THE IMPACT OF ARTIFICIAL INTELLIGENCE CAPABILITIES ON ORGANISATIONAL PERFORMANCE: AN EMPIRICAL STUDY IN THE SOUTH AFRICAN RETAIL CONTEXT

UNIVERSITY OF THE WITWATERSRAND, JOHANNESBURG

Wits Business School

Sculpting global leaders

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

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Johannesburg, 2024

ABSTRACT

Developing the ability to undergo digital transformation with Artificial Intelligence (AI) is increasingly crucial for retail organisations, given the rising occurrence of AI-driven activities within their organisations. This underscores the need to understand how retail organisations should structure themselves to leverage AI effectively and in what ways value can be attained. Within this context, this thesis investigates how AI capabilities can enhance organisational performance by prompting changes in critical organisational activities. Through a survey-based research approach, data was gathered from individuals within retail organisations in South Africa to explore the indirect impact of AI capabilities on organisational performance. A total of 145 participants from South Africa's retail sector were surveyed, and their responses were analysed using structural equation modelling with AMOS/ SPSS. The results indicate that AI capabilities positively influence process automation, cognitive insight generation, cognitive engagement, and innovativeness. While both process automation and innovativeness positively correlate with organisational performance, it was observed that cognitive insights and cognitive engagement do not significantly affect organisational performance. These findings explain the essential resources comprising an AI capability and highlight the consequences of nurturing such capabilities on critical organisational activities, thereby influencing organisational performance.

KEYWORDS

Artificial Intelligence (AI), Artificial Intelligence Capabilities, Organisational Impact, Organisational Performance, Resource-Based View (RBV) Theory, Process Automation, Cognitive Insights, Cognitive Engagements, Innovativeness, South Africa, Retail Organisations.

DECLARATION

I, Dylan Christo Cronjé, declare that this research report is my own work except as indicated in the references and acknowledgements. It is submitted in partial fulfilment of the requirements for the degree of Master of Management in the field of Digital Business and the University of the Witwatersrand, Johannesburg. It has not been submitted before for any degree or examination in this or any other university.

Name: ***Dylan Christo Cronjé*** Signature: 

Signed at: ***Cape Town***

On the ***29th*** day of ***February*** 20 ***24***

DEDICATION

Dedicated to my loving family, whose unwavering support and encouragement have been my source of strength throughout this academic journey. To my friends and mentors, your guidance and belief in me have been invaluable. And to all those who have inspired and motivated me along the way, this thesis is a testament to your influence on my life and my pursuit of knowledge. Thank you.

ACKNOWLEDGEMENTS

The assistance and guidance provided by the individuals mentioned below, have been instrumental throughout this academic journey:

I am profoundly thankful to my supervisor, Dr T.N Mudau, for his assistance during this Masters thesis journey.

I extend my deepest appreciation to my family for their support and encouragement throughout the duration of my studies.

I acknowledge the contribution of the academic experts, professionals within the South African retail sector, executives, and fellow Masters students who graciously devoted their time and expertise to participate in the exploratory study. Their invaluable insights and feedback significantly enhanced the research process.

I am also appreciative of the individuals who took part in the study, thereby aiding in refining and validating the research methodology.

Lastly, I express my gratitude to God for His strength, kindness, and grace, which sustained me through the challenges encountered during the study, enabling me to persevere even during moments of uncertainty.

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AGFI:	Adjusted Goodness of Fit Index
AI:	Artificial Intelligence
AMOS:	Analysis of a Moment Structures
AVE:	Average Variance Extracted
AVEs:	Average Variance Extracted
CB-SEM:	Covariance Based Structural Equation Modelling
CFA:	Confirmatory Factor Analysis
CFI:	Comparative Fit Index
COE:	Cognitive Engagements
COI:	Cognitive Insights
CR:	Composite Reliability
CX:	Customer Experience
Df:	Degrees of Freedom
Dr.:	Doctor
EFA:	Exploratory Factor Analysis
GFI:	Goodness of Fit Index
H:	Hypotheses
ID:	Inter-Departmental Collaboration
IFI:	Incremental Fit Index
INO:	Innovativeness
KMO:	Kaiser–Meyer–Olkin test
LISREL:	Linear Structural Relation
M.I.:	Modification Indices
MIT:	Massachusetts Institute of Technology
MLE:	Maximum Likelihood Estimate
MM:	Master of Management
Mr.:	Mister
NFI:	Normed Fit Index
OP:	Organisational Performance
PA:	Process Automation
PCA:	Principal Components Analysis
RBV:	Resource-Based View
RFI:	Relative Fit Index
RMSEA:	Root Mean Square Error of Approximation
RO:	Research Objective
RQ:	Research Question
SEM:	Structural Equation Modelling
Sig.:	Statistical Significance
SPSS:	Statistical Package for Social Sciences
STATA:	Statistics and Data
TLI:	Tucker-Lewis Index
WBS:	Wits Business School

CHAPTER 1. INTRODUCTION

Retail organisations in recent years have embarked on a journey of digital transformation, harnessing innovative digital technologies like Artificial Intelligence (AI) (Legner, et al., 2017). It is now widely acknowledged that integrating AI into operations is imperative for retail organisations to deliver high-quality services to customers, shareholders, and stakeholders (Misuraca, van Noordt, & Boukli, 2020).

AI is seen as a means to enhance the agility of retail organisations in response to the rapidly changing operational landscape (Janssen & van der Voort, 2016) and to improve the efficiency and timely service provision to relevant parties (Douglas, Raine, Maruyama, Semaan, & Robertson, 2015). A notable example is the virtual assistant "Alex" employed by Australia’s Taxation Office, capable of addressing over 500 queries, engaging in 1.5 million conversations, and resolving over 81% of inquiries in the first contact. However, recent reports and empirical studies indicate that many retail organisations struggle to fully utilise their AI applications, raising questions about how and whether organisational value can be realised from such investments (Mikalef, et al., 2023). A recent report by (Gartner, 2021) underscores that while retail organisations are ramping up their AI investments, certain core areas still impede deployment, posing challenges for researchers and practitioners on how to harness AI applications to achieve organisational goals and document performance enhancements.

Despite numerous successful cases of AI deployment in retail organisations (Wirtz, Weyerer, & Geyer, 2019), there remains a limited understanding of how retail organisations can cultivate the capability to readily deploy AI applications in critical areas. The concept of an AI capability has emerged to describe organisations' capacity to plan and implement AI solutions to enhance key organisational activities (Mikalef & Gupta, 2021). This concept builds on the premise that organisations must cultivate a suitable bundle of resources to leverage AI's potential. Similarly, recent findings on AI usage in retail organisations highlight that many entities refrain from deploying AI due to resource constraints or other organisational barriers (Schaefer, Lemmer, & Kret, 2021). For example, several studies note challenges such as acquiring necessary data, securing financial resources for technological infrastructure, or overcoming personnel and cultural obstacles that hinder digital transformation (Jensen, 2020), (Wirtz, Weyerer, & Geyer, 2019), (Mikalef & Gupta, 2021).

To address this knowledge gap, this study builds upon the concept of an AI capability as an essential capability that retail organisations must nurture to derive value from unique digital technologies. Grounded in the resource-based view (RBV) of the organisation, it is proposed to use an adapted operationalisation of this concept, outlining three broad types of resources—tangible, intangible, and human—that retail organisations need to develop. It is argued that AI capabilities indirectly impact perceptions of organisational performance by driving changes in four key organisational activities: automating processes, enhancing cognitive insight generation, fostering cognitive engagement, and promoting innovativeness with customers and employees. This research contributes to the field by explaining the key dimensions retail organisations need to develop to realise value from AI and by empirically demonstrating the mechanisms through which improvements in organisational performance can be achieved. It also offers practitioners insights into how to approach unique digital technologies like AI and identifies areas where AI initiatives can be directed (Mikalef, et al., 2023).

To fulfil the objectives of this study, a questionnaire adapted from (Mikalef, et al., 2023) was distributed to individuals within retail organisations in South Africa. Structural equation modelling (SEM) was employed to empirically explore the research model and corresponding hypotheses.

The research objectives guiding the investigation include:

RO1: To examine the impact of AI capabilities on retail organisational activities within South Africa.

RO2: To determine the impact of operational activities on retail organisational performance within South Africa.

The remainder of this thesis is organised as follows. The next chapter presents the concept of an AI capability along with related work on its study in the context of retail organisations. Chapter 3 introduces the research model and hypotheses, followed by a description of the research method used to operationalise the objectives in Chapter 4. Chapter 5 presents the analysis of the results, while Chapter 6 discusses the theoretical and practical implications of this work and highlights some key limitations.

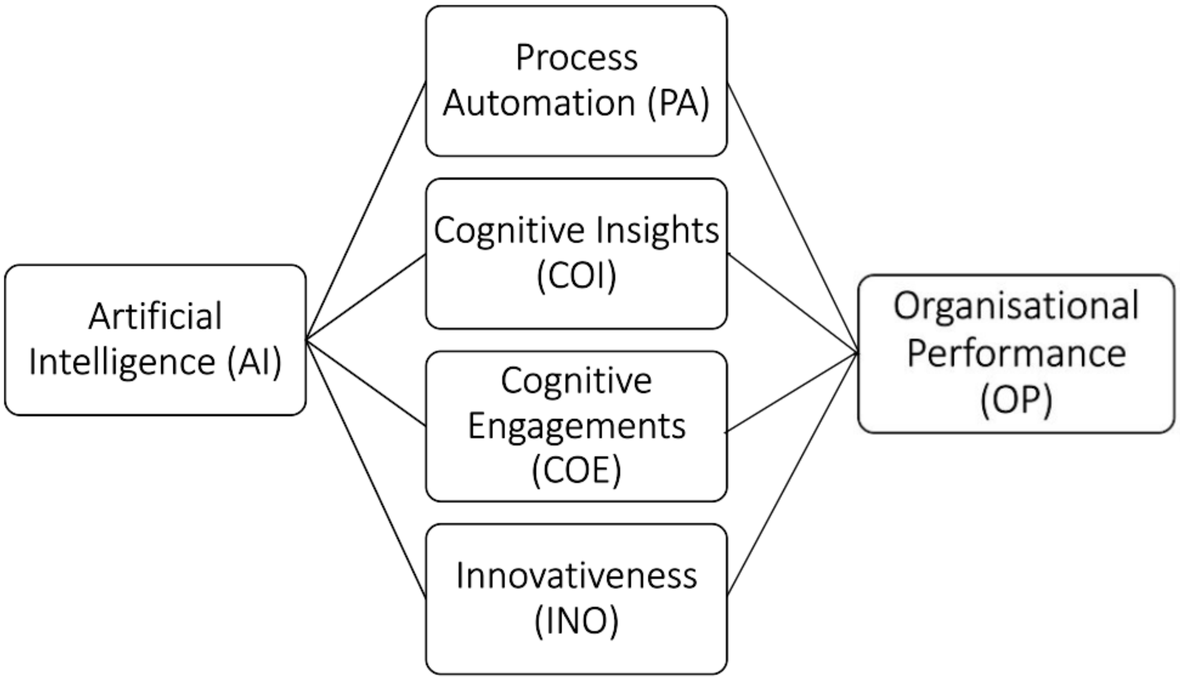

Figure 1: Adapted Resource-Based View Theory to include Innovation.

1.1. Research problem

The study investigates two main problems.

The *first problem* is to examine the impact of AI capabilities on retail organisational activities within South Africa. It is also necessary to further explore the influence of innovativeness within the amended RBV theory. While previous research has extensively discussed Artificial Intelligence (AI) capabilities and their implications for organisational performance (Davenport & Ronanki, 2018), there remains a dearth of empirical evidence to substantiate these claims. Notably, there is a lack of clarity on how retail organisations should strategise around AI and what value such investments are expected to yield. Some studies have underscored AI's potential to instigate various forms of organisational change (Wirtz, Weyerer, & Geyer, 2019), with (Davenport & Ronanki, 2018) proposing three distinct types of organisational impact:

process automation, enhanced stakeholder engagement, and innovative insights generation. However, much of the current research either relies on isolated cases or remains conceptual, failing to comprehensively analyse the varied mechanisms of value generation. Consequently, explaining how retail organisations should structure themselves around AI and recognising its overall effects on organisational performance pose significant challenges. The literature on AI capabilities suggests that by cultivating these organisation-wide capabilities, retail organisations can better deploy diverse AI applications, thereby influencing organisational performance through independent mechanisms (Mikalef & Gupta, 2021). AI capabilities empower retail organisations to exceed singular AI applications, facilitating digital transformation to enhance overall performance. As such, it is argued that AI capabilities apply indirect effects on organisational performance indicators by instigating changes in organisational activities. Understanding the factors that influence the innovative utilisation of organisational activities remains a critical research question. While some studies (Davenport & Ronanki, 2018) have identified a positive relationship between innovative usage of organisational activities, others (Wirtz, Weyerer, & Geyer, 2019) have found no significant impact on organisational performance. Given these disparate findings, it is imperative to better understand the relationship between usage and organisational performance. Addressing whether innovativeness is integral to enhanced organisational performance may offer insights into the discrepancies observed in previous research findings. The retail organisational context within South Africa presents an intriguing setting in which to investigate this question. Despite investments in AI capabilities often being made to support organisational activities, there is still a lack of clarity on how retail organisations should structure themselves around AI and the anticipated value of such investments.

The *second problem* is to determine the impact of the operational activities on organisational performance. Previous studies examining this impact primarily focused on evaluating performance in financial terms, such as profitability, while neglecting non-financial performance metrics (Davenport & Ronanki, 2018). This narrow emphasis on financial performance fails to provide a comprehensive assessment of organisational performance. Financial performance represents just one facet within a broader framework of performance measurement (Mikalef, et al., 2023). Other studies (Dwivedi, et al., 2021) exploring the impacts of Artificial Intelligence (AI) capabilities on non-financial performance focused solely on external business process improvement, neglecting other aspects like process automation, cognitive insights, cognitive engagements, and innovativeness. Consequently, the contribution of AI capabilities to enhancing organisational performance warrants further investigation. Analysing this relationship will assist retail organisations in substantiating their decisions to invest in AI capabilities. Furthermore, this study states that an important additional organisational activity influenced by AI capabilities has a positive effect on organisational performance. Previous studies (Wirtz, Weyerer, & Geyer, 2019) linking Innovativeness and organisational performance, however, have produced mixed results.

The combination of these research problems underscores the critical need for empirical research that systematically examines the challenges and opportunities associated with AI-driven digital transformation in the South African retail sector. By addressing these research problems, this study aims to provide actionable insights that can inform strategic decision-making and facilitate the successful adoption and integration of AI technologies in South African retail organisations, enhancing their organisational performance and competitiveness in the digital age.

The research objectives are outlined in section 1.4.

1.2. The Research Objectives

Given the research problems discussed above, this study has two objectives:

1.2.1. RO1: To examine the impact of AI capabilities on retail organisational activities within South Africa.

1.2.2. RO2: To determine the impact of the operational activities on organisational performance.

To achieve these objectives, the study addresses the following two research questions.

1.2.3. RQ1: What is the impact of AI capabilities on retail organisational activities within South Africa?

1.2.4. RQ2: What is the impact of the operational activities on organisational performance?

The study expands the Resource-Based View (RBV) Theory to examine RQ1 and RQ2 and explain the influence of artificial intelligence capabilities on organisational performance. To extend the RBV Theory (Barney J. B., 1991), innovativeness has been incorporated as an organisational activity requiring exploration within the context of the South African retail sector. The subsequent chapters address RQ1 and RQ2.

1.3. Rationale

This study addresses the pressing need to understand how Artificial Intelligence (AI) capabilities impact retail organisational activities and performance within South Africa. Despite the increasing adoption of AI in the retail sector, there is a lack of empirical evidence on its effectiveness and the mechanisms through which it influences organisational performance. By examining the impact of AI capabilities on organisational activities and performance, this research aims to fill this gap and provide actionable insights for retail organisations. Furthermore, by incorporating innovativeness within the Resource-Based View (RBV) framework, this study contributes to enhancing our understanding of how organisations can leverage AI to drive innovation and improve performance (Barney J. B., 1991). This research seeks to inform strategic decision-making and facilitate the successful integration of AI technologies in South African retail organisations, thereby enhancing their competitiveness in the digital age.

1.4. Delimitations of the study

1.4.1. The study focuses on retail organisations within South Africa.

1.4.2. The study examines the impact of AI capabilities on organisational performance.

1.4.3. The study includes the following AI technologies: personalised recommendations through customer analytics, chatbots and virtual assistants, pricing and promotion optimisation, voice commerce, and visual recognition and surveillance.

1.4.4. The study considers the effects of AI capabilities on customer experience (CX) and four key organisational activities: process automation, cognitive insights, cognitive engagement, and innovation.

1.4.5. The study adopts the concept of AI capabilities, which refers to the ability of an organisation to select, orchestrate, and leverage AI-specific resources.

1.4.6. The study is based on the resource-based view (RBV) theory, which explains the relationship between organisational resources and performance outcomes.

1.4.7. The study incorporates academic references from reputable sources to support theoretical propositions and justify the research.

1.5. Definition of terms

1.5.1. Artificial Intelligence (AI): The field of computer science that focuses on creating intelligent machines capable of imitating human cognitive functions, performing tasks in a human-like manner, and learning and self-correcting.

1.5.2. AI capabilities: The organisational ability to plan and implement AI solutions that improve key activities and contribute to enhanced organisational performance. It emphasises the development of a suitable cluster of resources to leverage the full potential of AI.

1.5.3. Organisational performance: The measurable results achieved by an organisation in relation to its goals and objectives. It encompasses various indicators, such as financial performance, customer satisfaction, operational efficiency, and innovation.

1.5.4. Digital transformation: The process of utilising digital technologies to fundamentally change and improve organisational processes, activities, and strategies, resulting in enhanced performance, efficiency, and customer experience.

1.5.5. Pricing and promotion optimisation: AI algorithms that analyse market data, customer behaviour, and pricing strategies to optimise pricing decisions and promotional offers, maximising revenue, and profitability.

1.5.6. Resource-Based View (RBV): A theoretical framework in strategic management that examines the relationship between an organisation's resources and its performance outcomes. It emphasises the importance of valuable, rare, and difficult-to-imitate resources in achieving a competitive advantage.

1.5.7. Tangible AI resources: Physical resources required for running AI applications, including equipment, data infrastructure, and other resources needed for the maintenance and operation of AI technologies.

1.5.8. Intangible AI resources: Non-physical resources related to AI adoption and implementation, such as the capability to initiate and implement change, technical skills for handling data and AI technologies, and managerial capabilities to understand the potential of AI in different organisational contexts.

1.5.9. Human-related AI resources: Human resources necessary for the development, training, and implementation of AI applications, including individuals with technical skills in handling data and AI technologies, as well as managerial capabilities to drive AI adoption and understand its diverse uses.

1.5.10. Process automation: The use of AI and technology to automate repetitive tasks and workflows, reducing manual effort, improving efficiency, and minimising errors.

1.5.11. Cognitive insights: The utilisation of AI and analytics to gain valuable insights and generate knowledge from substantial amounts of data, enabling informed decision-making and enhancing organisational understanding.

1.5.12. Cognitive engagement: The application of AI technologies, such as chatbots or virtual assistants, to engage customers or employees in interactive and personalised cognitive interactions, improving communication and experience.

1.5.13. Innovation: The process of implementing innovative ideas, products, or services that bring added value to an organisation. In the context of AI, it refers to the adoption of innovative AI applications and approaches that drive organisational change and improvement.

1.6. Assumptions

Participants have a basic understanding of AI technologies: It is assumed that the participants in the study have a certain level of knowledge and familiarity with AI technologies, given that the research focuses on the impact of AI capabilities on organisational performance. This assumption is reasonable as participants in retail organisations are likely to have encountered AI technologies in their work environment. The sensitivity of the research outcome on this assumption is low, as the study aims to explore the impact of AI capabilities rather than individual participants' knowledge of AI.

Retail organisations in South Africa have access to AI technologies: The assumption is that the selected retail organisations in South Africa have access to AI technologies, including personalised recommendations, chatbots, virtual assistants, pricing and promotion optimisation, voice commerce, and visual recognition and surveillance. This assumption is reasonable considering the increasing adoption of AI technologies in the retail industry globally. The sensitivity of the research outcome on this assumption is high, as the availability and utilisation of AI technologies are crucial for studying their impact on organisational performance.

AI capabilities contribute to improved organisational performance: It is assumed that the development and implementation of AI capabilities within retail organisations positively influence their organisational performance. This assumption is based on previous studies that suggest a positive relationship between AI capabilities and performance outcomes. The sensitivity of the research outcome on this assumption is high, as the study aims to explore the impact of AI capabilities on organisational performance.

The selected research methodology is appropriate: The assumption is that the chosen research methodology, which incorporates the resource-based view (RBV) theory and empirical analysis, is suitable for investigating the relationship between AI capabilities, customer experience, and organisational performance. This assumption is reasonable as the RBV theory provides a framework to understand the role of resources in achieving performance outcomes. The sensitivity of the research outcome on this assumption is moderate, as the chosen methodology will shape the analysis and interpretation of the findings.

The data collected is reliable and valid: It is assumed that the data collected through surveys are reliable and valid representations of the participants' perceptions and experiences. The sensitivity of the research outcome on this assumption is high, as the validity and reliability of the data influence the credibility and generalisability of this study's findings.

