. The use of online platforms poses limitations such as the inability to read body language, develop a rapport and over disclosure, that should be explored further in future research to better understand how to improve the online interview methods.

6.6 Recommendations for Practitioners

Organisations should focus on improving Big Data management practises such as information management and information security so that supply chain professionals can trust Big Data Analytics. Supply chain professionals should identify specific use cases that showcase the improvements in supply chain visibility, decision-making and the competitive advantage of the organisation that must be further developed, by supply chain managers, into sound business cases that support the adoption of Big Data Analytics in Supply Chain Risk Management. Supply chain managers should ensure that they support the adoption of Big Data Analytics in Supply Chain Risk Management by aligning business cases with the business strategy. Organisations should further reinforce the trust of supply chain professionals in Big Data Analytics by delivering on the use cases that have already been identified by the supply chain professionals and soliciting feedback from supply chain professionals on the implemented solutions. Organisations should also consider using consultants for rapid adoption and usage of Big Data Analytics with the caveat that new information, knowledge and skills must be shared with internal technical implementation partners. The findings suggest that organisations should consider investing in training interventions that are informed by a business need as identified in the business case.

6.7 Suggestions for further research

Future research should consider using focus groups to understand how supply chain professionals define terms such as Big Data, Big Data Analytics, and Supply Chain Risk Management. The objective of such a project would be to bridge the contestations between the literature and practitioners. Future research should also seek to find out how BDA is implemented to gain further insights into processes, techniques and methods utilised within the context of SCRM. The researcher also suggests a longitudinal study consisting of panel interviews of supply chain professionals and academics to understand better how the Information Management Body of Knowledge could be utilised to guide the implementation of Big Data Analytics in Supply Chain Risk Management.

6.8 Final Reflections

The reflexive philosophy guiding this study necessitates final reflections. This study utilised information and communication technology platforms to collect qualitative data using semi-structured interviews. This was advantageous in many respects, however, my speech impediment presented an additional challenge during the data collection that would ultimately influence the transcription. Considerations should be given about whether providing potential participants with written interview questions before or during the interview could significantly lower this barrier and whether this could ultimately influence the results of the study. With this in my mind, the transcription process can no longer be seen as a backroom task whose decisions cannot be made explicit. The researcher hopes that by reflecting on his own experience of the role speech disfluency may have had on the transcription process, that future and that transcription platforms such as the one employed in this study will be readily accessible for future researchers who can then dedicate a section in their methodology chapter describing their stance on the transcription process.

6.9 Final Conclusions

Manufacturers should consider that the organisational context, support systems, attitudes, competitive pressures, and Big Data management practices influence the adoption of Big Data Analytics in Supply Chain Risk Management. Supply chain professionals are concerned about budget constraints, technical support, training, skills availability, and data quality. Supply chain professionals require legal and technical protection mechanisms to build trust in Big Data Analytics.

6.10 Chapter Summary

The first three chapters of this mini dissertation provided the reader with the background to the research problem, it reviewed the literature relevant to the research problem, and outlined the theoretical framework to be utilised within the study. Chapter 4 detailed the research design and methodology, and Chapter 5 presented the results of the study. This chapter discussed the findings of the study per research objective within the context of the literature. The chapter also concluded on the main research question. The chapter further explicitly stated the significant original contribution to knowledge is the refined theoretical framework which lists the factors influencing the adoption of Big Data Analytics in Supply Chain Risk Management. The chapter also addressed the assumptions and limitations of the study, and expounded on the implications of the research findings for practitioners and suggested future areas of research based on the research findings. Finally, the researcher provided their final reflections of the research project given the reflexive nature of qualitative research.

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Appendix A: Interview Guide

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Research Instrument Interview Schedule
Interviewer: Mfundo Zwane
Date:

Section 1 – Introduction (0 – 3 minutes)

1.1. Thank participant for accepting invite
1.2. Indicate the duration of the interview
1.3. Discuss the focus of the interview
1.4. Remind the participant about Confidentiality of the interview
1.5. Request Consent and remind participant so submit written informed consent.

Section 2 – Demographics (3 – 5 minutes)

2.1. Age
- a. 18-29
- b. 30–39
- c. 40–49
- d. 50–59
- e. 60–69

2.2. Gender
- a. Male
- b. Female

2.3. Education
- a. Grade 12
- b. Diploma
- c. Bachelors
- d. Honours
- e. Masters
- f. PhD

2.4. Experience
- a. 0 – 3 years
- b. 3 -5 years
- c. 5 – 10 years
- d. 10 – 15
- e. 15+

2.5. Role
- a. Supply Chain Officer
- b. Supply Chain Analyst
- c. Supply Chain Manager
- d. Data Analyst
- e. Data Manager
- f. Executive

Section 3 – BDA Adoption Overview (5 – 10 minutes)

3.1. Is your organisation currently using Big Data Analytics (BDA) in Supply Chain Risk Management (SCRM)?
3.2. What, in your opinion, are the main drivers for the adoption (or lack thereof) of BDA in SCRM in your organisation?
3.3. What do you think may be limiting other organisations from adopting the adoption of BDA to support SCRM?