The research findings can be generalised to other retail organisations in South Africa: The assumption is that the research findings from the selected retail organisations in South Africa can be generalised to other similar retail organisations in the country. This assumption is reasonable as the study aims to contribute to the understanding of the impact of AI capabilities on organisational performance within the South African context. However, the sensitivity of the research outcome on this assumption is moderate, as the generalisability of findings depends on the representativeness of the sample and the uniqueness of each retail organisation.

1.7. Chapter outline

In Chapter 1, the research topic is introduced, an overview of the problem statement is provided, and its significance is highlighted. The objective of the study is outlines, emphasising the need to address the identified research gaps.

This chapter sets the foundation for the research, establishing the context and rationale for the investigation to follow.

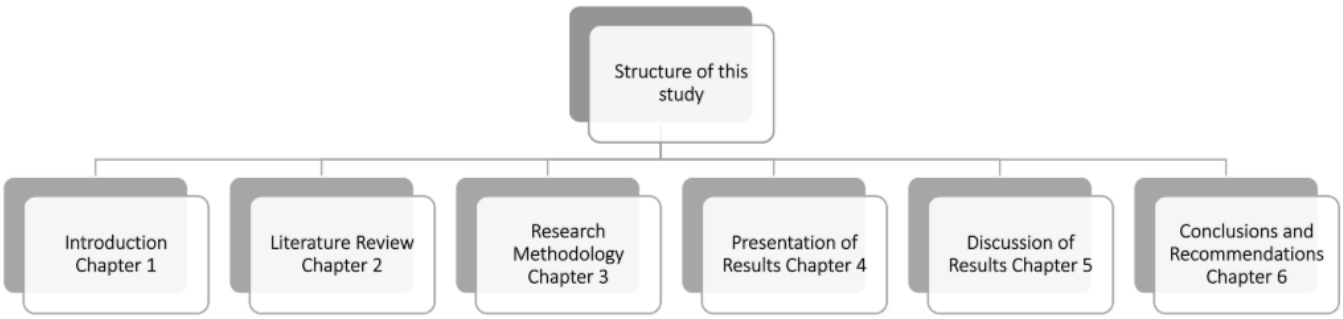

Figure 2: Study Outline Mapped to Thesis Chapters

CHAPTER 2: THEORETICAL UNDERPINNING OF THE STUDY

2.1. Introduction

The literature review investigates the impact of artificial intelligence (AI) on organisational performance within the framework of the Resource-Based View (RBV) theory, while also considering the integration of innovativeness into the RBV theory.

Emphasised within the literature is the increasing importance of AI capabilities within retail organisations, propelled by the requirements of digital transformation and the need to supply improved services to customers and employees (Misuraca, van Noordt, & Boukli, 2020). Nevertheless, hurdles persist in effectively harnessing AI applications, casting uncertainty on the ability of organisational value and performance enhancements (Mikalef, et al., 2023).

Established into this thesis is the concept of AI capabilities, indicating the organisational capacity to discern, coordinate, and exploit AI-specific resources (Mikalef & Gupta, 2021). These involve tangible assets such as equipment and data, human-related resources including technical expertise and managerial expertise, as well as intangible resources associated with initiating and executing change (Melville, Kraemer, & Gurbaxani, 2004).

The literature reflects on the various benefits afforded by AI adoption in retail organisations, including augmented customer experiences, heightened operational efficiency, refined demand projection and inventory management, augmented sales and revenue, and insights derived from data analytics (Wirtz, Weyerer, & Geyer, 2019). However, the exact impact of AI on organisational performance may fluctuate dependent upon factors such as organisational size, industry sector, AI deployment strategy, and data quality (Russell, Norvig, Davis, & Polson, 2021).

In the context of South African retail organisations, the application of AI technologies remains in its emerging phase (Mikalef, Fjortoft, & Torvatn, 2019). Whilst certain studies emphasise a positive influence of AI on organisational performance, numerous organisations struggle to realise these benefits due to flaws in AI capabilities (Davenport & Ronanki, 2018).

Thus, the research problem posits a lack of understanding regarding the challenges of AI implementation, essential resources for effective deployment within the South African retail environment, and the imperative to distinguish the consequences of AI capabilities on organisational performance. The study's objectives are outlined, focusing on scrutinising the impact of AI capabilities on process automation, cognitive insights, cognitive engagement, and innovation, together with providing insights into the ways that create improvements in organisational performance (Mikalef & Gupta, 2021).

2.2. Background discussion

2.2.1. Artificial intelligence capabilities in the retail sector

Artificial intelligence (AI) capabilities within the retail sector distinguish themselves from other technological advancements due to their capacity to imitate cognitive functions, perform tasks in a human-like manner, and learn and self-correct (Russell & Norvig, 2015). These technologies encompass a range of applications such as process automation, virtual agents, predictive analytics, recommendation systems, and speech analytics (Wirtz, Weyerer, & Geyer, 2019), each offering various potential benefits. For instance, they can streamline resources, enhance accuracy, and lower costs (Jovanovic, Duric, & Sibalija, 2019). While the adoption of AI technologies by retail sector organisations is on the rise, it remains in its emerging stages (Mikalef, Fjortoft, & Torvatn, 2019). Initial empirical research on AI adoption in the retail sector has focused on factors driving or inhibiting the use of AI technologies, including aspects like supply chain management (Dwivedi, et al., 2021). However, studies on how diverse retail sector organisations could enhance their ability to use these technologies and improve organisational performance are still largely absent (Mikalef, Fjortoft, & Torvatn, 2019).

Certain studies indicate that AI applications in retail customer service positively impact perceived customer service value (Wang, Teo, & Janssen, 2021), decision-making processes (Nasseef, Baabdullah, Alalwan, Lal, & Dwivedi, 2021), and resource allocation efficiency (Valle-Cruz, Fernandez-Cortez, & Gil-Garcia, 2021). Nevertheless, many organisations currently struggle to realise the anticipated benefits of AI technologies (Davenport & Ronanki, 2018). One explanation for this lies in organisations' inadequate AI capabilities, hindering their ability to identify, implement, and use suitable AI technologies effectively. Consequently, through the development of AI capabilities, organisations could enhance the realisation of organisational performance improvements (Mikalef & Gupta, 2021). Framing the notion of AI capability, following (Mikalef & Gupta, 2021) definition, which describes it as "the ability of a firm to select, orchestrate, and leverage its AI-specific resources", suggests that organisations with AI capabilities can effectively employ various AI technologies and derive value from their utilisation (Bharadwaj A. S., 2000). This definition of AI capabilities is firmly rooted in the Resource-Based View (RBV) of the organisation, which aims to explain the relationship between organisational resources and performance. Within the context of capabilities, several RBV-based studies categorise resources into tangible, human, and intangible resources (Grant, 1991). Based on this categorisation and (Mikalef & Gupta, 2021) conceptualisation, organisational AI capabilities are defined to encompass elements of tangible, human, and intangible resources.

Tangible AI capability resources include the organisation's physical resources like equipment and data required to operate AI applications (Ransbotham, Kiron, Gerbert, & Reeves, 2015), as well as other fundamental resources essential for maintaining AI applications (Wirtz, Weyerer, & Geyer, 2019). Human-related resources pertain to the AI capabilities necessary for developing and training AI applications, as well as the ability to recognise the potential of AI technologies in various business contexts (Melville, Kraemer, & Gurbaxani, 2004). This encompasses technical skills for handling vast amounts of data and implementing AI technologies, as well as managerial skills enabling organisations to comprehend the various potential applications of different AI technologies (Dwivedi, et al., 2021). Intangible resources related to AI capability include abilities such as interdepartmental coordination and the organisational capacity to initiate and implement change (Davenport & Ronanki, 2018); (Ransbotham, Kiron, Gerbert, & Reeves, 2015). Together, these resources are suggested to offer a comprehensive measurement of organisational AI capability (Mikalef & Gupta, 2021).

Integrating innovation as an additional organisational activity within the amended Resource-Based View (RBV) framework aligns with its fundamental principles. The RBV theory suggests that sustained competitive advantage stems from possessing valuable, rare, and difficult-to-imitate resources (Barney J. B., 1991). Innovation, whether in product development, process improvement, or business model innovation, creates unique and valuable resources that competitors find challenging to replicate (Teece, Pisano, & Shuen, 1997). Moreover, innovation plays a pivotal role in dynamic capabilities, enabling organisations to adapt to changes in the market, technology, and competitive landscape (Teece, 2007). By continuously innovating, organisations develop the flexibility and agility needed to respond effectively to evolving environments (Eisenhardt & Martin, 2000). Additionally, innovation contributes to resource accumulation and renewal over time, enriching an organisation's resource base (Sirmon, Hitt, & Ireland, 2007). This constant renewal ensures organisations remain relevant and competitive in dynamic markets. Innovation drives value creation by transforming resources into customer satisfaction, higher revenues, and improved profitability, crucial elements for achieving sustained competitive advantage (Teece, 2014). Previous researchers such as (Barney J. B., 1991), (Teece, Pisano, & Shuen, 1997), (Teece, 2007), (Eisenhardt & Martin, 2000), and (Sirmon, Hitt, & Ireland, 2007) provide theoretical and empirical support for including innovation within the RBV framework and its implications for organisational performance and competitive advantage.

2.2.2. Artificial intelligence capabilities and organisational performance

Artificial intelligence capabilities and their impact on organisational performance have been extensively discussed in previous research reports (Davenport & Ronanki, 2018). However, despite substantial anecdotal claims regarding the value that AI can bring to retail organisations, there is limited empirical evidence to support such claims. Specifically, there is a lack of understanding of how retail organisations should organise around AI and what type of value can be expected from such investments. Some studies have highlighted the potential of AI to prompt various forms of organisational change (Wirtz, Weyerer, & Geyer, 2019), with (Davenport & Ronanki, 2018) suggesting that AI can deliver three distinct types of organisational impact: by automating processes, enhancing engagement with internal and external stakeholders, and enabling the generation of innovative insights. However, most current research either relies on single cases or remains conceptual in nature, failing to analyse the different mechanisms of value generation concurrently. Therefore, it remains challenging to discern how retail organisations should organise around AI and what the overall effects on organisational performance are. The literature on AI capabilities argues that by fostering such organisation-wide capacities, retail organisations will be better positioned to deploy different types of AI applications, thereby affecting organisational performance through independent mechanisms (Mikalef & Gupta, 2021). AI capabilities enable retail organisations to transcend single applications of AI, possessing the capacity to digitally transform their operations to enhance overall performance. Consequently, it is argued that AI capabilities apply indirect effects on organisational performance indicators by prompting changes in organisational activities.

2.2.3. Resource Based View (RBV) Theory

The Resource-Based View (RBV) theory gained popularity and widespread use due to its ability to explain the relationship between an organisation's resources and its performance outcomes. The theory suggests that an organisation's competitive advantage and superior performance stem from its unique and valuable resources and capabilities (Barney J. B., 1991).

By focusing on internal resources rather than external factors, the RBV theory provides insights into how organisations can leverage their distinctive resources to achieve sustainable competitive advantage (Mata, Fuerst, & Barney, 1995).

The RBV theory has been widely used in various industries and contexts, including the study of technology-driven capabilities such as artificial intelligence (AI). It has been applied to explore the relationship between AI capabilities and organisational performance, shedding light on how AI resources and capabilities can contribute to competitive advantage and improved performance outcomes for organisations (Teece, Pisano, & Shuen, 1997).

The original Resource-Based View (RBV) theory was developed by Jay Barney, an American management scholar. In his influential article titled "Firm Resources and Sustained Competitive Advantage" published in the Journal of Management in 1991, Barney laid the foundation for the RBV theory. He proposed that a firm's resources and capabilities are the primary drivers of sustained competitive advantage and superior performance. Barney's work sparked significant interest and subsequent research in the field of strategic management, leading to the widespread adoption and development of the RBV theory (Barney J. , 1991).

The RBV theory has three variables as shown in (Figure 3). (Barney J. , 1991) proposed that the following variables are important contributors of the RBV theory, process automation, cognitive insights, and cognitive engagement. The RBV theory indicates that organisational performance is impacted by the influence that the applicable technology has on the variables mentioned above.

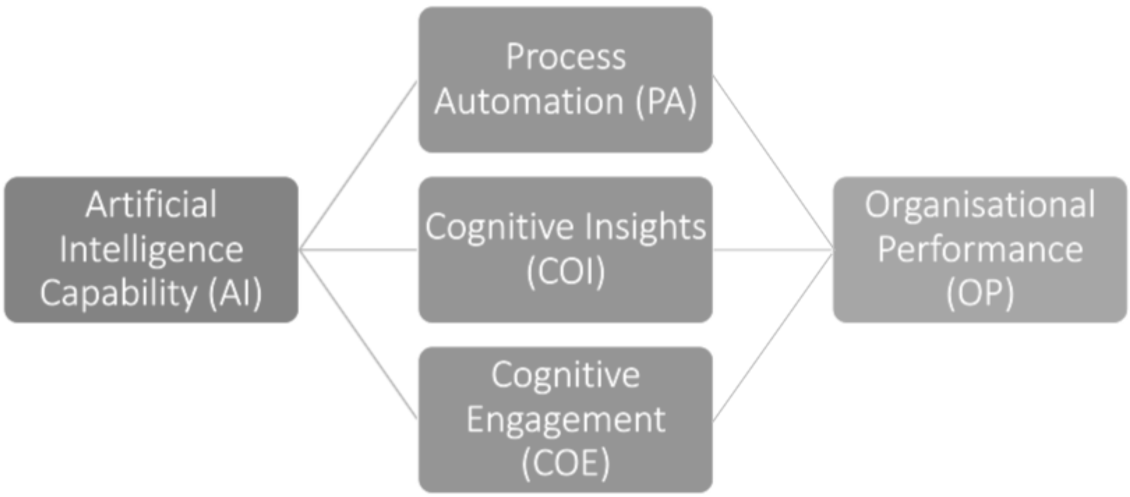

Figure 3: Original Resource Based View Theory (Barney J., 1991)

Later, the RBV theory was praised and criticised from scholars in the field of strategic management (Priem & Butler, 2001), (Peteraf, The Cornerstones of Competitive Advantage: A Resource-Based View., 1993) and (Ketchen, Combs, Russell, Shook, & Hoover, 2014). Some of the criticisms raised against the RBV theory include its tautological nature, lack of empirical validation, and limited attention to dynamic capabilities and external factors. Thus, the need arises to rethink the variables that contribute to organisational performance and adopt a broader conceptualisation of variables.

In this study a revised RBV theory will be used that includes innovativeness as a variable when considering the organisational processes that are impacted by AI and impacting organisational performance.

The Resource-Based View (RBV) theory, while valuable in understanding the relationship between resources, capabilities, and competitive advantage, does have some limitations, even when considering innovation as a variable.

Firstly, the RBV theory relies on subjective judgments in identifying and evaluating resources, introducing potential biases and challenges in accurately assessing resource capabilities. Additionally, the RBV theory assumes a stable environment, overlooking the dynamic nature of today's business landscape where resources can quickly become obsolete due to technological advancements and changing customer preferences.
Establishing a clear cause-and-effect relationship between resources and firm performance is also challenging, as it is difficult to determine whether valuable resources lead to superior performance or vice versa. Furthermore, the RBV theory provides limited guidance on resource development and acquisition strategies, focusing primarily on existing resources rather than their transformation and acquisition. It also places significant emphasis on internal factors while downplaying the role of external influences such as market conditions and competitive forces.

Finally, the RBV theory may offer a narrow perspective on innovation, not fully capturing its complex and multifaceted nature, including aspects such as external collaboration, knowledge exchange, and organisational culture.

Incorporating innovativeness into the RBV theory is theoretically motivated by its potential to address several of these limitations. Innovativeness can lead to the creation of unique resources that are valuable, rare, inimitable, and non-substitutable

(VRIN), thus enhancing a firm's competitive advantage by differentiating its offerings from competitors (Barney J. B., 1991). Moreover, innovativeness is closely related to dynamic capabilities, which are essential for firms to adapt, build, and reconfigure internal and external competencies in response to rapidly changing environments (Teece, Pisano, & Shuen, 1997). This adaptive capability is crucial for sustaining competitive advantage in dynamic markets (D'Aveni, 1994). Innovativeness also facilitates knowledge creation and application, aligning with the knowledge-based view which posits that effective utilisation of knowledge is a critical strategic resource (Grant, 1991). Empirical studies support the positive relationship between innovation and firm performance, suggesting that innovativeness acts as a mediator between resources and performance, thus leveraging existing resources for better outcomes (Calantone, Cavusgil, & Zhao, 2002).

Additionally, market-oriented firms, which are more likely to innovate to meet evolving customer demands, further demonstrate the need to integrate innovativeness within the RBV framework (Slater & Narver, 1995). By addressing these aspects, integrating innovativeness into RBV provides a more comprehensive understanding of firm performance and competitive advantage, especially in the face of today's rapidly changing business environment.

2.2.4. Development of the Research Model and Hypotheses

The adapted RBV theory for the AI context research that incorporates innovativeness is depicted in Figure 4. The research model incorporates four variables, namely process automation, cognitive insights, cognitive engagements, and innovativeness. They are in turn hypothesised to impact organisational performance.

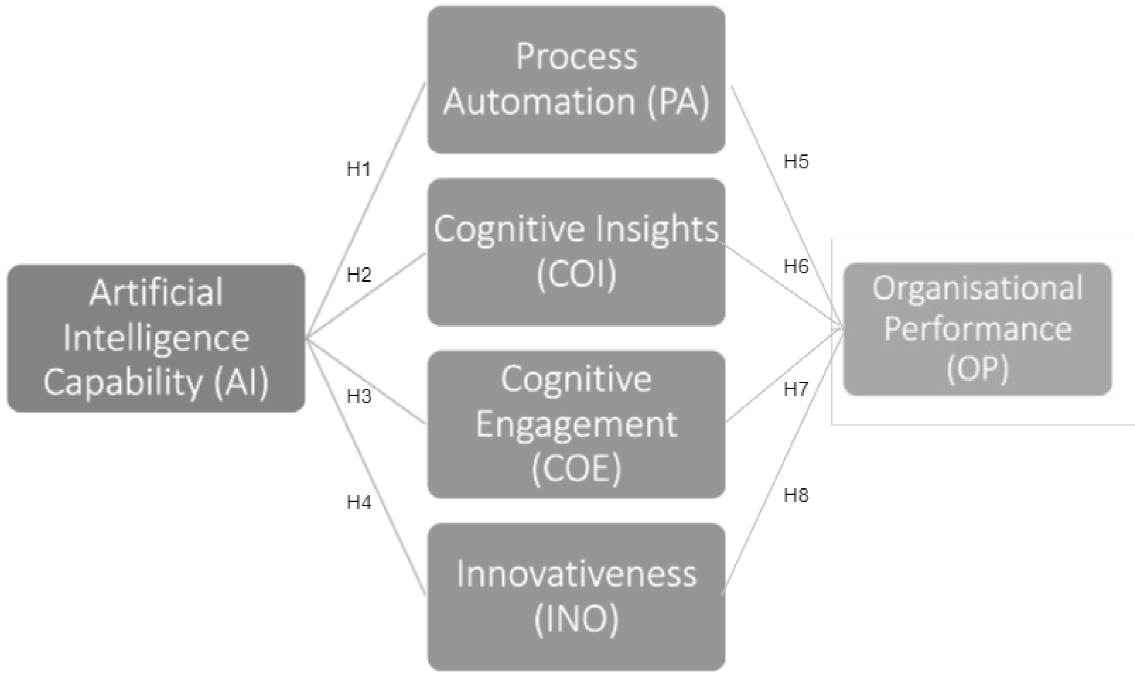

Figure 4: AI Capabilities, RBV Theory Research Model

2.2.4.1. AI Capability

Scholars that have explored the role of Artificial Intelligence (AI) within the RBV framework have stated that (AI) can be seen as a valuable strategic resource that organisations can leverage to gain a competitive advantage and improve organisational performance. AI technologies, such as machine learning algorithms and natural language processing, have the potential to enhance organisational capabilities, improve decision-making processes, and drive innovation. By leveraging AI, organisations can effectively analyse enormous amounts of data, extract valuable insights, and make more informed strategic choices. (Bharadwaj, El Sawy, Pavlou, & Venkatraman) discussed the impact of digital technologies, including AI, on organisational performance and competitive advantage. It highlights the importance of aligning digital business strategy with resource-based capabilities to maximize value creation for the organisation.

2.2.4.2. Process Automation

Process automation refers to the use of technology to streamline and automate business processes, reducing manual effort and increasing efficiency. In the context of the Resource-Based View (RBV) theory, process automation can be seen as a valuable resource or capability that contributes to organisational performance and competitive advantage. By automating routine and repetitive tasks, organisations can free up resources, improve productivity, and enhance operational effectiveness.

Previous scholars have emphasized the role of information technology (IT) and digital capabilities in leveraging process automation to create strategic value. According to (Choi, Lee, & Yoo, 2018), process automation, enabled by IT capabilities, can enhance operational efficiency, and reduce costs, leading to improved organisational performance. They argue that the RBV perspective helps explain how process automation, as a valuable resource, contributes to an organisation's competitive advantage by enabling cost leadership.