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Section 4 – Adoption Factors (10 – 20 minutes)

4.1. Do you think the adoption of BDA in SCRM has given your organisation a competitive advantage? And would you recommend it to other organisations and why do you say this? [*Performance Expectancy*]
4.2. Was it easy to find the skills and knowledge to adopt BDA within your organization? If no, were external consultants used or were skilled persons hired specifically for this implementation? [*Effort Expectancy*]
4.3. How does your organization support the adoption of BDA in SCRM? (Do staff receive enough time to learn how to operate the application? Did they motivate staff to use BDA?) [*Social Influence*]
4.4. How does BDA fit with the other SCRM systems you use during your work? And did you need technological infrastructure (hardware/software) changes to implement BDA in SCRM? [*Facilitating Conditions*]
4.5. Did you need external parties to assist with the implementation and integration of systems to implement BDA in SCRM? [*Facilitating Conditions*]
4.6. Are you able to get help from others when you have difficulties using BDA? [*Facilitating Conditions*]
4.7. Do you think you will have any constraints to use BDA in SCRM in future that we didnot cover yet? [*Behavioural Intention*]
4.8. Do you think you can trust BDA; and are there are legal and technological structures to protect you from problems with BDA? [*Trust*]

Section 5 – Conclusion (3 – 5 minutes)

5.1. Are there any other things you would like to ask or share regarding this study?
5.2. Would you like a copy of the transcript?
5.3. Would it be possible for me to contact you after this interview by email if I have further questions?

Section 6 – End

6.1. Thank participant for availing themselves for the interview

Appendix B: Questions Excluded from Final Interview Protocol

Questions Excluded from Final Interview Protocol

Interviewer: Mfundo Zwane

Pilot Interview Date: 03 November 2021

Big Data Analytics Adoption Factors

1. Performance Expectancy
    a. What expectations did you have of the added value of the adoption of BDA in support of SCRM?
    b. To what extent did BDA meet these expectations?
    c. Do you have any negative experiences of BDA in support of SCRM that you can share?
    d. Would you recommend it to other organisations and why do you say this?
2. Effort Expectancy
    a. What type of technical and business skills and knowledge were required prior to the adoption of BDA to support SCRM?
    b. Which expectations did you have of the effort needed learning to implement BDA in SCRM?
    c. And how was your experience regarding the actual effort needed to learn how to utilise BDA in SCRM?
    d. Which expectations did you have of the effort needed to use BDA in support of daily SCRM?
    e. And how was your experience regarding the actual effort needed to employ the application daily?
3. Social Influence
    a. What do your colleagues and supervisors think of the adoption of BDA in SCRM?
    b. How important and what influence does their opinion have on you?
4. Facilitating Conditions
    a. Do you believe you have the proper resources and knowledge to use BDA in SCRM? why? (If not, could you ask someone for help?)
    b. How does BDA fit with the other SCRM systems you use during your work?
    c. Did you need technological infrastructure (hardware/software) changes to implement BDA in SCRM?
5. Behavioural Intention
    a. How do you view your future use of BDA in SCRM? (more/less/equal/quitting)

Appendix C: Systematic Literature Review Protocol

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Systematic Literature Review Protocol

Reviewer: Mfundo Zwane

Research Question

The objectives of the Systematic Literature Review are to:

- Review the adoption Big Data Analytics in Supply Chain Risk Management.

The overall aim of the Systematic Literature Review is to determine:

- What is the role of Big Data Analytics in Supply Chain Risk Management?