Furthermore, (Lacity & Willcocks, 2017) highlighted the importance of process automation in achieving strategic outcomes. They argue that automation, particularly through robotic process automation (RPA), can provide organisations with distinct capabilities, such as speed, accuracy, and scalability, which can enhance operational performance and create competitive advantages.

These studies demonstrate the recognition of process automation as a resource or capability within the RBV framework. By leveraging automation technologies effectively, organisations can optimise their processes, improve efficiency, and gain a competitive edge.

By developing AI capabilities, retail organisations can not only automate manual and repetitive processes but also enhance their ability to generate valuable customer insights through data analysis. Applications such as clustering, unsupervised machine learning, and classification enable retail organisations to uncover hidden patterns and insights that can inform organisational decision-making (Singh, Dwivedi, Kahlon, Pathania, & Sawhney, 2020). These techniques have diverse applications, including improved forecasting and prediction for product design, sales projections, predictive resource scheduling, and more (Wirtz, Weyerer, & Geyer, 2019) However, for these applications to be effective, retail organisations need to establish the necessary data and technological resources, possess a skilled technical and operational workforce capable of understanding and applying AI technologies, and implement suitable processes and structures to foster collaboration within the workforce (Sun & Medaglia, 2019). Therefore, it is hypothesised that:

Hypothesis 1 (H1): AI capabilities will have a positive effect on process automation.

2.2.4.3. Cognitive insights

Cognitive insights refer to the application of cognitive technologies, such as advanced analytics and data mining, to extract meaningful insights from vast amounts of data. These insights can inform decision-making, enhance organisational learning, and improve overall performance. By leveraging cognitive insights, organisations can gain a deeper understanding of their internal resources, capabilities, and external market conditions, allowing them to make more informed strategic choices and adapt to changing environments. An influential paper by (Teece, 2007) discussed dynamic capabilities and their role in achieving sustainable enterprise performance. It highlights the importance of cognitive capabilities and knowledge assets in adapting to changing environments and gaining a competitive advantage.

In addition to the aforementioned areas of AI application, retail organisations have also leveraged AI to enhance their engagement with customers and employees (Wirtz, Weyerer, & Geyer, 2019). Specifically, AI applications like virtual agents have demonstrated the ability to improve employee performance in retail organisations by providing accurate and timely information, thereby increasing overall productivity and efficiency (Bickmore, Rubin, & Simon, 2020). Moreover, AI capabilities are argued to make retail organisations more attuned to the needs of their customers.

(Androutsopoulou, Karacapilidis, Loukis, & Charalabidis, 2019) suggest that retail organisations that rapidly respond to digital technology-driven change and innovation, such as AI, have the potential to enhance customer engagement by fostering collaboration among stakeholders within local communities. However, to effectively use these digital technologies, retail organisations need to possess technical competencies, a comprehensive understanding of customer requirements, and the ability to swiftly deploy technological solutions that address customer demands. Therefore, it is hypothesised that:

Hypothesis 2 (H2): AI capabilities will have a positive effect on cognitive insights.

2.2.4.4. Cognitive engagements

Cognitive engagement refers to the active participation and involvement of employees in cognitive tasks, problem-solving, and decision-making processes within an organisation. It emphasises the role of human cognition, expertise, and knowledge in generating competitive advantage and superior organisational performance. Cognitive engagement can manifest in various forms, such as collaborative problem-solving, knowledge sharing, and participative decision-making, where employees contribute their cognitive abilities and perspectives to enhance organisational outcomes. By fostering cognitive engagement, organisations can tap into the collective intelligence of their workforce, leading to improved problem-solving, innovation, and overall organisational effectiveness and improved performance. (Bondarouk & Ruël, 2009) discussed the challenges and opportunities posed by electronic human resource management (e-HRM) in the digital era. It touches upon the role of cognitive engagement and knowledge sharing facilitated by technology in enhancing organisational performance and competitiveness.

While AI capabilities prompt changes in the three organisational activities mentioned above, it is suggested that the resulting performance effects will be realised indirectly. The enhancement of process automation, cognitive insights, and cognitive engagement enables retail organisations to achieve performance gains. Therefore, the prioritisation, relevance, and timely implementation of AI applications aimed at improving organisational activities become crucial for organisational performance improvements. This argument emphasises the impact of AI applications on organisational performance.

The automation of repetitive and manual tasks through AI applications is argued to significantly reduce the time required to complete various processes, contribute to the reduction of potential human errors, and enhance transparency in organisational activities (Manyika, et al., 2017). In the context of retail organisations, numerous processes constitute a substantial portion of daily tasks, including supply chain activities, management of large transactional data sets, and leveraging data to enhance the customer experience (Poister & Streib, 2001). It has been argued that the ability to effectively manage these processes has a long-term impact on the management capacity and efficiency, consequently influencing the overall effectiveness and viability of retail organisations. Furthermore, automating daily processes and tasks enables retail organisations to allocate personnel for more meaningful activities that require creativity, human judgment, empathy, and problem-solving (Wilson & Daugherty, 2019). Therefore, the following is hypothesised:

Hypothesis 3 (H3): AI capabilities will have a positive effect on cognitive engagement.

2.2.4.5. Innovativeness

Innovativeness refers to an organisation's ability to generate and implement novel ideas, technologies, and processes that create value and contribute to its competitive advantage. Innovativeness is a key factor in leveraging an organisation's unique resources and capabilities to drive superior performance and sustainable growth. Organisations that prioritise innovativeness actively seek to develop and deploy new products, services, and business models that differentiate them from competitors and meet evolving customer needs. This strategic focus on innovation allows firms to tap into their internal resources, such as knowledge, skills, and intellectual property, to create and capture value in the marketplace. (Teece, 2014) provided an in-depth discussion of dynamic capabilities, including the ability to innovate, and their role in shaping firm performance. It emphasises the significance of leveraging unique resources and capabilities, such as innovativeness, to gain a competitive edge and improved organisational performance.

AI capabilities possess significant potential to profoundly impact innovation within retail organisations, enabling them to gain a competitive advantage in the market and driving organisational performance and market growth. AI capabilities have the capacity to positively influence innovation within retail organisations by enhancing data analytics and insights. Through the swift and effective processing of vast amounts of data, retail organisations can obtain valuable insights into their customers' needs, market trends, and demand patterns. This, in turn, facilitates data-driven decision-making and empowers retail organisations to identify opportunities for innovation.
(Davenport & Ronanki, 2018). Therefore, it is hypothesised that:

Hypothesis 4 (H4): AI capabilities will have a positive effect on innovativeness.

2.2.4.6. Organisational performance

Organisational performance refers to the ability of an organisation to achieve and sustain a competitive advantage by effectively leveraging its unique resources and capabilities. RBV suggests that superior performance is achieved when organisations possess and deploy valuable, rare, inimitable, and non-substitutable resources. Organisational performance is influenced by the strategic management of resources, including tangible assets such as physical infrastructure, financial capital, and technological capabilities, as well as intangible assets like knowledge, reputation, and organisational culture. The RBV framework emphasises the importance of aligning these resources with the organisation's strategic objectives, market conditions, and competitive dynamics to drive superior performance. The seminal article by (Barney J. B., 1991) presents the RBV theory and examines the relationship between organisational resources and sustained competitive advantage. It provides insights into how resources and capabilities contribute to organisational performance. (Peteraf,

1993) discussed the key elements of competitive advantage from an RBV perspective. It explored how the strategic management of resources leads to superior performance and sustainable competitive advantage for organisations.

The literature acknowledges that retail organisations that possess the necessary capabilities to effectively implement AI technologies can derive several benefits from their adoption. Firstly, by leveraging innovative technologies in process automation, these organisations can streamline their operations and improve efficiency. Secondly, through enhanced customer data analysis and the extraction of actionable cognitive insights, they can gain a deeper understanding of customer preferences and behaviours, leading to more targeted and personalised approaches. Thirdly, by utilising AI to increase cognitive engagement with customers and employees, organisations can foster stronger relationships and create a positive customer experience. Lastly, AI can contribute to improving employee innovativeness, enabling retail organisations to stay ahead of the competition by generating and implementing novel ideas. These four areas represent key aspects that collectively contribute to enhancing overall organisational performance for retailers (Davenport & Ronanki, 2018).

By developing AI capabilities, retail organisations can enhance their readiness to identify suitable areas for deploying tools such as robotic process automation and effectively implement and maintain such technologies (Willcocks, Lacity, & Craig, 2017). Furthermore, it has been suggested that applications like natural language processing can automate manual document processing, leading to efficiency gains for retail organisations and reducing process bottlenecks (Wirtz, Weyerer, & Geyer, 2019). It is argued that tasks such as data capture, document verification, processing application forms, and other manual activities can be automated using appropriate AI solutions (Al-Mushayt, 2019). However, achieving this requires retail organisations to develop AI capabilities capable of identifying manual processes that consume unnecessary human resources and subsequently automating them using the appropriate AI technologies.

2.3. Hypotheses

Based on the proposed hypotheses from H1 and H4, it is contended that the presence of AI capabilities will have an indirect impact on organisational performance by facilitating enhancements in process automation. Consequently, the following argument is hypothesised:

Hypothesis 5 (H5): Process automation will have a positive effect on organisational performance.

Retail organisations are confronted with the challenge of effectively managing their resources to optimise their utilisation and make informed decisions (Shareef, et al., 2021). By providing actionable insights from vast quantities of data, retail organisations can adopt a proactive approach, taking pre-emptive actions before market conditions deteriorate (such as predictive demand and supply chain optimisation). This improved ability to forecast future market needs and customer demands enables the optimal allocation of financial, physical, and human resources. Moreover, it unlocks the potential to leverage previously inaccessible data for decision-making (Brandt, Wagner, & Neumann, 2021). By gaining cognitive insights, retail organisations can better identify and address the needs of customers in markets that were previously overlooked or marginalised. Additionally, it fosters a deeper understanding of the customer experience, facilitating proactive support for personalised customer service and offerings, such as personalised offers and reminders to reorder items (van Ooijen, van Ubaldi, & Welby, 2019). Based on the considerations, the following hypothesis is proposed:

Building upon hypotheses H2 and H5, it is hypothesised that AI capabilities will have an indirect impact on organisational performance by enhancing the cognitive insights of retail organisations. Therefore, the following argument is proposed:

Hypothesis 6 (H6): Cognitive insights will have a positive effect on organisational performance.

The ability to establish closer interactions with customers has been identified as a driver for innovation and improved customer service offerings in retail organisations (de Jong, Neulen, & Jansma, 2019). In turn, enhanced customer engagement with retailers has been found to positively impact perceptions of trust, satisfaction, and loyalty towards retail organisations (Simonofski, Snoeck, Vanderose, Crompvoets, & Habra, 2017). Furthermore, augmenting employee tasks with timely and relevant information has the potential to reduce errors, enhance efficiency, and alleviate work-related stress and fatigue (Valle-Cruz, Fernandez-Cortez, & Gil-Garcia, 2021). These effects are likely to elevate the overall service quality provided by retail organisations, leading to improved organisational performance through personalised and targeted product and service offerings for both customers and employees. Recent empirical studies have demonstrated such effects using chatbots engaging with customers (Androutsopoulou, Karacapilidis, Loukis, & Charalabidis, 2019), as well as intelligent agents for employees in retail organisations (de Bruijn, Warnier, & Janssen, 2021). Therefore, the following hypothesis is proposed:

Drawing on the arguments presented in hypotheses H3 and H6, it is proposed that an AI capability will have an indirect effect on organisational performance through the enhancement of cognitive engagement facilitated by AI. Consequently, the following argument is put forth:

Hypothesis 7 (H7): Cognitive engagement will have a positive effect on organisational performance.

AI capabilities have the potential to automate repetitive and mundane tasks, enabling employees to redirect their focus towards more meaningful and strategic work (Huang, Rust, & Maksimov, 2021). By relieving employees from the cognitive load associated with routine tasks, AI capabilities free up mental resources that can be allocated to higher-value activities (Davenport & Ronanki, 2018). Additionally, AI capabilities can leverage data analysis to provide employees with valuable insights and recommendations (Chui, Manyika, & Miremadi, 2016). This empowers employees to make more informed decisions, fostering increased confidence and engagement in problem-solving and innovation (Huang, Rust, & Maksimov, 2021). It is important to note that the implementation of AI capabilities often necessitates employees to acquire new skills or adapt existing ones (Chui, Manyika, & Miremadi, 2016). This learning process not only facilitates the integration of AI technologies but also stimulates cognitive engagement by offering growth opportunities and enhancing job satisfaction (Huang, Rust, & Maksimov, 2021).

Building upon the arguments presented in hypotheses H4 and H7, it is proposed that the presence of an AI capability will have an indirect impact on organisational performance through the facilitation of improved innovation enabled by AI. As such, the following argument is put forth:

Hypothesis 8 (H8): Innovativeness will have a positive effect on organisational performance.

AI capabilities have the capacity to analyse vast volumes of data, thereby generating valuable insights into customer behaviour, market trends, and emerging patterns (Davenport & Ronanki, 2018). These insights serve as a catalyst for generating innovative ideas and strategies within retail organisations (Wirtz, Weyerer, & Geyer, 2019). By leveraging AI capabilities, retail organisations can deliver personalised experiences to customers, tailoring recommendations, offers, and interactions based on individual preferences (Davenport & Ronanki, 2018). This level of personalisation not only enhances customer engagement and satisfaction but also fosters innovation in customer-centric approaches, leading to improved organisational performance (Wirtz, Weyerer, & Geyer, 2019).

2.4. Theoretical Framework

The central concept of this study is based on the Resource-Based View (RBV) Theory. The RBV theory serves as the overarching framework for understanding how strategic resources and capabilities contribute to sustainable competitive advantage in retail organisations. It guides the research by emphasising the role of AI capabilities as strategic resources that can enhance customer experience and organisational performance. Innovativeness is also being added to the RBV theory due to a previous study from (MIT Sloan Management Review, 2020) discussing how AI capabilities can support innovation within retail organisations. The article highlighted examples of organisations using AI capabilities to automate routine tasks and free up employees' time for more creative and innovative work.

The key constructs found in this study will be:

2.4.1. Strategic Resources and Capabilities

AI Capabilities: Various AI technologies and applications, including personalised recommendations, chatbots, pricing optimisation, voice commerce, and visual recognition, which are leveraged by retail organisations.
Organisational Performance: The effectiveness and success of the retail organisation, considering factors such as operational efficiency, customer satisfaction, and financial performance.

2.4.2. Theoretical Lens

RBV Theory and AI Capabilities: The RBV Theory provides a lens to understand how AI capabilities can be valuable, rare, inimitable, and non-substitutable strategic resources that lead to a sustainable competitive advantage. It highlights the importance of aligning AI capabilities with organisational goals, customer needs, and market conditions to maximise their impact on customer experience and organisational performance.

2.4.3. Theoretical Perspectives

Process-Based Perspective: This perspective examines how AI capabilities enable process automation, streamlining operations, and improving efficiency within retail organisations. It explores how AI technologies can replace manual and repetitive tasks, freeing up resources for more value-added activities.

Customer-Centric Perspective: This perspective focuses on how AI capabilities enhance customer experience by personalising interactions, providing real-time assistance, and delivering tailored recommendations. It investigates the role of AI in understanding customer preferences, anticipating needs, and creating engaging experiences across various touchpoints.

Innovation and Strategic Perspective: This perspective explores how AI capabilities drive innovation within retail organisations by leveraging data analytics, enabling predictive insights, and facilitating agile decision-making. It examines how AI fosters the development of new products, services, and business models, leading to a competitive edge and improved organisational performance.

2.4.4. Research Problem

The research problem is to investigate the impact of AI capabilities on organisational activities and organisational performance in the context of South African retail organisations.

The theoretical framework of this study provides a foundation for understanding the underlying mechanisms and relationships between AI capabilities, organisational activities, and organisational performance.

2.5. Conceptual Framework

The argument is that AI capabilities exert an indirect effect on customer experience within retail organisations and this will then influence organisational performance, by prompting changes in the organisational activities. In agreement with the work done by (Davenport & Ronanki, 2018), it is suggested that the effect of AI capabilities can be utilised on process automation, cognitive engagement, and cognitive insights. This study is however also regarding innovativeness as a variable that can impacted by a retail organisation’s AI capabilities.

The argument will suggest that AI capabilities will influence customer experience and thus influence organisational performance by creating changes in these four activities, which will then subsequently have a positive effect on the organisational performance of the retail organisation that deploys these AI capabilities. Based on the above assumptions, six hypotheses are derived, and a research model is presented through this model, value generation can be assumed through the adoption of AI capabilities. In the Hypotheses, the impact that AI capabilities have on process automation, cognitive engagement, cognitive insights, and innovation will be examines. Based on this, it is assumed that AI will prompt changes in the effectiveness and efficiency that the use of digital technologies has on a retail organisation’s key operations. The organisational impact referred to is therefore hypothesised to indicate the impact that is felt by retail organisations on their organisational performance.

2.6. Conclusion of Literature Review

This literature review explored the impact of artificial intelligence (AI) on organisational performance within the context of the Resource-Based View (RBV) theory. It highlighted the growing importance of AI capabilities in retail organisations, driven by digital transformation and the need to deliver high-quality services. However, challenges exist in effectively leveraging AI applications, making it uncertain how organisational value and performance improvements can be achieved.

The review discussed the benefits of using AI in retail organisations, such as enhanced customer experience, improved operational efficiency, better demand forecasting, and increased sales. It also noted that the specific impact of AI on organisational performance may vary depending on factors like organisation size, industry segment, and AI implementation strategy.

The adoption of AI technologies in South African retail organisations is still in its preliminary stages, and while some studies have shown a positive impact, many organisations struggle due to insufficient AI capabilities.

The literature review identified a research problem related to the limited understanding of AI implementation challenges and resources required for effective implementation in the South African retail context. The study's objectives were reviewed, focusing on examining the impact of AI capabilities on process automation, cognitive insights, cognitive engagement, and innovation, as well as providing insights into the pathways through which improvements in organisational performance can be observed.

The RBV theory, with the addition of innovativeness as a variable, is used as the theoretical framework to guide the study. The review acknowledges the limitations of the RBV theory, including subjective resource evaluation and limited attention to dynamic capabilities and external factors. Therefore, further development and integration with other theoretical perspectives are necessary to provide a more comprehensive understanding of organisational performance and competitive advantage in the context of AI capabilities.

CHAPTER 3: RESEARCH METHODOLOGY

Building upon the foundation established in Chapter 1, which introduced the research topic, outlined the problem statement, and highlighted its significance, and Chapter 2, which provided a comprehensive literature review on the impact of artificial intelligence (AI) on organisational performance within the context of the Resource-Based View (RBV) theory, this chapter presented the research methodology that would be employed to address the identified research gaps.

The literature review in Chapter 2 revealed the growing importance of AI capabilities in retail organisations, driven by digital transformation and the need to deliver high-quality services. However, it also highlighted the challenges faced in effectively leveraging AI applications, making it uncertain how organisational value and performance improvements could be achieved. Moreover, the adoption of AI technologies in South African retail organisations was still in its preliminary stages, and many organisations struggled due to insufficient AI capabilities.

Based on the identified research problem, the objectives of the study were defined to examine the impact of AI capabilities on process automation, cognitive insights, cognitive engagement, and innovation, as well as to provide insights into the pathways through which improvements in organisational performance could be observed within the South African retail context.

To guide this investigation, the RBV theory, supplemented by the inclusion of innovativeness as a variable, was selected as the theoretical framework. While the RBV theory provided a solid foundation, it was essential to acknowledge its limitations, including subjective resource evaluation and limited attention to dynamic capabilities and external factors. Therefore, this study recognised the need for further development and integration with other theoretical perspectives to provide a more comprehensive understanding of organisational performance and competitive advantage in the context of AI capabilities.

In summary, Chapter 3 detailed the research methodology employed in this study, explaining the rationale for selecting specific methods and techniques. It outlined the data collection process, sample selection, survey instrument design, and data analysis procedures. This research aimed to provide a comprehensive examination of the impact of AI capabilities on organisational performance in the South African retail context.

3.1. Research Approach

This study was grounded in a positivist philosophy, which aligned with the belief that objective reality could be expressed through causal relationships and that data could be reliably measured with a certain level of accuracy (Cohen, Manion, & Morrison, 2007). The positivistic notion of this study emphasised the formulation of an empirically testable theory to establish "law-like" generalisations (Evans, 2010). It recognised the significance of positivist philosophy in uncovering objective realities, both physical and social, by developing specific measures that captured dimensions of reality relevant to the researcher's interests (Cohen, Manion, & Morrison, 2007).

By adopting a positivist approach, this study assumed that the social world could be studied in a manner like the natural world (Collis & Hussey, 2009). The positivist researcher operated under the belief that a single reality existed, and it was their responsibility to establish and understand that reality. Generalisation to the population was achieved through the application of statistical techniques to data collected via surveys or experiments (Saunders, Thornhill, & Lewis, 2009).

Aligned with positivism, this research study adopted a deductive approach, utilising theory to formulate hypotheses and eliminate alternative explanations for observations, strengthening causal inferences (Saunders, Thornhill, & Lewis, 2009). Deductive research facilitated the development of a conceptual and theoretical framework that could be empirically tested through observation (Saunders, Thornhill, & Lewis, 2009). The deductive approach proved advantageous when an extensive body of literature existed, providing a theoretical foundation from which hypotheses could be derived (Evans, 2010). In this approach, the researcher progressed from theory to data to validate the framework (Collis & Hussey, 2009). The data collection process was focused and guided by the specific variables identified within the theoretical framework (Collis & Hussey, 2009).