Search Strategy

2.1. Data Sources

a. Web of Science: https://www.webofscience.com/wos/woscc/basic-search

b. Scopus: http://www.scopus.com

2.2. Search String

(("big data analytics" OR "BDA") AND ("supply chain risk management" OR "SCRM"))

Selection Criteria

3.1. Inclusion Criteria

- Peer Reviewed Article

3.2. Exclusion Criteria

- Book Chapter
- Conference Paper
- Conference Review
- Document Not Found
- Non-English Language
- Review

Quality Assessment Criteria

Criteria	Response		
Is the study of value for research or practice?	Yes	Partially	No
Is this a research paper?	Yes	Partially	No
Is there a clear statement of the aims of the research?	Yes	Partially	No
Is there an adequate description of the context in which the research was conducted?	Yes	Partially	No
Was the research design appropriate to address the aims of the research?	Yes	Partially	No
Was the recruitment strategy appropriate to the aims of the research?	Yes	Partially	No
Was there a control group with which to compare treatments?	Yes	Partially	No
Was the data collected in a way that addressed the research issue?	Yes	Partially	No
Was the data analysis significantly rigorous?	Yes	Partially	No
Has the relationship between the researcher and participants been considered to an adequate degree?	Yes	Partially	No
Is there a clear statement of findings?	Yes	Partially	No
Was the data collected in a way that addressed the research issue?	Yes	Partially	No
Was the data analysis significantly rigorous?	Yes	Partially	No
Has the relationship between the researcher and participants been considered to an adequate degree?	Yes	Partially	No

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Data Extraction

4.1. Data to be Collected:

- ID
- Date
- Bibliographic reference
- Type of Article
- Study aims
- Objectives
- Design of study
- Research Method
- Research hypothesis
- Research Question
- Definition of Big Data Analytics
- Industry
- Use Case/Application
- Theoretical Framework
- Setting of study
- Sample description
- Control group
- Data collection
- Data Analysis
- Findings and conclusions
- Validity
- Relevance

Appendix D: Ethical Clearance

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60 YEARS *of hope, action & knowledge*

20 July 2021

Mr M Zwane
Information Systems
Faculty of Economic and Management Sciences

HSSREC Reference Number:	HS21/5/27
Project Title:	The adoption of big data analytics in supply chain risk management: A case in the Manufacturing industry semi-structured interviews with supply chain professionals.
Approval Period:	16 July 2021 – 16 July 2024

I hereby certify that the Humanities and Social Science Research Ethics Committee of the University of the Western Cape approved the methodology and ethics of the above mentioned research project.

Any amendments, extension or other modifications to the protocol must be submitted to the Ethics Committee for approval.

Please remember to submit a progress report by 30 November each year for the duration of the project.

The permission to conduct the study must be submitted to HSSREC for record keeping purposes.

The Committee must be informed of any serious adverse events and/or termination of the study.

Ms Patricia Josias
Research Ethics Committee Officer
University of the Western Cape

Director: Research Development
University of the Western Cape
Private Bag X 17
Bellville 7535
Republic of South Africa
Tel: +27 21 959 4111
Email: research-ethics@uwc.ac.za

NHREC Registration Number: HSSREC-130416-049

FROM HOPE TO ACTION THROUGH KNOWLEDGE.

Appendix E: Interview Information Form

Private Bag X17, Belville, 7535
South Africa
Tel: +27 (0) 21 959 3680
Fax: +27 (0) 21 959 3522
www.uwc.ac.za

Faculty of Economic and Management Sciences
Department of Information Systems
Interview Information Sheet

Project Title:	The adoption of big data analytics in supply chain risk management: A case in the manufacturing industry

What is this study about?
My name is Mfundo Njabulo Zwane, a student at the University of the Western Cape (South Africa) pursuing a Master of Commerce in Information Management specialising in e-Logistics. The purpose of this research study is to determine the factors that influence supply chain professionals to adopt big data analytics in support of supplychain risk management of a selected manufacturer in the Western Cape.

What will I be asked to do if I agree to participate?
If you agree to participate in this research project, you will be required to participate in an interview for the purpose of this study. Completion of this interview will take approximately 45 – 60 minutes. If you do not want to answer any question, you do not have to.

Would my participation in this study be kept confidential?
You are not required to provide any personal details, such as your name, address or identity number. The participants' responses will remain strictly confidential and anonymous.

What are the risks of this research?
There are no known risks associated with participating in this research process. This research will not expose you to any harm as a consequence of your participation.

What are the benefits of this research?
The outcomes of this study will give manufacturers a deeper understanding of the factors that impact the integration of big data analytics within supply chain risk management processes.

Do I have to be in this research and may I stop participating at any time?
Your participation in this survey is completely and entirely voluntary. You are free to withdraw from the study at any point in time.

What if I have questions?
If you have any questions feel free to contact the study leader:

Contact details of student
Name: Mfundo Njabulo Zwane
Telephone:
Email:

Contact details of project leader (study supervisor)
Name: Dr Carolien van den Berg
The University of the Western Cape, Department of InfoOrmation Systems
Telephone:
Email:

NOTE: *This research project has received ethical approval from the Humanities & Social SciencesResearch Ethics Committee of the University of the Western Cape, Tel. 021 959 2988, email: research- ethics@uwc.ac.za.*

Appendix F: Technical Information Sheet

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Faculty of Economic and Management Sciences
Department of Information Systems

Interview Technical Sheet

As you are aware, the pandemic COVID-19 has presented some challenges in conducting qualitative research interviews. Universities have recommended the use Microsoft Teams when conducting interviews that require confidentiality and have specific data protection requirements.