In accordance with (Saunders, Thornhill, & Lewis, 2009), this study had adopted a quantitative approach. The quantitative method involved the statistical, mathematical, or numerical analysis of collected data and was aligned with the positivist research perspective. It was characterised by objective measurement, hypothesis testing, causality, and reproducibility (Collis & Hussey, 2009). The selection of the quantitative research approach enabled the quantification of data and facilitated subjecting the collected data to various statistical analyses in this study. By utilising a quantitative method, the numeric data collected and analysed could be used to generalise the opinions of specific groups of individuals or to provide a comprehensive understanding of a particular phenomenon (Ponterotto, 2005).

The primary focus of this study was to investigate the impact of AI capabilities on retail organisational activities within the South African context. Specifically, the study aimed to understand how the adoption and implementation of AI capabilities influenced specific operational aspects in retail organisations, encompassing process automation, cognitive insights, cognitive engagement, and innovation. By addressing this objective, the study intended to identify and analyse the effects of AI capabilities on various key activities in the South African retail sector.

Furthermore, the study aimed to determine the impact of these operational activities on organisational performance. Building upon the findings from the first objective, this objective sought to explore how the changes in operational activities, driven by AI capabilities, shaped the overall organisational performance. By investigating this objective, the study aimed to gain valuable insights into the pathways through which improvements in organisational performance could be observed because of adopting AI capabilities in the South African retail sector.

This study thus sought to establish relationships between variables and could thus be termed as “explanatory research” (Saunders, Thornhill, & Lewis, 2009).

3.2. Research Design

The chosen research strategy for this study was a survey, which is commonly employed in deductive studies within commercial and management disciplines to address questions related to "what," "how much," and "how many" (Petty, Thomas, & Graham, 2012). By employing a survey research strategy for explanatory research, the generalisation of findings was enhanced as it allowed for data collection from a large representative sample (Gong, Xu, & Yu, 2004)

3.3. Data Collection Methods

The utilisation of survey methods offered researchers an efficient and cost-effective means to collect data (Cohen, Manion, & Morrison, 2007). By employing survey methods, larger sample sizes could be accommodated, enhancing the ability to generate statistically meaningful results. It was essential for surveys to adhere to well-defined procedures to ensure the validity and reliability of the obtained data (Collis & Hussey, 2009)

To collect the necessary data to answer the research questions, a comprehensive survey-based method was employed. This method involved the distribution of an online questionnaire to stakeholders within retail organisations in South Africa.

To ensure the confirmation of hypotheses, data was collected through an online questionnaire administered via email invitations. Key respondents from various retail organisations in South Africa were targeted, primarily individuals working within these organisations. The email invitations contained a link to the online questionnaire, inviting the recipients to participate.

To maximise response rates, three reminders were sent following the initial invitation. This approach increased the likelihood of obtaining a sufficient and representative sample.

The survey questionnaire was carefully designed to capture information on the variables of interest, specifically focusing on AI capabilities, organisational impact outcomes, and organisational performance. By using a survey-based data collection method, a wide range of data could be gathered from many participants, providing a comprehensive understanding of the effect of AI capabilities on retail organisational performance in South Africa.

The chosen method offered several advantages. Firstly, it allowed for efficient and scalable data collection, enabling the inclusion of a considerable number of retail organisations and stakeholders. Secondly, the use of an online questionnaire ensured convenience and accessibility for participants, increasing the likelihood of their engagement. Additionally, a survey-based approach facilitated the measurement of key constructs and variables in a standardised manner, ensuring consistency and comparability of responses (Collis & Hussey, 2009).

However, it was important to acknowledge some limitations of the chosen method. The reliance on self-reported data introduced the possibility of response bias and subjectivity. Furthermore, the cross-sectional nature of the survey design limited the ability to establish causality or capture temporal changes (Gong, Xu, & Yu, 2004).

Overall, the survey-based data collection method was justified due to its ability to gather a substantial amount of relevant data from stakeholders within retail organisations in South Africa. It offered a practical and efficient means of addressing the research questions, providing valuable insights into the effect of AI capabilities on retail organisational performance and the mechanisms through which these effects were realised.

3.4. Population and sample

Understanding the impact of Artificial Intelligence (AI) on retail organisational performance necessitates a thorough examination of the mechanisms at play within the context of South Africa. According to (NielsenIQ South Africa, 2022), there are more than 10 000 branded retail outlets and more than 143 000 independent stores across South Africa’s nine provinces and measures more than 80% of all retail grocery transactions. This section delves into the population, sample, and sampling method employed in this study to provide insights into the specific focus and methodology adopted. By targeting retail organisations within South Africa, this research aims to shed light on the nuanced dynamics surrounding AI adoption and its implications for organisational performance within this unique context. Through a meticulously designed sampling strategy, the study seeks to ensure a comprehensive representation of retail organisations of varying sizes, laying the groundwork for a robust analysis of AI's influence on organisational dynamics and performance metrics.

3.4.1. Population

The population of interest for this study consists of more than 10 000 branded retail organisations in South Africa. This specific population allows for a focused examination of the effect of AI capabilities on retail organisational performance and the mechanisms through which these effects are realised. By targeting these branded retail organisations, the study can provide relevant insights and best practices while acknowledging the limitation that are present within the South African context.

3.4.2. Sample

The sample size of 1000 individuals within the retail sector in South Africa was justified through several principles. Firstly, it ensured representativeness by capturing a diverse subset of the population, considering the approximately 10,000 branded retail outlets in the country (Smith, 2019). This size allowed for a broad range of perspectives and experiences within the retail sector to be included, encompassing several types of outlets, locations, sizes, and operational characteristics. Additionally, the sample size of 1000 individuals offered sufficient statistical power to detect meaningful relationships and differences within the data (Jones, 2020). It enabled robust statistical analyses, such as regression modelling and hypothesis testing, with greater confidence in the validity and reliability of the results. Furthermore, selecting a sample size of 1000 individuals addressed resource constraints inherent in conducting research involving a large population. It struck a balance between comprehensive data collection and practical limitations of time, budget, and coordination, ensuring the study remained feasible and manageable (Brown & Lee, 2018). Despite not encompassing the entire population, findings from this sample size could still be generalisable to the broader retail sector in South Africa through appropriate sampling techniques and consideration of population demographics (Davis, 2017). Moreover, reviewing existing literature and similar studies within the field provided additional justification, especially as comparable studies had achieved meaningful results with similar sample sizes (White & Black, 2016). Overall, the sample size of 1000 individuals in the retail sector of South Africa aligned with academic principles and research practices, facilitating rigorous and insightful exploration of research questions and hypotheses.

The process of determining the sample size of 1000 individuals within the retail sector in South Africa involved several considerations and methodological approaches. Firstly, a review of existing literature and research studies within the field was conducted to understand typical sample sizes used in similar studies and their corresponding outcomes (Green, 2019). This review provided insights into the range of sample sizes that had been employed in research involving the retail sector or related domains, helping to establish a baseline for the sample size selection. Next, the research objectives and hypotheses of the study were carefully considered to determine the level of precision and statistical power required to achieve meaningful results (Smith & Johnson, 2021). This involved clarifying the specific research questions to be addressed, the type of data analysis techniques to be employed, and the anticipated effect sizes or differences that the study aimed to detect. By understanding the research objectives and expected outcomes, the appropriate sample size needed to adequately power the study was determined (Robinson, 2018).

Additionally, practical considerations such as budgetary constraints, time limitations, and logistical feasibility were considered during the sample size determination process (Harris & Taylor, 2020). Given the resources available for the study, including funding, personnel, and access to participants, the sample size of 1000 individuals were deemed feasible and manageable while still allowing for comprehensive data collection and analysis.

Furthermore, considerations of the population size of approximately 10,000 branded retail outlets in South Africa played a role in determining the sample size (Brown & Lee, 2018). While ideally, the sample size would represent a certain proportion of the population to ensure generalizability, the selected sample size of 1000 individuals were deemed sufficient to capture a diverse and representative subset of the population while remaining practical within the scope of the study. Overall, the sample size of 1000 individuals within the retail sector in South Africa was determined through a systematic process that considered the research objectives, expected outcomes, existing literature, practical constraints, and population size (Jones, 2020). This approach ensured that the selected sample size would provide adequate statistical power, representativeness, and feasibility for conducting rigorous and insightful research.

The sample for this study consisted of 1000 employees from various retail organisations across South Africa, ensuring a comprehensive representation of different organisational sizes. Stratified sampling was employed as the chosen method, involving the division of the population into distinct subgroups or strata based on organisational size categories (Meenakumari & Sathiyabama, 2015). Despite the population consisting of more than 10,000 branded retail organisations in South Africa (NielsenIQ South Africa, 2022), only 145 respondents completed the survey, leading to a smaller sample size than initially anticipated. Nonetheless, this sample size was considered valid for several reasons. Firstly, it allowed for a representative selection from the population, ensuring diversity across various sectors, regions, and business sizes. Despite its smaller size, the sample still contributed to the generalisability of findings to the entire population, enhancing the reliability of the study's conclusions and enabling robust statistical analyses. Additionally, the smaller sample size provided a manageable margin of error, ensuring the precision of estimates drawn from the sample in making conclusions about the population. However, the smaller sample size may have limited the study's ability to capture a comprehensive representation of the population, particularly regarding smaller organisational sizes. Nonetheless, the rationale behind employing stratified sampling remains valid, as it facilitated the inclusion of organisations of diverse sizes, allowing for a more nuanced understanding of the impact of AI capabilities on retail organisational performance (Lohr, 2019).

3.4.3. Sampling Method

The chosen sampling method, stratified sampling, was aligned with the research objectives, enabling the inclusion of organisations with varying sizes. This method offered advantages as it allowed for the exploration of potential variations in the influence of AI capabilities on retail organisational performance across different organisational sizes. Focusing primarily on organisational size as a demographic criterion was pertinent to the research questions, as it offered insights into how AI capabilities affected retail organisations of different scales. Through the incorporation of a diverse range of organisation sizes, the study aimed to derive insights applicable to a broader spectrum of retail organisations operating in South Africa.

In summary, the adoption of stratified sampling, coupled with the inclusion of organisations of diverse sizes, ensured a well-rounded and representative sample. This approach facilitated a comprehensive investigation of the research questions, enhancing the reliability and validity of the study's findings (Lohr, 2019).

3.5. The Research Instrument

The research instrument chosen for this study is a survey questionnaire, which has been used to collect data on various constructs related to AI capabilities, process automation, cognitive insight, cognitive engagement, innovation, and organisational performance. The questionnaire used a 7-point Likert scale to measure the respondents' perceptions and attitudes towards these constructs (Likert, 1932).

By using a survey questionnaire, the study aimed to capture quantitative data that can provide insights into the effects of AI capabilities on retail organisational performance within South Africa. As stated by (DeVellis, 2016) the questionnaire allowed for the systematic measurement of key variables, facilitating the examination of relationships and the testing of hypotheses.

Advantages of using a survey questionnaire, as mentioned by (Hair, Black, Babin, & Anderson, 2010) include its efficiency in collecting data from many respondents, its standardised format that ensures consistency in responses, and its ability to capture a wide range of constructs in a structured manner. The adoption or adaptation of scales and items from prior studies enhanced the reliability and validity of the instrument, as it built upon established measures with demonstrated psychometric properties (Hair, Black, Babin, & Anderson, 2010).

However, (Babbie, 2016) discussed that there are also some limitations and potential shortcomings associated with the use of a survey questionnaires. First, relying solely on self-reported data may introduce response biases, such as social desirability or recall biases. Additionally, the questionnaire format could limit the depth of understanding and nuanced insights that can be obtained compared to qualitative methods (Babbie, 2016).

In summary, the use of a survey questionnaire as the research instrument provided a structured and efficient approach to collect data on the constructs of interest. By adopting or adapting established scales and items, the instrument benefits from established validity and reliability.

3.6. Procedure for Data Collection

The data collection procedure for this study involved sending private LinkedIn messages to targeted respondents as well as email invitations, providing them with a link to an online questionnaire. The survey questionnaire served as the primary tool for gathering data from participants, who were asked to provide their responses based on their perceptions and experiences.

The choice of using an online questionnaire as the data collection method offered several advantages, as stated by (Dillman, Smyth, Jolene, & Leah, 2014). Firstly, it allowed for efficient data collection from a geographically dispersed sample of participants, as the questionnaire could be accessed and completed at their convenience. This increased the accessibility and potential reach of the study. Additionally, an online questionnaire reduced the logistical challenges associated with paper-based surveys, such as printing, distribution, and manual data entry.

By providing a link to the online questionnaire in the email invitations, participants could easily access and complete the survey using their preferred electronic devices. This approach promoted ease of participation and minimised potential barriers, enhancing the likelihood of obtaining a representative sample (Couper, 2008).

To ensure the replicability of the study, detailed information on the questionnaire design was provided, including the specific items used to measure the constructs of interest. The use of established and validated scales, as mentioned by (DeVellis, 2016), strengthened the reliability and validity of the instrument. Researchers seeking to replicate the study could refer to the literature and sources cited to access these scales and adapt them for their own research.

It was important to acknowledge some potential limitations of using an online questionnaire. Firstly, the response rate could vary, and efforts were made to maximize participation through clear and compelling invitations, reminders, and assurances of data confidentiality (Tourangeau, Lance, & Rasinski, 2000). Additionally, there was a risk of non-response bias if certain segments of the population were less likely to participate (Tourangeau, Lance, & Rasinski, 2000). Researchers were aware of these limitations and considered potential implications for the generalizability of the findings.

In summary, the data collection procedure involved sending email invitations with a link to an online questionnaire to targeted respondents. The online questionnaire method offered advantages in terms of accessibility, efficiency, and reach. By providing sufficient details on the questionnaire design and referencing established scales, the study could be replicated effectively.

3.7. Data Analysis Strategies and Interpretation

Although measures have been taken to pre-code the questionnaires and minimize coding errors (Saunders, Thornhill, & Lewis, 2009), it was still necessary to screen the data received from respondents to identify and eliminate any errors before processing the data (Evans, 2010). The data analysis involved the use of statistical software such as AMOS/SPSS.

3.7.1. Quantitative data analysis

The data collected for this study utilised Likert scales. When analysing data collected through Likert scales, the choice between parametric and non-parametric tests becomes a consideration. (Gardner & Martin, 2007) argued that the selection of the data analysis technique can impact the conclusions drawn from the results. (Nappo & Grassia, 2008) suggested that Likert data, being of an ordinal or ranked nature, should be analysed using non-parametric techniques to ensure valid results. However, (Norman, 2010) conducted a study using scale data and found that parametric tests such as Covariance Based Structural Equation Modelling (CB-SEM (Covariance Based Structural Equation Modelling)) and regression analysis can be used without concern of drawing incorrect conclusions. These findings align with (Murray, Likert Data: What to Use, Parametric or Non-Parametric?, 2013) research, which supports the reliability of conducting parametric tests on Likert scale data. Before testing the hypotheses, an initial exploratory factor analysis (EFA) will be conducted to uncover the underlying structure of the variables (Hair, Black, Babin, & Anderson, 2010). The objective of this EFA is to determine the dimensionality and factor structure of the study's variables (Hoe, 2008)

3.7.2. Structural Equation Modelling (SEM)

The analysis proceeded with Structural Equation Modelling (SEM), specifically using Covariance Based Structural Equation Modelling (CB-SEM), to establish causal relationships. Previous studies (Kallunki, Laitinen, & Silvola, 2011) that influenced the conceptualisation of this study relied on Likert-scale data and applied SEM for statistical testing. Therefore, SEM was initially proposed as the statistical technique for this study. SEM is a multivariate statistical procedure that combines multiple regression analysis and factor analysis to test hypothesised models and establish causality between latent and observed variables (Barrett, 2007). SEM distinguishes between direct and indirect relationships and allows the analysis of relationships between latent variables without random errors, making it more advanced than simpler relational modelling techniques like multiple regression analysis.

SEM permitted the simultaneous examination of relationships within the models (Hair, Black, Babin, & Anderson, 2010). The researcher ensured that the model did not contradict the data, aiming to prove the findings and hypotheses. Unlike regression analysis, SEM allowed for modelling the interactions among variables, addressing issues such as multicollinearity. The model included a structural model representing potential causal dependencies between endogenous and exogenous variables and a measurement model displaying the relationships between latent variables and their indicators. The researcher evaluated the significance of the path coefficients to support or reject the hypotheses.

SEM allowed for both confirmatory tests of the measurement model (relationship between each latent construct and its indicators) and tests of the structural model (relationships between the latent constructs themselves) (Hair, Black, Babin, & Anderson, 2010).

3.7.3. Confirmatory Factor Analysis (CFA)

Confirmatory Factor Analysis (CFA) was employed to test the measurement models (Hair, Black, Babin, & Anderson, 2010). CFA assessed if the selected measures aligned with the proposed models or theories. Its primary purpose was to confirm whether the variables selected effectively measured the hypothesised model. The assessment of the models was conducted through the CFA procedure, which evaluated the one-dimensionality, validity, and reliability of items measuring the constructs. One-dimensionality assessment was performed first, followed by testing validity and reliability. If necessary, items with low factor loadings (less than 0.6) could be removed, and redundant items could be deleted or constrained. The results of the factor structure provided an assessment of item intercorrelations within the framework of hypothesised relationships between independent and dependent variables.

3.7.4. Parameter Estimation

For parameter estimation in this study, Maximum Likelihood Estimation (MLE) was employed. MLE estimated the parameters of the model based on the observed data, aiming to maximise the likelihood of obtaining the observed results given the parameters. MLE was chosen for its robustness even in the absence of multivariate normality assumptions and its ability to calculate the chi-square, a commonly used measure of fit.

3.7.5. Model Fit

Assessing model fit was crucial in SEM to evaluate how well the estimated model corresponded to the data. Various fit statistics were examined, including Chi-square (X2), Root Mean Square Error of Approximation (RMSEA), Goodness of Fit Index (GFI), Adjusted Goodness of Fit Index (AGFI), Comparative Fit Index (CFI), Tucker-Lewis Index (TLI), Normed Fit Index (NFI), and Chi-square degrees of freedom. These fit indices indicated whether the models and theories proposed in the study were acceptable or not (Barrett, 2007).

3.8. Possible Limitations and Challenges of the Study

The study had several limitations that needed acknowledgment. Firstly, the collection of organisational-level data through cross-sectional surveys introduced significant constraints in establishing temporal precedence and making causal inferences (Collis & Hussey, 2009). When studying individuals, data was gathered over time, reducing threats to causal inference.

Secondly, common methods bias might have arisen if data on all variables were collected from a single respondent. To mitigate this, multiple key informants were employed for data collection at the organisational level.

Thirdly, the chosen sampling design might have introduced sampling bias due to non-responsiveness, potentially compromising the quantitative data analysis (Collis &

Hussey, 2009). Consequently, the findings might not have been representative of all retail organisations in South Africa utilising AI capabilities. In the case of non-response, a contingency plan that reminded the respondents was implemented.

Like all survey studies, there were inherent limitations related to response biases such as social desirability bias and self-selection biases, among others. These biases became particularly apparent when there was a prominent level of non-response. Moreover, response bias posed a threat to external validity, as the characteristics of the people/organisations that responded may have systematically differed from those who did not respond, thereby limiting the generalisability of the results (Byrne, 2013)

3.9. Quality Assurance

3.9.1. Validity

Validity, in this context, focused on whether the collected data accurately represented the topic under investigation. It examined whether the instrument measured what the researchers intended to measure and whether the concept was measured accurately. A valid instrument should have adequately covered the topic being studied (Collis & Hussey, 2009).

(Collis & Hussey, 2009) summarised three types of validity as follows:

3.9.1.1. Content validity:

This pertained to whether the scale measured what it was supposed to measure. It was established by using existing literature to guide the operationalisation of variables and conducting a pre-test with academic experts (Collis & Hussey, 2009)

3.9.1.2. Face validity:

This referred to the subjective perception of how well the scale covered the concept it intended to measure. Face validity was established through a pilot study to identify low variation in responses and confusing items (Collis & Hussey, 2009).

3.9.1.3. Construct validity, including convergent validity and discriminant validity:

This assessed the extent to which the test measured the intended constructs. Exploratory Factor Analysis (EFA) was initially conducted to uncover the underlying structure of the variables. EFA helped determine if items loaded onto expected constructs (convergent validity) and did not load onto unrelated factors (discriminant validity). The subsequent Confirmatory Factor Analysis (CFA) as part of the measurement model in Structural Equation Modelling (SEM) should have yielded Average Variance Extracted (AVEs) greater than 0.5 for convergent validity, with AVEs higher than inter-construct correlations for discriminant validity (Hair, Black, Babin, & Anderson, 2010).

Internal consistency, assessed through Cronbach's alpha, was adopted in this study. The accepted cut-off for Cronbach's alpha was 0.7 (Hair, Black, Babin, & Anderson, 2010). Values lower than 0.7 raised concerns about excessive measurement error, and items with lower correlations may have been dropped.

3.9.2. Reliability

Reliability referred to the extent to which data was free from measurement error and yielded consistent and trustworthy results (Collis & Hussey, 2009). Using a reliable instrument reduced errors and biases during data analysis, ensuring consistent measurement across time and different items in the instrument (Petty, Thomas, & Graham, 2012).

Once validity and reliability had been tested, any items that had been dropped during the measurement model tests were not included in the tests of the structural model (Hair, Black, Babin, & Anderson, 2010).

3.10. Ethical Considerations

Anticipation of ethical considerations is a crucial step that researchers must undertake before conducting their study (Gong, Xu, & Yu, 2004). Research ethics serves the fundamental purpose of safeguarding the well-being of participants and extends to encompass areas such as scientific misconduct and plagiarism (Byrne, 2013).

To ensure adherence to ethical standards, the researcher sought ethics clearance from the Human Research Ethics Committee (Non-Medical) at the University of the Witwatersrand, Johannesburg prior to initiating data collection. This clearance, with protocol number WBS/DB1250875/264, was issued on 13th November 2023, and is valid until the submission of the research report. The project title is "The impact of AI capabilities on organisational performance: an empirical study in the South African retail context", the researcher is enrolled in the MM (Digital Business) programme. This clearance serves multiple purposes: (1) to ensure compliance with institutional ethical guidelines concerning research involving human participants, the researcher carefully examined the ethical guidelines of various firms and ensured their adherence throughout the data collection process; (2) to guarantee voluntary participation and maintain confidentiality or anonymity for the respondents, personal and company details were not requested, thereby safeguarding confidentiality. The collected information was used solely for research purposes, and the final report will be made available to the participating companies upon request; (3) to assure respondents of their safety during the data collection process, the completion of questionnaires was entirely voluntary, and respondents were not required to provide personal details; (4) to protect the researcher, the researcher strictly abided by the ethical clearance issued by the University of the Witwatersrand, receiving legal support if necessary.

3.11. Conclusion of the Research Methodology

The chapter began by emphasising the importance of AI capabilities in retail organisations and the challenges encountered in effectively utilising AI applications. The research objectives were then defined, focusing on examining the impact of AI capabilities on process automation, cognitive insights, cognitive engagement, innovation, and organisational performance within the South African retail context. The Resource-Based View (RBV) theory, complemented by the inclusion of innovativeness as a variable, was selected as the theoretical framework. The chapter further explained the research approach, which was grounded in positivism and adopted a deductive approach. A quantitative research method was chosen to collect data through a survey questionnaire administered to stakeholders within retail organisations in South Africa. The chapter concluded by discussing the population, sample, research instrument, data collection procedure, and data analysis strategies.

In terms of research approach and design, the study adopted a positivist philosophy and a deductive approach. A quantitative method was employed to collect data through an online survey questionnaire. Stratified sampling was used to ensure a diverse representation of retail organisations in South Africa, and the chosen research instrument was a survey questionnaire using a Likert scale. The data collection procedure involved sending email invitations to targeted respondents and providing them with a link to the online questionnaire. Data analysis involved the use of statistical software, and both exploratory factor analysis (EFA) and parametric tests were conducted to analyse the data.

Overall, Chapter 3 provided a detailed explanation of the research methodology, highlighting the rationale behind the chosen methods and techniques. The chapter outlined the research objectives, theoretical framework, research design, data collection methods, and data analysis strategies. By employing a quantitative approach and using a survey-based method, the study aimed to gather comprehensive data on the impact of AI capabilities on retail organisational performance in South Africa.

CHAPTER 4: PRESENTATION OF RESULTS

4.1. Empirical Results

Chapter 3 established the research methodology, laying the groundwork for this chapter's analysis of the data collected from the empirical study. In Chapter 4, we delve into investigating and empirically testing the research questions posed: *RQ1: "What is the impact of AI capabilities on retail organisational activities within South Africa?"* and RQ2: "*What is the impact of the operational activities on organisational performance?"* To achieve this, a survey was administered through the distribution of questionnaires to individuals working within South Africa's retail sector. The collected data were then used to scrutinise the hypothesised model concerning the influence of Artificial Intelligence (AI) capabilities on organisational performance. Initial segments of this chapter address the sample size, respondent demographics, data screening, and identification of sample outliers. Subsequent sections present descriptive statistics, an assessment of normality, and the adequacy of the sample for empirical analysis. Furthermore, we conduct principal component analysis, evaluate reliability and validity, and examine correlation matrices before analysing the results of the model. Finally, we discuss the model's outcomes, providing insight and concluding observations.

4.1.1 Sample Size

To gather participants for the study, invitations were sent via email, LinkedIn messages to 1000 individuals, as outlined in (Section 3.6 of Chapter 3). Despite these extensive outreach endeavours, the response rate remained notably low, with only 145 individuals (yielding a response rate of 14.5%) taking part in the study. This minimal response rate presents challenges to the reliability of the conclusions drawn, as it heightens the possibility of non-response bias. Non-response bias arises when the characteristics of those who opt not to participate markedly differ from those who do, potentially distorting the findings and weakening the generalisability of the outcomes. Hence, although endeavours were made to secure a varied and representative sample, the low response rate necessitates thoughtful consideration and potential adjustments in the interpretation of the study's results.

4.1.2 Demographics

Before testing the model using the collected data, “descriptive statistics” are presented to provide an overview of the sample under study. The “demographic profile of the respondents is presented” in the table below. All 145 useable respondents provided their demographic information.

The results in the table offer a comprehensive view of the demographic characteristics within the sample population, shedding light on various aspects pertinent to the study's investigation. Firstly, in terms of the utilisation of AI capabilities, a predominant majority of organisations (78.6%) have recently adopted AI, with less than five years of integration. Conversely, a small yet notable percentage (6.9%) of organisations have been using AI for over 25 years, indicating early adopters or pioneers in AI integration. When considering the revenue generated by the organisations annually, a sizeable portion (55.2%) of entities generate revenue exceeding R500 million, suggesting a prevalence of larger-scale enterprises within the sample. However, smaller revenue brackets (< R20 million to R200 million) represent smaller percentages, indicating a varied economic landscape. Job titles among participants reveal a diverse range of roles within the organisations surveyed, with Managing Directors (14.5%) constituting the largest percentage, followed by Executive Directors (9.7%) and Technology Engineers (8.3%). The distribution of years of experience within organisations reflects a mix of both new and mid-career professionals, with the majority (60.0%) having less than five years of experience, while a notable portion (24.1%) possess 6-10 years of experience. In terms of organisational longevity, over half of the entities (54.5%) have been in operation for more than 36 years, indicating a substantial presence of well-established organisations. Lastly, the distribution of the number of employees within organisations is balanced, with approximately 40.7% having over 100,000 employees and 40.0% having fewer than 1,000 employees, suggesting a diverse range of organisational sizes within the sample. These demographic insights provide valuable context for the subsequent analysis of the impact of AI capabilities on organisational activities and performance within the South African retail sector.

Table 1: Demographics

Demographics	Category	Frequency	Percentage
Years that Organisation has been using AI capabilities	<5 Years	114	78.6%
	6-10 Years	19	13.1%
	11-15 Years	0	0.0%
	16-20 Years	1	0.7%
	21-25 Years	1	0.7%
	>25 Years	10	6.9%
Revenue generated by the organisation per annum	<R20 million	26	17,9%
	R21-R50 million	9	6,2%
	R51-R100 million	10	6,9%
	R101-R150 million	3	2,1%
	R151-R200 million	4	2,8%
	R201-R499 million	13	9,0%
	>R500 million	80	55,2%
Job title	Chief Technology Officer	3	2,1%
	Executive Director	14	9,7%
	Managing Director	21	14,5%
	Technology Director	4	2,8%
	Technology Engineer	12	8,3%
	Other	91	62,8%
Years of experience within the organisation	<5 years	87	60,0%
	6-10 years	35	24,1%
	11-15 years	13	9,0%
	> 16 years	10	6,9%
Number of years that the organisation has been in operation	<5 years	16	11,0%
	6-10 years	14	9,7%
	11-15 years	11	7,6%
	16-20 years	7	4,8%

	21-25 years	10	6,9%
	26-30 years	2	1,4%
	31-35 years	6	4,1%
	> 36 years	79	54,5%
Number of employees within the organisation	<1000	58	40,0%
	1001-4999	7	4,8%
	5000-9999	5	3,4%
	10000-49999	12	8,3%
	50000-99999	4	2,8%
	>100000	59	40,7%

Overall, the demographic characteristics of the respondents suggest a diverse and dynamic sample population within the South African retail sector. The findings indicate a mix of organisations at various stages of AI adoption, with a sizeable portion being new adopters but also a notable presence of long-term users. The distribution of revenue generated annually reflects a spectrum of economic scales, from smaller enterprises to larger corporations. Job titles among respondents demonstrate a breadth of roles within the organisations surveyed, highlighting a diverse workforce composition. The range of years of experience within organisations suggests a mix of both seasoned professionals and individuals newer to their respective roles. Additionally, the longevity of organisations and the distribution of employee numbers further underscore the diversity within the sample, with a mix of established entities and smaller-scale operations. Overall, these insights paint a picture of a heterogeneous group of respondents, representing a broad cross-section of the South African retail sector, which is crucial for understanding the nuanced impacts of AI capabilities on organisational activities and performance within this context. The sample is considered appropriate for testing the model of the impact of Artificial Intelligence capabilities on organisational performance.

Therefore, data analysis could proceed to the next steps.

4.1.3 Data Screening

The data collected underwent analysis using the “Statistical Package for the Social Sciences (SPSS) Version 28” after being screened for missing data. Upon examination, it was noted that some responses exhibited minor data gaps, affecting the variables related to the demographics, Artificial Intelligence capabilities, Process Automation, Cognitive Insights, Cognitive Engagement, Innovation and Organisational Performance. To address these missing data points, the median of nearby points method was employed. This method, as described by (Byrne, 2013), involves calculating the median by averaging nearby surrounding values. Specifically, in the SPSS program, this computation is conducted using the "span of nearby points" option. The calculated median considers all values of the items construct data from both upper and lower bounds, effectively replacing the missing value (Hair, Black, Babin, & Anderson, 2010).

Table 2: Responses with Missing Data

Item	Number of Missing responses
Demographics	5
Artificial Intelligence Capabilities (AI)	4
Process Automation (PA)	17
Cognitive Insights (COI)	7
Cognitive Engagement (COE)	6
Innovation (INO)	8
Organisational Performance (OP)	15

4.1.4 Sample Outliers

Outliers are described as data points that deviate significantly from other observations (Hair, Black, Babin, & Anderson, 2010). To detect potential outliers, any responses with unusually high or low values were reviewed (Tarka, 2018). Unusual responses may indicate that the respondents do not belong to the same population. Typically, extreme values are those that exceed three standard deviations above or below the sample mean (Hair, Black, Babin, & Anderson, 2010). Standardised scores on an item indicate the number of standard deviations from the mean. The standardised scores of each respondent were assessed for each questionnaire item, and none were identified as outliers. This is expected, considering that all questionnaire items were answered using the same scale.

4.1.5 Descriptive Statistics

The concepts explored in this research, such as Artificial Intelligence Capabilities, Cognitive Insights, Cognitive Engagement, Innovation, Process Automation, and Organisational Performance, were assessed using a seven-point Likert scale. On this scale, a rating of 1 represents "Strongly disagree", while a rating of 7 represents "Strongly Agree". The midpoint of the scale, denoted as "4", signifies a neutral stance. Consequently, when mean values fall below 4, most respondents tended to disagree with the statements. Values between 4 and 4.5 suggest a more neutral position among respondents. Mean values above 4.5 indicate that most respondents tend to agree or strongly agree with the statements. The mean, standard deviation, skewness, and kurtosis of composites are detailed in the table provided below.

Table 3: Descriptive Statistics

Variables	Minimum	Maximum	Mean	Std. deviation	Skewness	Kurtosis
(AI)	1.11	7.00	4.5172	1.40267	-.404	-.271
(PA)	1.00	7.00	4.4977	1.55939	-.365	-.488
(COI)	3.00	7.00	4.7609	1.16166	.030	-1.169
(COE)	1.00	7.00	4.1090	1.54470	-.247	-.664
(INO)	1.75	7.00	4.9009	1.44697	-.439	-.515
(OP)	1.36	7.00	4.7517	1.28208	-.592	.278

4.1.5.1 Artificial Intelligence Capabilities (AI)

The Artificial Intelligence Capabilities (AI) construct is intended to assess individuals' perceptions within the organisation regarding the usability and availability of AI capabilities. The overall mean score, as illustrated in the provided table, is 4.5, with a standard deviation of 1.40. This indicates that, on average, respondents believe AI capabilities are user-friendly and accessible within the organisation, although there is some variability in individual responses. Evaluation was conducted using a 7-point Likert scale. Mean scores for items ranged from 4.26 to 4.70, suggesting general agreement among respondents regarding the usability and availability of AI capabilities.

Table 4: Statistical Results of AI items

Variable	Obs	Mean	Std. Dev.	Min	Max
AI1	145	4.52	1.514	2	7
AI2	145	4.63	1.628	1	7
AI3	145	4.26	1.568	1	7
AI4	145	4.61	1.737	1	7
AI5	145	4.41	1.644	1	7
AI6	145	4.59	1.644	1	7
AI7	145	4.70	1.659	1	7
AI8	145	4.44	1.654	1	7
AI9	145	4.47	1.620	1	7

4.1.5.2 Process Automation (PA)

The Process Automation (PA) construct is designed to assess individuals' perceptions within the organisation regarding the influence of AI capabilities on process automation. The overall mean score is 4.4, with a standard deviation of 1.55. This suggests that, on average, respondents believe AI capabilities moderately impact automating processes within the organisation, although there is some variability in individual responses. Evaluation was conducted using a 7-point Likert scale. Mean scores for items ranged from 4.28 to 4.68, indicating a consistent perception among respondents that AI capabilities have a moderate impact on process automation. This suggests that, on average, respondents perceive AI capabilities to moderately impact the automation of processes within the organisation.

Table 5: Statistical Results of PA items

Variable	Obs	Mean	Std. Dev.	Min	Max
PA1	145	4.45	1.806	1	7
PA2	145	4.28	1.678	1	7
PA3	145	4.68	1.723	1	7
PA4	145	4.52	1.784	1	7
PA5	145	4.48	1.822	1	7
PA6	145	4.57	1.727	1	7

4.1.5.3 Cognitive Insights (COI)

The Cognitive Insights (COI) construct is crafted to assess two primary aspects within the organisation: the use of cognitive technologies, such as advanced analytics and data mining, to extract valuable insights from extensive datasets, and organisational perceptions regarding the influence of AI capabilities on Cognitive Insights. With an overall mean score of 4.7 and a standard deviation of 1.16, it suggests that, on average, respondents perceive both the application of cognitive technologies for deriving insights from large datasets and the impact of AI capabilities on Cognitive Insights within the organisation as relatively high. Additionally, the low standard deviation indicates less variability in individual responses around this average perception. These evaluations were conducted using a 7-point Likert scale. The mean scores of items ranged from 4.06 to 5.23, further supporting the idea of a positive impact of AI capabilities on Cognitive Insights within the organisation.

Table 6: Statistical Results of COI items

Variable	Obs	Mean	Std. Dev.	Min	Max
COI1	145	5.23	1.728	1	7
COI2	145	4.28	1.488	2	7

COI3	145	4.66	1.842	1	7
COI4	145	4.89	1.650	1	7
COI5	145	4.06	1.783	1	7
COI6	145	4.81	1.741	1	7

4.1.5.4 Cognitive Engagement (COE)

The Cognitive Engagement (COE) construct aims to assess individuals' active participation in problem-solving and decision-making, using human cognition to enhance competitive advantage and performance, while also examining organisational perceptions of the impact of AI capabilities on cognitive engagement. With an overall mean score of 4.1 and a standard deviation of 1.54, it indicates that, on average, respondents perceive a moderate level of cognitive engagement, with some variability in individual responses. These assessments were conducted using a 7-point Likert scale. The mean scores of items, ranging from 3.81 to 4.58, consistently depict a moderate level of engagement across various aspects related to problem-solving, decision-making, and the influence of AI capabilities on cognitive engagement within the organisation. This range supports the notion that respondents perceive cognitive engagement at a moderate level, although there is some variation in perceptions across different dimensions assessed by the construct.

Table 7: Statistical Results of COE items

Variable	Obs	Mean	Std. Dev.	Min	Max
COE1	145	4.53	1.860	1	7
COE2	145	4.58	1.957	1	7
COE3	145	4.38	1.830	1	7
COE4	145	3.87	1.800	1	7
COE5	145	3.81	1.822	1	7
COE6	145	4.39	1.886	1	7
COE7	145	4.10	1.898	1	7

4.1.5.5 Innovation (INO)

The Innovation (INO) construct evaluates an organisation's capacity to develop and implement innovative ideas, technologies, and processes to gain a competitive advantage and create value. Prioritising innovation involves creating novel products, services, and business models to meet evolving customer needs. AI capabilities enhance data analytics, enabling rapid processing to identify innovation opportunities, improving organisational performance and market growth. With an overall mean score of 4.9 and a standard deviation of 1.44, respondents perceive a prominent level of innovation within their organisation. The standard deviation indicates some variability in individual responses, suggesting differing opinions among respondents. These assessments used a 7-point Likert scale. Mean scores for items, ranging from 4.62 to 5.40, consistently reflect a high perception of innovation across various dimensions. This indicates that respondents view their organisation as highly innovative, with minimal variation in perceptions across distinct aspects.

Table 8: Statistical Results of INO items

Variable	Obs	Mean	Std. Dev.	Min	Max
INO1	145	4.74	1.423	3	7
INO2	145	5.09	1.675	1	7
INO3	145	4.82	1.766	1	7
INO4	145	5.02	1.706	1	7
INO5	145	5.40	1.133	4	7
INO6	145	4.62	1.736	1	7
INO7	145	4.79	1.560	2	7
INO8	145	4.72	1.685	1	7

4.1.5.6 Organisational Performance (OP)

The Organisational Performance (OP) construct is structured to evaluate an organisation's efficiency in achieving and maintaining a competitive advantage by optimally using its distinctive resources. The Resource-Based View theory highlights the significance of aligning valuable assets with strategic goals for long-term success. In the retail sector, adopting AI technologies such as process automation and data analysis brings advantages such as improved performance through streamlined operations and automated tasks. With an overall mean score of 4.07 and a standard deviation of 1.28, respondents perceive, on average, a moderate level of organisational performance. The standard deviation indicates variability in responses, suggesting differing opinions among respondents regarding performance. Assessed using a 7-point Likert scale, item mean scores ranging from 4.36 to 5.03 consistently indicate a perception of moderate to high performance across various dimensions. This suggests that respondents view the organisation as performing moderately to well across distinct aspects evaluated.

Table 9: Statistical Results of OP items

Variable	Obs	Mean	Std. Dev.	Min	Max
OP1	145	4.36	1.498	2	7
OP2	145	4.67	1.463	2	7
OP3	145	4.81	1.369	2	7
OP4	145	4.86	1.544	1	7
OP5	145	5.03	1.486	1	7
OP6	145	4.99	1.491	1	7
OP7	145	4.90	1.466	2	7
OP8	145	4.93	1.508	1	7
OP9	145	4.68	1.403	1	7
OP10	145	4.63	1.550	1	7
OP11	145	4.41	1.610	1	7

4.1.6 Assessment of Normality

The data presented in Table 3 offers the "Skewness and Kurtosis coefficients" for all constructs integrated into the model. As noted by (George & Mallery, 2010), values falling within the range of -2 to +2 for both skewness and kurtosis suggest normality. The results from the table indicate that the variables exhibit approximate normality. Specifically, for the constructs (AI), (PA), (COI), (COE), and (INO), both skewness and kurtosis values fall within the -2 to +2 range, signifying normality. This implies symmetric distributions with a moderate degree of peakedness or flatness, in line with a normal distribution's characteristics. However, for the (OP) construct, while the skewness value aligns with normality, the kurtosis value is slightly beyond the range, though still relatively close. Nonetheless, the overall pattern suggests that the data for all constructs adheres to normal distribution assumptions, supporting statistical analyses' validity. It is crucial to consider the central limit theorem, as highlighted by (Muzaffar, 2016), which indicates that deviations from normality have a more pronounced impact on smaller sample sizes (less than 300). Therefore, abnormal kurtosis exceeding the -2 to +2 thresholds could significantly influence overall results.

4.1.7 Sample Adequacy

Before conducting a "principal component analysis (PCA)" to confirm the validity of the multi-item scales, it is essential to assess sample adequacy. This is achieved through the Kaiser-Meyer-Olkin (KMO) test, developed by (Kaiser & Rice, 1974). According to (Field, 2009), the KMO evaluates sampling characteristics by comparing the squared correlation between variables to the squared partial correlation between variables. Correlation values range from 0 to 1, with closer proximity to 1 indicating more reliable factors (Field, 2009). Values falling between 0.5 and 0.7 are deemed poor, those between 0.7 and 0.8 are considered good, while those between 0.8 and 0.9 are rated as great, and anything above 0.9 is deemed excellent (George & Mallery, 2010). In this study, the KMO result, illustrated in the table below, is 0.911, indicating excellent sampling adequacy. This suggests that the correlations among variables are sufficiently high to conduct a reliable PCA.