Microsoft Teams can be used to facilitate interviews where the discussion is expected to include sensitive data. We have scheduled the interview with you as follows:

Location: Microsoft Teams Platform (Big Data Analytics in SCRM Team)
Date: 03 November 2021
Time: 09h00 – 10h00
Meeting Link: Join Here

What is Microsoft Teams?

Microsoft Teams is an app that brings conversations, meetings and files together in one place. Teams is accessible via the internet and you can download the desktop app for Mac /Windows PC's and laptops. The interview will record and transcribe the interview on Microsoft Teams platform.

Hardware Requirements

1. Microsoft Teams

The interview will be conducted online via Microsoft Teams and therefore certain requirements will need to be met. To avoid this issue we advise that you join the interview via your browser in Cognito/Private Mode so as to protect your identity and confidentiality of this research.

If you will be using a desktop version of the Microsoft Teams, you may check the hardware requirements here.

2. Audio-visual

You may use a pair of earphones should you wish. It is important that your microphone on the earphone be clear and in working order prior to the interview.

Access to a device with a camera is not required for this interview so as to ease the network connectivity. The participant and the researcher may be required to switch the camera on for identification purposes.

3. Networking

Kindly ensure that you have accessible and reliable internet, and that your camera is switched off to conserve bandwidth.

Appendix G: Consent Forms

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University of the Western Cape
Faculty of Economic and Management Sciences
Department of Information Systems

Research Participant Consent Form: Questionnaire

Project Title:	**The adoption of big data analytics in supply chain risk management: A case in the manufacturing industry**

Please tick Yes or No to each of the following

	Yes	No
1. I confirm that I have read and understand the information sheet explaining the above research project and I have had the opportunity to ask questions about the project.	☑	☐
2. I understand that my participation is voluntary and that I am free to withdraw at any time without giving any reason and without there being any negative consequences.	☑	☐
3. I understand that should I not wish to answer any particular question or questions, I am free to decline.	☑	☐
4. I understand my responses and personal data will be kept strictly confidential. I give permission for members of the research team to have access to my anonymised responses. I understand that my name will not be linked with the research materials, and I will not be identified or identifiable in the reports or publications that result for the research.	☑	☐
5. I agree for the data collected from me to be used in future research.	☑	☐
6. I agree to take part in the above research project.	☑	☐
7. I consent to being recorded and my data being processed for purpose of this research project.	☑	☐

Name of Participant Date Signature

Name of person taking consent Date Signature

Contact details of study supervisor:
Name:
University of the Western Cape
Department of InfoOrmation Systems
Telephone:
Email:

Appendix H: Codebook

Theme	Sub-Theme	Category	Code
Attitude	Adoption Willingness	Willingness to adopt	I am willing to adopt
		Willingness to recommend adoption	I am willing to recommend adoption
	Involuntary Usage	Superior	Improving Utilization
			Incentives and rewards
Competitive Pressures	Competitive Advantage	Competitors	Competitive culture
		Decision-making	Improved decision-making
		Supply chain visibility	End-to-end SCRM
		Insight and Foresight into risks	Predictive risk management
Information Management	Information Management	Cloud technology	No new hardware
			Data Lake
		Legacy systems	New software
			System Integration
	Information Security	Information Security	Data protection
			Data anonymization
			Legal Protection
	Trust in Big Data Analytics	Data Analytics	Analytics Use Cases
		Data Quality	Improving data quality
			Poor data quality
Organisational Support	Business Strategy	Business case	Budget constraints
		Operational Structure	Inability to scale
		Organisational culture	Siloes
			SCM Maturity
		Consensus on Contestations	Consensus on Big Data & BDA definition
			SCRM definition
	Drivers	Availability of data	Availability of data
		Business strategy	Business strategy

	Extent of Adoption	Usage	Adoption in phases
			Limited adoption
Support System	Experts and Consultants	External consultants	Best-practices
			New information
	Skills Availability	Shortage of technical skills	Lack of business knowledge
			Talent shortage
		Internal skills	It was not difficult to find skills
			It was difficult to find skills
	System Support	Technical support	Assistance with difficulties
			Assistance from colleagues
			External assistance
	Centre of excellence	Users buy-in	Technical skills support
			Technology infrastructure
			Internal colleagues
	Training	Lack of training	Training interventions