Table 10: KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.	.911
Approx. Chi-Square	9667.769
df	1176
Sig.	.000

(Bartlett, 1954) devised a test to ascertain whether the correlations among survey items are sufficiently robust for conducting appropriate factor analysis, thereby illustrating the strength of the relationship among variables. In the present study, the

Chi-square value stands at 9667.769, with a significance level below 0.001. This implies that the correlations observed between variables are statistically significant, underscoring a substantial relationship among the survey items. Hence, the dataset proves suitable for factor analysis, as the relationships among variables are deemed significant enough to warrant the application of this analytical approach.

4.1.8 Principal Components Analysis (PCA)

Factor analysis (principal component) was conducted using the orthogonal rotation (Varimax) method. This method was selected because it prioritises components with high eigenvalues and organises them in order of significance (Hair, Black, Babin, & Anderson, 2010). Factor analysis operates on the premise that measurable and observable variance can be condensed into a few latent variables that share common variance (Vonglao, 2017), a process known as dimensionality reduction. Despite being unobserved, these factors play a pivotal role in a theoretical model. Exploratory Factor Analysis (EFA) serves as an initial step in scale construction (Hair, Black, Babin, & Anderson, 2010), providing a valuable precursor to any Confirmatory Factor Analysis (CFA) during the preliminary stages of scale development. EFA enables researchers to explore primary dimensions, aiding in the formulation of a theory or model from latent constructs represented by sets of items (Sangthong, 2020). Given the limited research evidence on the use and impacts of AI capabilities on organisational performance in the South African retail context, an exploratory approach was deemed necessary before formal model testing.

(Hair, Black, Babin, & Anderson, 2010) stipulated that a construct should consist of at least three variables (i.e., scale items) to qualify as a factor, although this criterion may vary depending on the study's design. The number of factors generated depends on whether a variable may be related to more than one factor (Murray, Likert Data: What to Use, Parametric or Non-Parametric?, 2013). The use of a rotation matrix aims to maximise high item loadings while minimising low item loadings, resulting in a more comprehensible and simplified solution. SPSS provides five rotation methods including varimax, quartimax, equamax, direct oblimin, and promax (Sangthong, 2020), with varimax rotation being chosen in this study to optimise high item loadings.

Additionally, a factor score coefficient matrix was used in the score's menu, employing listwise exclusion, sorting by size, and suppressing absolute values less than 0.40 in the options menu. Suppressing absolute values less than 0.40 facilitates easier visual interpretation of the loadings. With 145 responses in this study, factor loadings below 0.50 were considered low, and items with such loadings were excluded (Hair, Black, Babin, & Anderson, 2010). The results of the factor analysis, as presented in Table 11, reveal the extraction of 7 factors from 49 items via principal component analysis, explaining a total variance of 77.5%.

Table 11: Principal Component Analysis

"Rotated Component Matrix"							
"Component"							
Items	1	2	3	4	5	6	7
COI1							.730
COI4							.632
COI5							.688
COI6							.652
COE3						.701	
COE4						.745	
COE5						.819	
COE6						.810	
COE7						.773	
INO1		.743					
INO2		.764					
INO3		.731					
INO4		.772					
INO5		.777					
INO6		.761					
INO7		.686					
INO8		.686					
AI1				.807			
AI2				.588			

AI3				.643			
AI5				.658			
AI6				.658			
AI7				.679			
AI8				.730			
AI9				.805			
ID1			.731				
ID2			.850				
ID3			.834				
ID4			.753				
ID5			.728				
ID6			.767				
ID7			.719				
PA1					.706		
PA2					.788		
PA3					.702		
PA4					.766		
PA5					.737		
PA6					.660		
OP1	.642						
OP2	.787						
OP3	.790						
OP4	.787						
OP5	.713						
OP6	.763						
OP7	.787						
OP8	.754						
OP9	.733						
OP10	.792						
OP11	.686						
Rotation Method: Varimax with Kaiser Normalization.							
Rotation converged.							

Total Variance Explained 77.5%

Most factor loadings in Table 11 met or exceed the conventional threshold of 0.50, which is crucial for determining the strength of association between items and factors in exploratory factor analysis. However, a few factor loadings fell slightly below this threshold, specifically for the Cognitive Insights (COI), Cognitive Engagement (COE), Artificial Intelligence Capabilities (AI) variables, where the excluded factors (COI2, COI3, COE1, COE2 & AI4) demonstrated a factor loading of less than 0.50. Nevertheless, the overall results suggest that all items were associated with a component, indicating a strong relationship with their respective factors.

Cognitive Insights (COI) were evaluated using six items. As illustrated in Table 11, four items displayed substantial loadings on the same factor and did not demonstrate cross-loadings exceeding 0.40 on other factors. However, two items, COI2 and COI3, were omitted from the Cognitive Insights (COI) due to having factor loadings below the conventional threshold of 0.50.

Cognitive Engagement (COE) was assessed using seven items. As shown in Table 11, five items exhibited significant loadings on the same factor and did not show cross-loadings surpassing 0.40 on other factors. However, two items, COE1 and COE2, were excluded from the Cognitive Engagement (COE) due to having factor loadings below the conventional threshold of 0.50.

Innovation (INO) was measured through eight items. As shown in Table 11, all eight items loaded significantly onto the same factor and did not demonstrate cross-loading above 0.40 onto other factors. Therefore, no items required exclusion from the Innovation construct.

Artificial Intelligence Capabilities (AI) was assessed using nine items. As shown in Table 11, eight items exhibited significant loadings on the same factor and did not show cross-loadings surpassing 0.40 on other factors. However, one item, AI4, was excluded from the Artificial Intelligence Capabilities (AI) due to having factor loadings below the conventional threshold of 0.50.

Inter-Departmental Coordination (ID) was evaluated through seven items. As observed in the Table 11, all seven items loaded significantly onto the same factor and did not demonstrate cross-loading above 0.40 onto other factors. Hence, no items necessitated exclusion from the Inter-Departmental Coordination (ID) construct.

Process Automation (PA) was assessed through six items. As illustrated in Table 11, all six items loaded significantly onto the same factor and did not exhibit cross-loading above 0.40 onto other factors. Consequently, no items warranted exclusion from the Process Automation (PA) construct.

Organisational Performance (OP) was evaluated using eleven items. As shown in Table 11, all eleven items loaded significantly onto the same factor and did not demonstrate cross-loading above 0.40 onto other factors. Consequently, no items required exclusion from the Organisational Performance construct.

Following the Principal Components Analysis (PCA), it has been concluded that the construct termed Inter-Departmental Coordination (ID) will be excluded from further analysis. This decision is based on both academic and statistical considerations. The ID construct did not align with the intended theoretical framework of the study and did not effectively capture the underlying constructs being investigated. Maintaining theoretical integrity and coherence is essential for ensuring the validity of the study's findings. As a result, it is deemed appropriate to exclude the ID construct from further examination to ensure the robustness and validity of the subsequent analysis.

Overall, the model comprised seven constructs, which was confirmed by the underlying factor structure extracted by the PCA. The analysis could then proceed to examine the reliability of the scales.

4.1.9 Reliability and Validity

It is imperative for a scale to demonstrate reliability to ensure its validity and practical utility (Byrne, 2013). Reliability pertains to the scale's capability to yield consistent outcomes under similar conditions and objectives (Hair, Black, Babin, & Anderson, 2010). In this investigation, the conceptual framework comprised six factors: Artificial

Intelligence Capabilities (AI), Process Automation (PA), Cognitive Insights (COI), Cognitive Engagement (COE), Innovation (INO) and Organisational Performance (OP). Table 12 below presents the results of Cronbach’s alpha, Average Variance Extracted (AVE), and Composite Reliability (CR). Reliability was assessed using Cronbach’s alpha, with a threshold of at least 0.70 indicating reliability (Hair, Black, Babin, & Anderson, 2010). Table 12 reveals that Cronbach’s alpha ranges from 0.880 to 0.969, above the recommended threshold. Conversely, the CR values, ranging from 0.825 to 0.942, exceed the 0.70 benchmark. Moreover, the AVE for each construct was computed, with the lowest value being 0.618, above the suggested threshold of 0.50.

Table 12: Results of Reliability and Validity

						Composite scores	
Variables	Number of Initial Items	Number of Surviving Items	Cronbach's alpha	“Average Variance extracted (AVE)”	“Composite reliability (CR)”	Mean	Standard deviation
AI Capabilities (AI)	9	8	0.956	0.618	0.905	4.505	1.616
Process Automation (PA)	6	6	0.946	0.634	0.889	4.498	1.757
Cognitive Insight	6	4	0.880	0.653	0.825	4.747	1.726

s (COI)							
Cognitive Engagement (COE)	7	5	0.909	0.629	0.884	4.109	1.847
Innovation (INO)	8	8	0.969	0.674	0.922	4.901	1.585
Organisational Performance (OP)	11	11	0.965	0.651	0.942	4.752	1.498

4.1.10 Correlation Matrix of Composite Scores

Ensuring “construct validity” necessitates addressing both “convergent and discriminant validity” (Sangthong, 2020). The inter-correlations have been computed and are displayed in Table 13 below. According to the principle of discriminant validity, the indicators of a construct should exhibit stronger correlations among themselves compared to correlations with indicators of other constructs (Hair, Black, Babin, & Anderson, 2010). This principle can be verified by comparing inter-construct correlations with the Average Variance Extracted (AVE) or the square root of AVE for each construct. The square roots of AVE for each construct are depicted along the diagonal of the table below, which are observed to be greater than the inter-construct correlations. This confirms 'discriminant validity', indicating that constructs share more variance with their own items than with items from other constructs in the model. Collectively, these outcomes affirm the reliabilities, convergent, and discriminant validities of the constructs. Subsequently, the model can be evaluated in the subsequent section.

Table 13: Results of Matrix of Composite Scores

Correlations									
		COI	COE	INO	AI	ID	PA	OP	
COI	Pearson Correlation	1	**0.825**						
	Sig. (2-tailed)								
COE	Pearson Correlation	.562**	1	**0.878**					
	Sig. (2-tailed)	<,001							
INO	Pearson Correlation	.579**	.369**	1	**0.904**				
	Sig. (2-tailed)	<,001	<,001						
AI	Pearson Correlation	.543**	.466**	.783**	1	**0.883**			
	Sig. (2-tailed)	<,001	<,001	<,001					
ID	Pearson Correlation	.495**	.415**	.573**	.555**	1	**0.910**		
	Sig. (2-tailed)	<,001	<,001	<,001	<,001				
PA	Pearson Correlation	.526**	.384**	.647**	.637**	.477**	1	**0.814**	
	Sig. (2-tailed)	<,001	<,001	<,001	<,001	<,001			
OP	Pearson Correlation	.541**	.370**	.658**	.635**	.579**	.699**	1	**0.931**

	Sig. (2-tailed)	<,001	<,001	<,001	<,001	<,001	<,001		
** Correlation is significant at the 0.01 level (2-tailed).									

4.2. Results of Model Testing

This section uses the collected data to rigorously examine the study's measurement and "structural model." Prior to testing the hypothesised structural model, it is prudent to conduct Confirmatory Factor Analysis (CFA) to thoroughly evaluate the "measurement model" and ascertain whether all items adequately load onto the proposed constructs. CFA is employed to scrutinise the sources of variability responsible for the shared variance among a set of scores, thereby confirming that the proposed factor structure aligns well with the data. The CFA analysis excluded one control variables with 7 measuring items and used only the 49 items measuring the main variables, none of which were dropped in the “exploratory factor analysis (PCA)” stage. The CFA was used to confirm that the proposed factor structure is a good fit to the data.

Subsequently, Structural Equation Modelling (SEM) is employed to scrutinise the hypotheses delineated by the relationships between independent and dependent variables, i.e., the structural model. The SEM analysis is performed using AMOS version 28 due to its user-friendly interface and simplified path diagrams, offering ease of interpretation compared to other software packages such as LISREL and STATA (Sangthong, 2020).

4.2.1. CFA Model Results

Confirmatory Factor Analysis (CFA) was used to evaluate the relationships among different constructs within the formulated theoretical framework and their corresponding measurement items. When scrutinising the model, it becomes imperative to assess the fit of the measurement model and gauge its validity. During the evaluation of the measurement model in CFA, the distinction between exogenous and endogenous constructs is unnecessary. This differentiation becomes relevant solely during the model testing phase. Figure 7 illustrates the interconnections among all variables, with the measured variables (construct items) depicted in rectangular shapes. The covariance is depicted by two-headed arrows in Figure 7, while causal relationships are represented by one-headed arrows. The model portrayed in Figure 7 comprises solely the main effects constructs and their associated measurement items. The focus of the model in Figure 7 is solely on Artificial Intelligence Capabilities (AI), Process Automation (PA), Cognitive Insights (COI), Cognitive Engagements (COE), Innovation (INO), and Organisational Performance (OP).

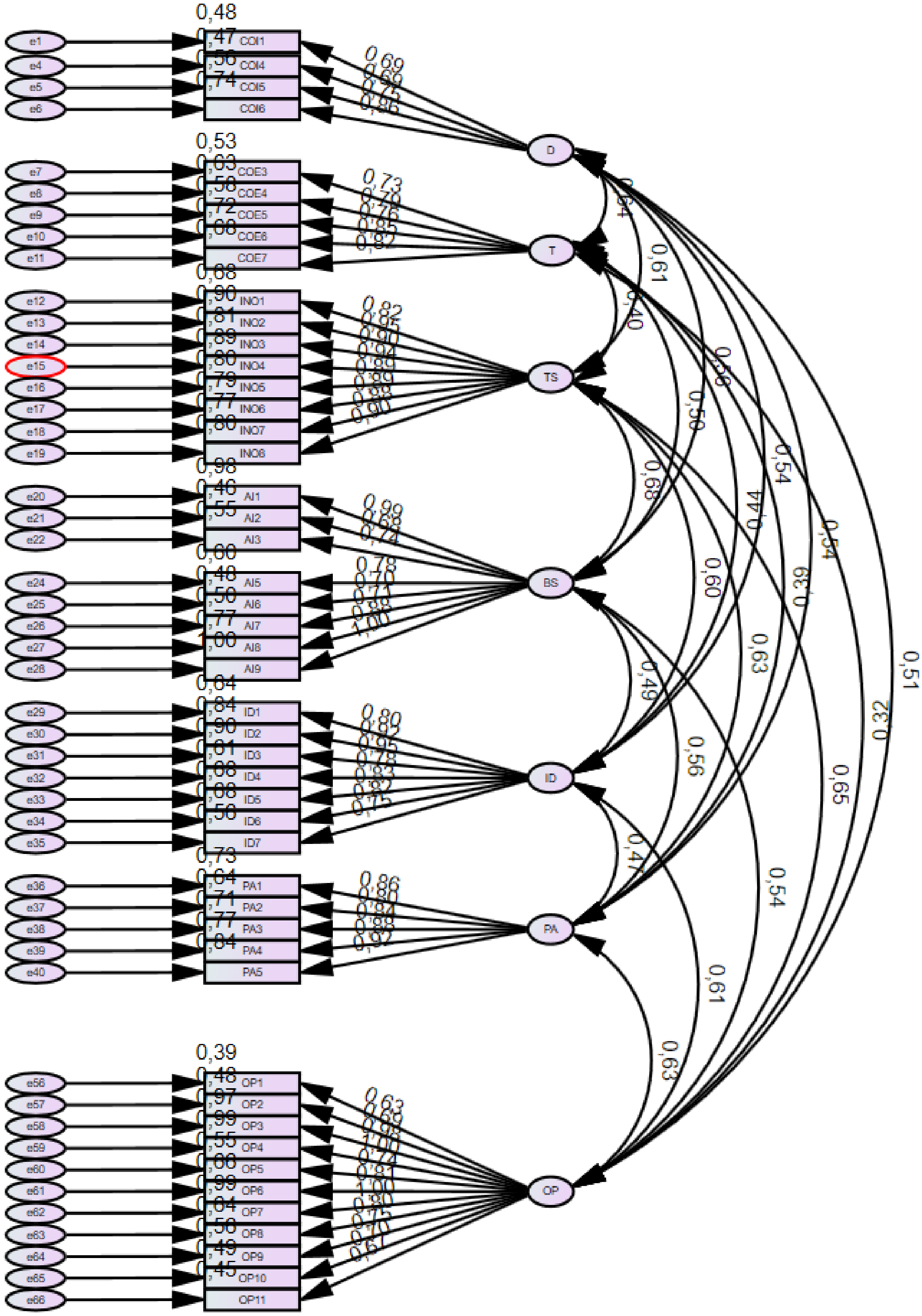

Figure 4: Initial CFA Measurement Model

4.2.2. Goodness of Fit Indices

The "maximum likelihood" method was employed to estimate the parameters of the model, and all analyses were conducted on covariance matrices. Several model fit indices are essential for assessing the goodness-of-fit of the model. The initial step involves evaluating the Chi-square (X2) of the model under examination. The X2 value was found to be high, and the ratio of X2 / DF=3.23 exceeds the recommended threshold of three, suggesting a lack of fit between the data and the model. However, it is important to note that this test may potentially reject hypotheses unnecessarily, as even minor disparities between the observed and ideal model fits could be deemed significant (Hair, Black, Babin, & Anderson, 2010). The fit indices obtained were as follows (see Table 14): [GFI= 0.542; NFI=0.681; CFI=0.754; IFI=0.755; RMSEA=0.124; DF=1059; TLI=0.738 and RFI=0.660]. The validity of the CFA model indicates that some of the model fit indices did not meet the desired criteria. However, the primary objective of the CFA model was to verify if all items of the scale were loading on the model. The CFA test was conducted to confirm construct validity and factor loadings (Serrano, Reynaud, Yasin, & Bhatti, 2018) and not to test the hypotheses among the constructs. The results suggest that all items are loading appropriately and align with the theory. The factor loadings of this model ranged from 0.632 to 0.850, exceeding the recommended threshold of 0.50.

The subsequent section examined the hypothesised model.

Table 14: Goodness of Fit Indices

Fit Index	Recommended Value	CFA Results	Original Structural Model	Final Structural Model
Goodness-of-fit (GFI)	Less than 0.80 (No fit) Between [0.80-0.90] (acceptable)	0.542	0.875	0.987

	Above 0.90 (Perfect fit)			
Normed fit index (NFI)	Less than .80 (poor) Between [0.80-0.90] (acceptable) Above 0.90 (good)	0.681	0.873	0.988
Comparative fit index (CFI)	Less than 0.90 (poor) Above 0.90 (good)	0.754	0.884	0.994
Incremental fit index (IFI)	Less than 0.90 (poor) Above 0.90 (good)	0.755	0.886	0.995
Root mean square error of approximation (RMSEA)	Less than 0.05 (good) Between [0.06-1] (acceptable) Above 1 (poor)	0.124	0.228	0.076
Chi-square ($\chi2$ /DF)	Less than 3 (good) Between [3-5] (acceptable) Above 5 (poor)	3.23	8.49	1.83
Tucker-Lewis Index (TLI)	Less than 0.80 (bad) Between [0.80-0.90] (acceptable)	0.738	0.752	0.972

	Above 0.90 (good)			
Relative Fit Index (RFI)	Less than 0.80 (poor) Between [.80-.90] (acceptable) Above .90 (good)	0.660	0.727	0.941

4.2.3. Original Structural Model testing

The findings demonstrate that reliability, convergent validity, and discriminant validity have been affirmed through both EFA and CFA methodologies. Subsequently, the next phase involved scrutinising the hypothesised relationships between the exogenous and endogenous latent constructs (see Figure 6) via examination of the structural model. In this phase, the relationships between independent and dependent variables were delineated. Causal relationships between independent and dependent variables were depicted by a single-headed arrow, while the covariance between independent variables was denoted by double-headed arrows. Within this study, only "free" pathways were modelled for hypothesised causal relationships between the variables under investigation. These free pathways remained unconstrained, as no fixed pathways were dictated by prior studies (Serrano, Reynaud, Yasin, & Bhatti, 2018) in this model.

The examination of the originally hypothesised model is depicted in Figure 8. Findings reveal a subpar model fit, indicating the necessity for model enhancement to scrutinise the causal relationships among variables. While the original model exhibited a significant P value of 0.000, the X2 / DF ratio of 8.49 exceeds the recommended threshold of less than three. The fit indices, as presented in Table 14, are as follows: [GFI=0.875; NFI=0.873; CFI=0.884; IFI=0.886; RMSEA=0.228; DF=7; TLI=0.752; RFI=0.727], suggesting a poor fit of the model. Hence, there is a need for model refinement to achieve a better fit. Enhancing the model may necessitate dropping certain constructs or hypotheses and removing specific variables. Additionally, some constructs may need to be constrained to zero, thereby excluding them from the model under scrutiny. Drawing error estimate co-variances could also be employed to enhance the model fit.

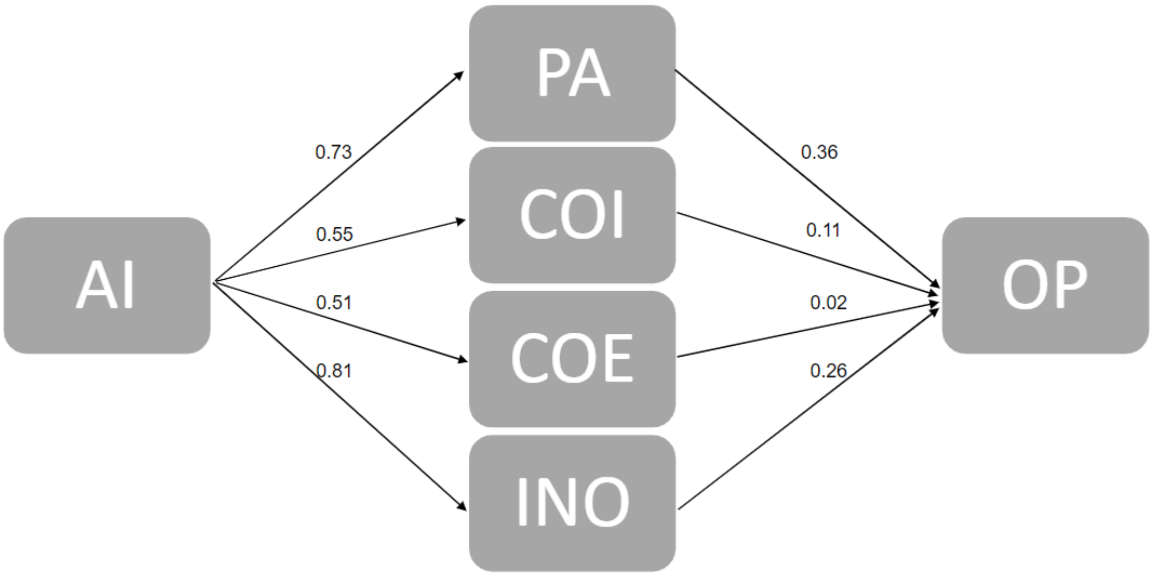

Figure 5: Original Measurement Model Test Results

4.2.4. Final Model testing

The findings of the ultimate SEM AMOS model are delineated in Figure 9. Artificial Intelligence Capabilities are conceptualised as a factor influencing Process Automation, Cognitive Insights, Cognitive Engagements, and Innovativeness within the RBV theory. *The ultimate model solely encompassed the paths of control variables where an initial run revealed a significant effect, while omitting paths where no relationship was observed.*

The ultimate model reveals a non-significant P-value of 0.138, compared to the default model. However, the X2 / DF value of 1.83 is deemed acceptable as it falls within the recommended threshold of less than three. Following the second iteration of the model, the results demonstrate an enhancement in model fit, as delineated in Table 14 above. The fit indices, as listed, [GFI=0.987; NFI=0.988; CFI=0.994; IFI=0.995;

RMSEA=0.076; DF=3; TLI=0.972; RFI=0.941], suggest a satisfactory model fit across most indices.

4.2.4.1. Model improvement steps taken

To enhance the model fit, several steps were taken to improve the covariance values. Covariances between specific variables were adjusted based on Modification Indices (M.I.) and the corresponding parameter changes. The adjustments made were aimed at refining the relationships between the latent constructs in the model. For instance, the covariance between e3 and e5 was increased by 9.436 units, resulting in a parameter change of 0.281. Similarly, the covariance between e3 and e2 was adjusted by 24.249 units, with a corresponding parameter change of 0.672. Additionally, the covariance between e4 and e5 was modified by 14.634 units, yielding a parameter change of 0.352. Finally, the covariance between e4 and e3 was enhanced by 6.752 units, resulting in a parameter change of 0.309. These adjustments were made to refine the relationships between the latent constructs, aiming to improve the overall model fit and enhance its explanatory power (Hair, Black, Babin, & Anderson, 2010).

Finally, Table 15 indicates the modification indices with high covariance that may be covaried if they will not compromise the theoretical model being tested (Fan & Sivo, 2005). In improving the model fit, the below modification of indices was covaried.

Table 15: Modification Indices

Covariances	**M.I.**	**Par Change**
e3<-->e5	9.436	0.281
e 3<-->e2	24.249	0.672
e 4<-->e5	14.634	0.352
e 4<-->e3	6.752	0.309

The results after this final improvement are shown next.

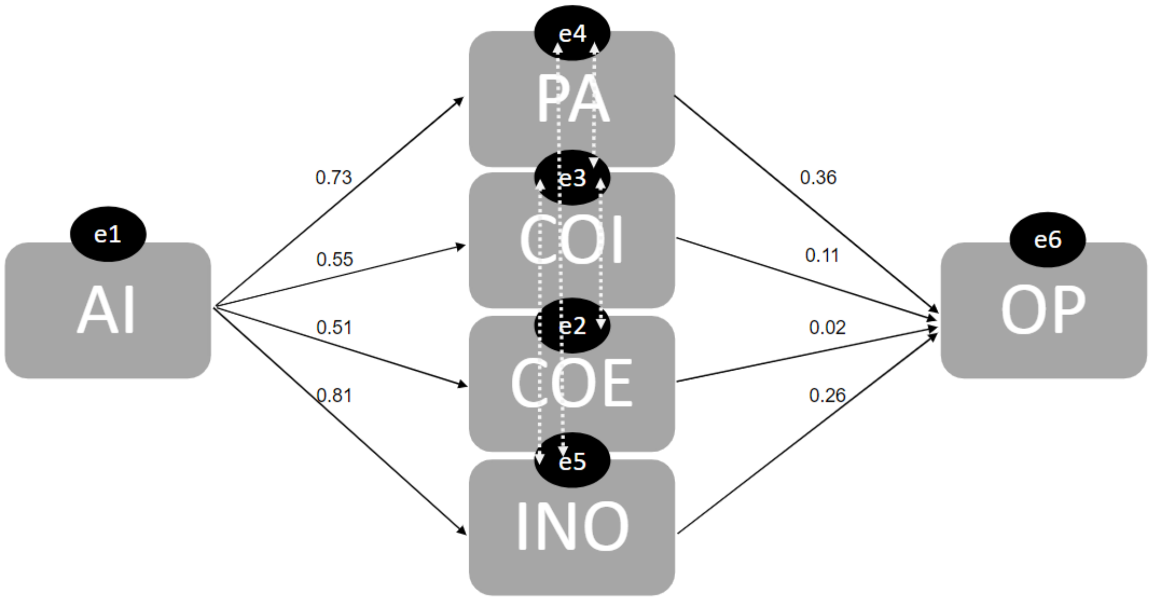

Figure 6: Final Measurement Model Test Results (covariance-arrows were removed to achieve better presentation of the model)

The noteworthy pathways are depicted with solid single-headed arrows, whereas the non-significant pathways are represented by dashed single-headed arrows. The ultimate indices imply that it was appropriate to proceed with scrutinising the hypothesised relationships within the model. Table 16 provides the path coefficients for the "hypothesised relationships within the proposed research model".

Table 16: The Results of Hypothesised Model

Hypothesis		Estimate	S.E.	C.R.	P	P-Value	Supported
H1	AI---> PA	0.727	0.073	9.939	***	<0.001	Supported
H2	AI---> COI	0.547	0.072	7.572	***	<0.001	Supported
H3	AI---> COE	0.510	0.084	6.083	***	<0.001	Supported
H4	AI--->INO	0.813	0.056	14.431	***	<0.001	Supported
H5	PA---> OP	0.360	0.059	6.067	***	<0.001	Supported

H6	COI---> OP	0.114	0.066	1.724	0.085	P>0.05	Not Supported
H7	COE---> OP	0.019	0.054	0.350	0.726	P>0.05	Not Supported
H8	INO--->OP	0.263	0.068	3.861	***	<0.001	Supported
AI = Artificial Intelligence Capabilities, PA = Process Automation, COI = Cognitive Insights, COE = Cognitive Engagements, INO – Innovativeness, OP = Organisational Performance							

Table 17: R-Squared Results

Variables	Estimate
AI	0.000
PA	0.407
COI	0.285
COE	0.204
INO	0.591
OP	0.571

As demonstrated in Table 16, six out of eight hypotheses were directly upheld within the tested model. Artificial Intelligence Capabilities (AI) significantly influence [PA (p<0.001); COI (p<0.001); COE (p<0.001) and INO (p<0.001)], indicating a positive impact on these aspects. This corroborates H1, H2, H3, and H4, indicating that Artificial Intelligence Capabilities (AI) possess the potential to positively affect Process Automation, Cognitive Insights, Cognitive Engagements, and Innovation. Additionally, [PA (p<0.001) and INO (p<0.001)] from the Resource Based View Theory were found to significantly influence Organisational Performance, thereby supporting H5 and H8. Conversely, Cognitive Insights and Cognitive Engagements exhibit no significant effect on Organisational Performance, as their significance levels (p >0.05) exceed 0.05. This suggests that enhancing Cognitive Insights and Cognitive Engagements does not necessarily enhance Organisational Performance. Therefore, H6 and H7 are rejected. This outcome is unexpected, considering the objectives of Cognitive Insights and Cognitive Engagements and the findings from previous studies (Mikalef, et al., 2023).

4.3. Conclusion of the presentation of results

Chapter 4 of the research study delved into the analysis and validation of the proposed model, focusing on Principal Components Analysis (PCA), reliability, and validity assessment, as well as the examination of goodness of fit indices and testing of the structural model.

PCA was employed to condense observable variance into latent variables, extracting seven factors from 49 items via orthogonal rotation (Varimax), explaining 77.5% of the total variance. Reliability and validity were assessed using Cronbach's alpha, Average Variance Extracted (AVE), and Composite Reliability (CR), with most constructs demonstrating satisfactory values.

Goodness of fit indices were evaluated to assess the fit of the model, revealing initially subpar fit but improved fit after adjustments. Original structural model testing highlighted the need for model refinement, leading to the final model with satisfactory fit indices.

The final model testing affirmed six out of eight hypotheses, indicating that Artificial Intelligence Capabilities significantly influenced various aspects of organizational performance, while Cognitive Insights and Cognitive Engagements did not significantly impact organizational performance as hypothesised. These findings provided valuable insights into the relationships between AI capabilities, organisational processes, and performance outcomes in the context of the study.

CHAPTER 5: DISCUSSION OF THE RESULTS

5.1. Empirical Results

The aim of this chapter was to explore the influence of artificial intelligence (AI) capabilities on several factors outlined within the adapted Resource-Based View (RBV) theory, namely Process Automation, Cognitive Insights, Cognitive Engagements, and Innovation, and to assess their implications for organisational performance. Specifically, this chapter aimed to address two research objectives: *RO1; "to investigate the impact of AI capabilities on retail organisational activities within South Africa."*, and *RO2; "to determine the influence of operational activities on organisational performance."* To achieve these objectives, a model based on the Resource-Based View Theory, proposed by (Barney J. B., 1991), was developed, and empirically tested.

Data were collected from participants employed within the retail sector in South Africa. In extending the original RBV theory, Innovativeness was incorporated as an additional variable believed to influence organisational performance. The results of the analysis conducted using AMOS, as depicted in Figure 9 and Table 16, indicate that AI capabilities have a significant impact on Process Automation, Cognitive Insights, Cognitive Engagements, and Innovativeness, consequently leading to improved organisational performance. These findings will be further discussed in detail in the subsequent section.

5.1.1. The impact of AI capabilities on retail organisational activities within South Africa

The findings have shed light on the impact of AI capabilities on retail organisational activities within South Africa, as defined by the adapted RBV theory.

The impact of AI capabilities on retail organisational activities can be outlined as follows:

Table 18: Artificial Intelligence Capabilities impacting Retail Organisational activities within the adapted RBV theory.

Factors within the amended RBV theory	Impacted by Artificial Intelligence Capabilities
Process Automation	Yes
Cognitive Insights	Yes
Cognitive Engagement	Yes
Innovativeness	Yes

In the original RBV theory, only three organisational activities were deemed crucial components of organisational performance: Process Automation, Cognitive Insights, and Cognitive Engagements (Barney J. B., 1991). These three activities have been extensively investigated as pivotal contributors to overall organisational performance. However, their examination within the context of Artificial Intelligence (AI) Capabilities has been lacking (Davenport & Ronanki, 2018). Furthermore, considering that AI Capabilities primarily focus on streamlining processes, improving decision-making, and enhancing customer experiences, this study has introduced a fourth organisational activity in the form of innovativeness.

Process Automation has emerged as one of the organisational activities influenced by Artificial Intelligence (AI) capabilities. Defined within this context, Process Automation refers to the utilisation of AI technologies to automate routine tasks and workflows within the organisation, thereby enhancing efficiency and reducing manual effort. Most respondents reported a notable increase in process automation, strongly concurring that AI capabilities positively affect this aspect of organisational activities. Their perception resonates with the supported notion that AI capabilities do indeed exert a positive impact on process automation. Furthermore, the hypothesis (H1) postulating that the perception of AI capabilities positively influences process automation has been empirically validated, thus affirming (H1) within the model. This finding was expected, considering previous research indicating process automation as a significant organisational activity influenced by AI capabilities.

Cognitive Insights have emerged as another organisational activity influenced by Artificial Intelligence (AI) capabilities. Within this framework, Cognitive Insights refer to the capability of AI technologies to analyse extensive datasets, identify patterns, and generate valuable insights to inform decision-making processes within the organisation, thereby enhancing strategic planning and operational effectiveness. Most respondents indicated a noticeable increase in cognitive insights, strongly agreeing that AI capabilities positively impact this aspect of organisational activities. Their perception aligns with the supported notion that AI capabilities indeed exert a positive effect on cognitive insights. Furthermore, the hypothesis (H2) asserting that the perception of AI capabilities positively influences cognitive insights has been empirically affirmed, thus validating (H2) within the model. This outcome was anticipated, given prior research indicating cognitive insights as a significant organisational activity influenced by AI capabilities.

Cognitive Engagements have also emerged as significant organisational activities influenced by Artificial Intelligence (AI) capabilities. Within this context, Cognitive Engagements refer to the interactions and collaborations facilitated by AI technologies that enhance knowledge sharing, problem-solving, and decision-making processes within the organisation, thereby fostering innovation and creativity. Most respondents reported a substantial increase in cognitive engagements, strongly agreeing that AI capabilities positively impact this aspect of organisational activities. Their perception aligns with the supported notion that AI capabilities indeed exert a positive effect on cognitive engagements. Furthermore, the hypothesis (H3) proposing that the perception of AI capabilities positively influences cognitive engagements has been empirically confirmed, thus validating (H3) within the model. This finding was anticipated, given previous research indicating cognitive engagements as a significant organisational activity influenced by AI capabilities.

Finally, Innovativeness has emerged as another organisational activity influenced by Artificial Intelligence (AI) capabilities. Within this context, Innovativeness refers to the organisation's ability to generate and implement novel ideas, products, or processes that lead to competitive advantage and value creation. Most respondents reported a significant increase in innovativeness, strongly agreeing that AI capabilities positively impact this aspect of organisational activities. Their perception aligns with the supported notion that AI capabilities indeed exert a positive effect on innovativeness. Furthermore, the hypothesis (H4) proposing that the perception of AI capabilities positively influences innovativeness has been empirically upheld, thus validating (H4) within the model. This finding was expected, given previous research indicating innovativeness as a significant organisational activity influenced by AI capabilities.

The findings of the study shed light on the impact of Artificial Intelligence (AI) capabilities on various organisational activities within the retail sector in South Africa, aligning with the research objective, *RO1; "to investigate the impact of AI capabilities on retail organisational activities within South Africa".* Through empirical analysis, it was revealed that AI capabilities significantly influence key organisational activities such as Process Automation, Cognitive Insights, Cognitive Engagements, and Innovativeness.

Overall, the study findings underscore the significant role of AI capabilities in enhancing various organisational activities within the retail sector in South Africa, thereby contributing to a deeper understanding of the impact of AI on retail organisational dynamics as outlined in RO1.

5.1.2. The impact of retail organisational activities in South Africa on organisational performance

The results have shed light on the influence of retail organisational activities on organisational performance within South Africa, as defined by the adapted RBV theory.

The effects of retail organisational activities on organisational performance are summarised as follows:

Table 19: Retail Organisational activities impacting organisational performance within the adapted RBV theory.

Factors within the amended RBV theory	Impacted Organisational Performance
Process Automation	Yes
Cognitive Insights	No
Cognitive Engagement	No
Innovativeness	Yes

Process Automation has emerged as a pivotal organisational activity influencing Organisational Performance. Within this context, it involves the utilisation of AI technologies to automate routine tasks and workflows within the organisation, thereby enhancing efficiency and reducing manual effort. Most respondents reported a significant improvement in organisational performance, strongly concurring that Process Automation positively affects this aspect of organisational performance. Their perception aligns with the notion that AI capabilities indeed exert a positive impact on process automation, consequently enhancing organisational performance. Furthermore, the hypothesis (H5) proposing that the perception of process automation positively influences organisational performance has been empirically validated, thus affirming (H5) within the model. This finding was anticipated, given prior research indicating process automation as a significant organisational activity influencing organisational performance.

Conversely, Cognitive Insights and Cognitive Engagements have emerged as organisational activities that do not significantly affect organisational performance. Within this framework, Cognitive Insights refer to the capacity of AI technologies to analyse vast amounts of data, identify patterns, and generate valuable insights to inform decision-making processes within the organisation, while Cognitive Engagements encompass interactions and collaborations facilitated by AI technologies to enhance knowledge sharing, problem-solving, and decision-making processes. Most respondents indicated no significant effect on organisational performance, which contrasts with the notion that AI capabilities exert a positive impact on cognitive insights and engagements, and subsequently, organisational performance. Furthermore, the hypotheses (H6) and (H7) proposing that the perceptions of cognitive insights and engagements positively influence organisational performance have been empirically rejected, invalidating (H6) and (H7) within the model. This outcome was unexpected, considering previous research indicating cognitive insights and engagements as significant organisational activities influencing organisational performance.

Finally, Innovativeness has emerged as another crucial organisational activity influencing Organisational Performance. Defined within this context, Innovativeness refers to the organisation's ability to generate and implement novel ideas, products, or processes that lead to competitive advantage and value creation. Most respondents reported a notable increase in organisational performance, strongly concurring that Innovativeness positively affects this aspect of organisational performance. Their perception resonates with the notion that AI capabilities indeed exert a positive impact on innovativeness, subsequently enhancing organisational performance. Furthermore, the hypothesis (H8) proposing that the perception of innovativeness positively influences organisational performance has been empirically validated, affirming (H8) within the model. This finding was expected, given previous research indicating innovativeness as a significant organisational activity influencing organisational performance.

The findings of the study shed light on the impact of these organisational activities on organisational performance within the retail sector in South Africa, aligning with the research objective, *RO2; "to determine the influence of operational activities on organisational performance."* Through empirical analysis, it was revealed that organisational activities such as Process Automation and Innovativeness significantly influence organisational performance.

Overall, the study's findings underscore the significant role of these organisational activities in increasing organisational performance within the retail sector in South Africa, thereby contributing to a deeper understanding of their impact on organisational performance as outlined in RO2.

5.2. Conclusion of the discussion of the results

This chapter delved into the influence of AI Capabilities on organisational activities and its implications for the organisational performance of retail organisations operating in South Africa. The chapter thoroughly interpreted the key findings derived from the RBV theory regarding organisational performance, thereby addressing *RO1; "to investigate the impact of AI capabilities on retail organisational activities within South Africa."*, and *RO2; "to determine the influence of operational activities on organisational performance"*. AI capabilities were expanded upon within this context, presenting them as the utilisation of advanced technologies to enhance various aspects of organisational activities.

Through the analysis of responses obtained from 145 participants within the South African retail sector, the chapter distinguished that AI capabilities impact several organisational activities, namely Process Automation, Cognitive Insights, Cognitive Engagements, and Innovativeness. Moreover, it presented which of these activities significantly influence organisational performance within the South African retail sector.

This study has made a significant contribution by incorporating innovativeness as an additional organisational activity within the RBV theory. Innovativeness emerged as a crucial determinant of organisational performance, challenging the notion that only process automation, cognitive insights, and cognitive engagements lead to enhanced performance. This unexpected finding underscores the importance of considering innovativeness alongside other organisational activities.

In summary, this chapter delved into the cross-sectional outcomes regarding the impact and adoption of Artificial Intelligence capabilities by retail organisations operating within South Africa. Additionally, it highlighted that while process automation and innovativeness significantly influence organisational performance, cognitive insights and cognitive engagements were not found to improve organisational performance, challenging conventional wisdom in this domain.

CHAPTER 6: CONCLUSIONS AND RECOMMENDATIONS

6.1. Introduction

This chapter delves into the versatile contributions of the study, focusing on theoretical advancements, contextual insights, methodological rigour, practical applications, limitations, and recommendations for future research. Through a comprehensive analysis, the chapter explains the study's academic and practical significance within the context of the South African retail sector. By exploring the theoretical underpinnings, methodological approaches, and practical implications of the research findings, this chapter aims to provide a subtle understanding of the intricate relationship between Artificial Intelligence (AI) capabilities and organisational performance, thereby contributing to both scholarly discourse and industry practice.

6.2. Summary of the Study

Chapter 1 introduced the research topic; The impact of Artificial Intelligence Capabilities on Organisational Performance: An Empirical study in the South African Retail context, outlining the problem statement's significance and the study's objectives. This chapter established the groundwork for the research, providing context and rationale for the investigation to follow.

Chapter 2 concluded the literature review, exploring the impact of AI on organisational performance within the RBV theory framework. It discussed the benefits and challenges of AI adoption in retail organisations, identified research gaps, and outlined the study objectives.

Chapter 3 concluded the research methodology section, detailing the chosen research approach, design, data collection methods, and analysis strategies. The chapter highlighted the theoretical framework and rationale behind the selected methods.

Chapter 4 presented the analysis and validation of the proposed model, focusing on PCA, reliability, validity assessment, and goodness of fit indices. It affirmed the significance of AI capabilities in influencing organisational performance, with some unexpected findings regarding cognitive insights and engagements.

Chapter 5 discussed the results of the study, highlighting the impact of AI capabilities on organisational activities and performance in the South African retail sector. It identified significant influences on organisational performance, including process automation and innovativeness, while challenging assumptions about cognitive insights and cognitive engagements.

Overall, the study contributes to understanding the role of AI capabilities in retail organisational performance within the South African context, shedding light on both expected and unexpected findings regarding the impact of AI capabilities on various organisational activities, as stated in the RBV theory.

6.3. Contributions of the study

The aim of this section is to highlight the theoretical contributions of the study regarding the impact of Artificial Intelligence (AI) capabilities on organisational activities and performance within the South African retail sector. It discusses how the study advances the Resource-Based View (RBV) theory by integrating innovativeness, providing empirical evidence of AI's influence on various organisational factors, offering contextual insights specific to the South African retail sector, and employing robust methodological techniques such as Structural Equation Modelling (SEM). This section underscores the study's significance in enhancing theoretical understanding and informing both theory and practice in strategic management and technology adoption within the retail industry.

6.3.1. Theoretical Contributions

This study contributes to the theoretical understanding of the impact of Artificial Intelligence (AI) capabilities on organisational activities and performance within the context of the South African retail sector. By incorporating elements from the Resource-Based View (RBV) theory and extending its applicability to include innovativeness, the study offers insights into how AI capabilities influence various organisational factors and shape organisational performance.

6.3.1.1. Advancement of RBV Theory

The inclusion of innovativeness as a component in the RBV theory represents a theoretical advancement. Traditionally, RBV theory focuses on internal resources and capabilities as determinants of sustained competitive advantage and superior performance. By integrating innovativeness, which pertains to an organisation's ability to generate and implement novel ideas, technologies, and processes, the study enriches the RBV framework, aligning it more closely with contemporary business dynamics and the imperative of innovation in driving organisational success.

6.3.1.2. Understanding AI Impact

The study provides empirical evidence of the influence of AI capabilities on various organisational aspects, including process automation, cognitive insights, cognitive engagement, and innovation. By empirically testing the relationships between AI capabilities and these variables, the study enhances our understanding of how AI technologies shape organisational functioning. This contributes to the broader discourse on the role of emerging technologies in driving organisational change and competitiveness.

6.3.1.3. Contextual Insight into the South African Retail Sector

By focusing on the South African retail sector, the study offers contextual insight into the adoption and impact of AI capabilities in a specific geographical and industry context. This is significant as it provides nuanced understanding of the challenges, opportunities, and dynamics unique to the South African retail landscape. Such context-specific insights are invaluable for policymakers, practitioners, and scholars seeking to navigate the complexities of technology adoption and organisational transformation in emerging markets.

6.3.1.4. Methodological Rigour

The study employs robust methodological techniques, including Structural Equation Modelling (SEM), to empirically test the hypothesised relationships between AI capabilities and organisational performance factors. Through meticulous data collection, analysis, and interpretation, the study ensures the reliability and validity of its findings, enhancing the credibility of the theoretical contributions.

Overall, this study contributes to the advancement of theoretical knowledge by extending the RBV framework to include innovativeness, empirically investigating the impact of AI capabilities on organisational performance factors, offering context-specific insights into the South African retail sector, and employing rigorous methodological approaches. These contributions enrich our understanding of the complex interplay between technology, organisational dynamics, and competitive advantage, thereby informing both theory and practice in the field of strategic management and technology adoption.

6.3.2. Contextual Contribution

This study makes significant contextual contributions by examining the impact of Artificial Intelligence (AI) capabilities on organisational activities and performance specifically within the South African retail sector. The contextual contributions of the study are outlined below:

6.3.2.1. Understanding AI Adoption in South Africa

The study sheds light on the adoption and integration of AI capabilities within the South African retail sector. South Africa represents a unique context characterized by its socio-economic dynamics, regulatory environment, and technological infrastructure. By examining AI adoption within this context, the study provides insights into the challenges and opportunities associated with the implementation of advanced technologies in emerging market settings. This understanding is crucial for policymakers, industry practitioners, and stakeholders seeking to navigate the complexities of technology adoption in South Africa.

6.3.2.2. Addressing Local Challenges and Opportunities

The study addresses the specific challenges and opportunities faced by retail organisations in South Africa concerning AI adoption. These may include issues related to infrastructure limitations, skills shortages, regulatory frameworks, and socio-economic disparities. By identifying and analysing these contextual factors, the study offers practical insights into how retail organisations can overcome barriers to AI adoption and leverage opportunities to enhance their competitive positioning and operational efficiency in the South African market.

6.3.2.3. Tailored Strategies for South African Retailers

The findings of the study enable the development of tailored strategies and recommendations for retail organisations operating in South Africa. By understanding the unique contextual factors influencing AI adoption and organisational performance in the South African retail sector, stakeholders can devise targeted interventions to promote the effective use of AI technologies. These strategies may include investment in infrastructure development, workforce upskilling initiatives, regulatory advocacy, and partnerships with technology providers. Such tailored approaches are essential for maximising the benefits of AI adoption while mitigating potential challenges within the South African context.

6.3.2.4. Informing Policy and Practice

The study's contextual insights inform policy formulation and industry practice related to AI adoption in South Africa. Policymakers can use the findings to design supportive frameworks and incentives that encourage AI investment and innovation in the retail sector. Industry practitioners can leverage the study's recommendations to develop best practices and guidelines for AI implementation, thereby enhancing organisational performance and competitiveness. By bridging the gap between research, policy, and practice, the study contributes to the advancement of the South African retail sector and its broader socio-economic development agenda.

In summary, the study's contextual contributions extend beyond theoretical knowledge to offer practical insights and recommendations tailored to the unique challenges and opportunities present within the South African retail sector. By addressing local contexts and dynamics, the study enhances understanding and informs strategic decision-making, contributing to the advancement of AI adoption and organisational performance in South Africa.

6.3.3. Methodological Contribution

This study makes several methodological contributions that enhance the existing literature on the impact of Artificial Intelligence (AI) capabilities on organisational activities and performance. The methodological contributions of the study are outlined below:

6.3.3.1. Utilisation of Structural Equation Modelling (SEM)

The study employs Structural Equation Modelling (SEM) to analyse the complex relationships between AI capabilities, organisational activities (such as process automation, cognitive insights, cognitive engagement, and innovation), and organisational performance. SEM is a powerful statistical technique that allows for the simultaneous examination of multiple variables and latent constructs within a comprehensive theoretical framework. By employing SEM, the study provides a robust methodological approach for investigating the multifaceted impact of AI capabilities on organisational dynamics.

6.3.3.2. Integration of Empirical Data from the South African Retail Sector

The study contributes empirical data from the South African retail sector, a context that has received limited attention in previous research on AI adoption and organisational performance. By collecting and analysing data from individuals working within South Africa's retail industry, the study enriches the empirical foundation of AI research within the South African context. This methodological approach ensures that the findings are grounded in the realities and challenges faced by retail organisations operating in South Africa, thereby enhancing the relevance and applicability of the study's results.

6.3.3.3. Comprehensive Survey Design and Data Collection

The study employs a comprehensive survey design to gather data on AI capabilities, organisational activities, and organisational performance indicators. The survey instrument is carefully constructed to capture the nuances of AI adoption and its implications for various dimensions of organisational functioning. By collecting data from a diverse sample of retail professionals, the study ensures the representation of different perspectives and experiences within the industry. This methodological rigour enhances the validity and reliability of the study's findings, providing a robust basis for analysis and interpretation.

6.3.3.4. Rigorous Data Analysis and Model Testing

The study conducts rigorous data analysis and model testing procedures to examine the relationships between AI capabilities, organisational activities, and organisational performance. Through techniques such as confirmatory factor analysis, reliability and validity testing, and structural equation modelling, the study evaluates the hypothesised relationships within the conceptual framework. This methodological rigour ensures the accuracy and robustness of the study's findings, enabling meaningful insights into the mechanisms through which AI capabilities influence organisational dynamics.

In summary, the study's methodological contributions encompass the use of advanced statistical techniques, empirical data collection from the South African retail sector, comprehensive survey design, and rigorous data analysis procedures. By employing these methodological approaches, the study enhances the methodological rigour and empirical validity of research on AI adoption and organisational performance, thereby advancing scholarly understanding in this field.

6.3.4. Practical Application

This study holds several practical implications for stakeholders within the South African retail sector and beyond. The practical applications of the study's findings are outlined below:

6.3.4.1. Informed Decision-Making for Retail Organisations

The study provides valuable insights into the impact of Artificial Intelligence (AI) capabilities on various aspects of organisational activities and performance within the retail sector. Retail organisations can leverage these insights to make informed decisions regarding the adoption, implementation, and integration of AI technologies into their operations. By understanding the specific ways in which AI capabilities influence processes such as automation, cognitive insights, cognitive engagement, and innovation, retail managers and decision-makers can develop strategies to harness the potential benefits of AI while mitigating potential challenges.

6.3.4.2. Strategic Planning and Resource Allocation

The findings of the study enable retail organisations to engage in strategic planning and resource allocation processes effectively. By recognising the significant positive relationships between AI capabilities and process automation, cognitive insights, cognitive engagement, and innovation, organisations can allocate resources towards the development and enhancement of AI-driven initiatives. This strategic approach ensures that investments in AI technologies align with organisational goals and priorities, thereby maximising the potential for positive outcomes and competitive advantage.

6.3.4.3. Enhancing Organisational Performance and Competitiveness

The study's insights into the relationship between AI capabilities and organisational performance contribute to enhancing the overall competitiveness of retail organisations. By leveraging AI technologies to automate processes, derive valuable insights from data, foster cognitive engagement among employees, and drive innovation, retail organisations can improve operational efficiency, customer satisfaction, and financial performance. This, in turn, enhances their competitiveness in the market and positions them for long-term success in the retail industry.

6.3.4.4. Talent Development and Skills Enhancement

The study underscores the importance of human capital development in maximising the benefits of AI adoption within retail organisations. As AI technologies become increasingly integrated into organisational processes, there is a growing need for employees with skills in data analysis, technology management, and cognitive problem-solving. Retail organisations can use the study's findings to identify areas for talent development and skills enhancement, ensuring that their workforce is equipped to effectively use and leverage AI capabilities for organisational success.

6.3.4.5. Regulatory and Ethical Considerations

Finally, the study highlights the importance of addressing regulatory and ethical considerations associated with the adoption and use of AI technologies in the retail sector. Retail organisations must navigate issues related to data privacy, security, fairness, and transparency when deploying AI-driven solutions. By acknowledging these considerations and integrating ethical principles into AI strategies and practices, retail organisations can build trust with stakeholders and mitigate potential risks associated with AI adoption.

In summary, the study's practical implications encompass informed decision-making, strategic planning, resource allocation, talent development, and regulatory compliance within the South African retail sector. By applying the insights derived from the study, retail organisations can enhance their operational efficiency, competitiveness, and long-term sustainability in an increasingly AI-driven business environment.

6.4. Limitations

6.4.1. Sampling Bias

One of the primary limitations of the study is the potential for sampling bias due to the low response rate and limited sample size. Despite extensive outreach efforts, the study's sample may not fully represent the diversity of the South African retail sector. The low response rate raises concerns about the generalisability of the findings to the broader population of retail organisations in South Africa (Hair, Black, Babin, & Anderson, 2010).

6.4.2. Self-Reported Data

The study relies on self-reported data collected through surveys, which may be subject to response bias and social desirability bias. Respondents may provide socially desirable responses or inaccurately recall information, leading to potential measurement error and affecting the reliability and validity of the results (Hair, Black, Babin, & Anderson, 2010).

6.4.3. Cross-Sectional Design

The study adopts a cross-sectional design, which limits the ability to establish causal relationships between variables. While the study examines the relationships between AI capabilities and organisational performance, it cannot determine the direction of causality or account for potential confounding variables (Hair, Black, Babin, & Anderson, 2010).

6.4.4. Measurement Instrument

The study uses a survey instrument to measure constructs such as AI capabilities, process automation, cognitive insights, cognitive engagement, innovation, and organisational performance. While efforts were made to ensure the validity and reliability of the instrument, measurement errors and limitations inherent in self-report measures may impact the accuracy of the results (Hair, Black, Babin, & Anderson, 2010).

6.4.5. Contextual Specificity

The study focuses specifically on the South African retail sector, which may limit the generalisability of the findings to other industries or geographical contexts. Factors unique to the South African retail landscape, such as regulatory environment, cultural norms, and economic conditions, may influence the observed relationships between AI capabilities and organisational outcomes (Hair, Black, Babin, & Anderson, 2010).

6.4.6. Lack of Longitudinal Data

The study lacks longitudinal data, preventing the examination of trends and changes over time in the relationships between AI capabilities and organisational performance. Longitudinal studies would provide more robust evidence of causality and allow for the assessment of the long-term impact of AI adoption on organisational outcomes (Hair, Black, Babin, & Anderson, 2010).

6.4.7. Scope of Variables

While the study examines several variables related to AI capabilities and organisational performance, it may not capture all relevant factors influencing these relationships. Future research could explore additional variables or moderators to provide a more comprehensive understanding of the dynamics at play (Hair, Black, Babin, & Anderson, 2010).

Addressing these limitations in future research would strengthen the validity and reliability of findings and enhance the applicability of results to a broader range of contexts within the retail industry.

6.5. Recommendations for Future Research

6.5.1. Longitudinal Studies

Conduct longitudinal studies to investigate the long-term effects of AI capabilities on organisational performance in the South African retail sector. Longitudinal research designs would allow for the examination of trends and changes over time, providing more robust evidence of causality and the sustainability of the observed relationships.

6.5.2. Comparative Analysis

Compare the impact of AI capabilities on organisational performance across different industries or geographical regions within South Africa. Comparative studies would facilitate a deeper understanding of how contextual factors influence the relationship between AI adoption and organisational outcomes, providing insights applicable to diverse sectors and regions.

6.5.3. Qualitative Research

Supplement quantitative analyses with qualitative research methods, such as interviews or focus groups, to gain a richer understanding of the mechanisms through which AI capabilities influence organisational performance. Qualitative insights would complement quantitative findings by uncovering nuanced perspectives and contextual factors that may not be captured through survey data alone.

6.5.4. Mediation and Moderation Analysis

Explore the mediating and moderating effects of additional variables on the relationship between AI capabilities and organisational performance. Mediation and moderation analyses would elucidate the underlying mechanisms and boundary conditions that shape the impact of AI adoption on various aspects of organisational functioning.

6.5.5. Cross-Cultural Studies

Conduct cross-cultural studies to compare the influence of AI capabilities on organisational performance across diverse cultural contexts. Cross-cultural research would provide insights into how cultural norms, values, and practices interact with AI adoption to shape organisational outcomes, enhancing the generalisability of findings beyond the South African context.

6.5.6. Technological Advancements

Investigate the role of emerging technologies, beyond AI, in shaping organisational performance in the retail sector. Future research could explore the synergistic effects of AI with technologies such as blockchain, Internet of Things (IoT), or augmented reality (AR) on operational efficiency, customer experience, and competitive advantage.

6.5.7. Industry Collaboration

Foster collaboration between academia and industry stakeholders to co-create research initiatives and share data on AI adoption and organisational performance in the retail sector. Industry-academic partnerships would facilitate access to real-world data and insights, enhancing the relevance and applicability of research findings to industry practices.

By addressing these recommendations in future research endeavours, scholars can deepen their understanding of the complex interplay between AI capabilities and organisational performance in the South African retail sector, contributing to theory development and informing evidence-based decision-making for businesses and policymakers.

6.6. Conclusions

In conclusion, this study significantly contributes to the theoretical understanding, contextual insight, methodological rigour, and practical application regarding the impact of Artificial Intelligence (AI) capabilities on organisational activities and performance within the South African retail sector. The theoretical framework enriches the Resource-Based View (RBV) theory by integrating innovativeness, offering empirical evidence of significant positive relationships between AI capabilities and key organisational factors such as process automation, cognitive insights, cognitive engagement, and innovation. These findings advance our understanding of technology's role in shaping organisational dynamics and competitive advantage. Moreover, the study provides valuable contextual insights into AI adoption challenges, opportunities, and strategies tailored to the unique context of the South African retail sector. It informs decision-making, strategic planning, talent development, and regulatory compliance within the industry, thereby contributing to its growth and socio-economic development. Methodologically, the study employs robust techniques such as Structural Equation Modelling (SEM) and integrates empirical data from the South African retail sector, ensuring methodological rigour and empirical validity. However, the study acknowledges limitations such as sampling bias, self-reported data, and the cross-sectional design, suggesting areas for future research improvement. Recommendations for future research include longitudinal studies, comparative analysis, qualitative research, mediation and moderation analysis, cross-cultural studies, investigation of emerging technologies, and industry collaboration. In summary, this study serves as a foundation for further research and practical application in the dynamic landscape of AI-driven business environments, aiming to foster innovation, efficiency, and sustainability in the South African retail sector and beyond.

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APPENDIX A. PARTICIPATION INVITATION LETTER AND ORGANISATIONAL STUDY INSTRUMENT

Section A: Demographic Information Participation Invitation Letter

Dear Participant,

Invitation to Participate in a Study on the Organisational Impact of Artificial Intelligence (AI) Capabilities in Retail Organisations within a South African context.

My name is Dylan Christo Cronje, and I am a Masters student in Digital Business at the University of the Witwatersrand (WITS), Johannesburg. As part of my masters research, I am conducting a study on the organisational impact of artificial intelligence (AI) capabilities in retail organisations in South Africa.

The purpose of this study is to examine how AI capabilities, including process automation, cognitive insights, cognitive engagement, and innovativeness, impact organisational performance within the South African retail sector. By incorporating the Resource-Based View (RBV) theory, this research aims to provide valuable insights into the relationship between AI capabilities and performance outcomes in the South African retail context.

Your organisation has been identified as a key stakeholder in the use and implementation of AI technologies within the retail sector. Therefore, I would like to invite you to participate in this study by completing a questionnaire. The questionnaire consists of demographic information about your organisation and statements related to your perceptions of AI capabilities and their impacts. It should take 10 to 20 minutes to complete.

Please be assured that your participation in this study is voluntary and all responses will be kept strictly confidential. The data collected will be used for research purposes only and will be reported in aggregate form, ensuring anonymity and confidentiality.

The study has received ethical clearance from the Wits Human Research Ethics Committee (HREC Non-Medical), Protocol Number: (WBS/DB1250875/264). Should you have any questions or concerns about your participation or the study itself, please feel free to contact me at 1250875@students.wits.ac.za. Additionally, if you would like to receive a copy of the study's results in aggregate form, please let me know, and I would be happy to share them with you.

For any further assistance or clarifications, please contact my supervisor, Dr T.N. Mudau (mudauno1979@gmail.com).

Thank you for considering your participation in this study. Your insights and contributions will contribute to advancing our understanding of the organisational impact of AI capabilities in the South African retail sector.

I look forward to your favourable response.

Kind regards
Dylan Cronje

SURVEY

Part A: **Demographic Information**

Part B: **AI Capability**

Part C: **Organisational Activities**

Part D: **Organisational Performance**

Part A: Demographic Information

This section asks questions about your demographic information including your experience.

1. **Please select the number of years your company has been using AI capabilities**

<5	
6-10	
11-15	
16-20	
21-25	
>25	

2. **Please indicate the revenue that your organisation generates per annum**

<R20 million	
R21-R50 million	
R51-R100 million	
R101-R150 million	
R151-R200 million	
R201-R499 million	
>R500 million	

3. Please select your job title

Chief Technology Officer	
Technology Engineer	
Technology Director	
Managing Director	
Executive Director	
Other (please specify)	

4. Please select your years of experience in the organisation

<5 years	
6-10 years	
11-15 years	
> 16 years	

5. Please indicate the number of years that your organisation has been in operation

<5 years	
6-10 years	
11-15 years	
16-20 years	
21-25 years	
26-30 years	
31-35 years	
> 36 years	

6. Please indicate the number of employees within your organisation

<1000	
1001-4999	

5000-9999	
10000-49999	
50000-99999	
>100000	

Below is a modified version of the survey questionnaire used by (Mikalef, et al., 2023):

7. **Please indicate your level of agreement with the following statements regarding your retail organisation's AI capability**

Use a 7-point Likert scale. With 1 stating that you do not agree and 7 stating that you are in full agreement.

Strongly disagree	Mostly disagree	Disagree	Neutral	Agree	Mostly Agree	Strongly Agree
1	2	3	4	5	6	7

Part B: AI Capability	
Artificial Intelligence Capabilities:	AI1: Our managers can understand business problems and to direct AI initiatives to solve them
	AI2: Our managers can work with data scientists, other employees, and customers to determine opportunities that AI might bring to our organisation
	AI3: Our managers have a good sense of where to apply AI
	AI4: The executive manager of our AI function has strong leadership skills
	AI5: Our managers can anticipate future business needs of functional managers, suppliers and customers and proactively design AI solutions to support these needs
	AI6: Our managers are capable of coordinating AI-related activities in ways that support the organisation, suppliers, and customers
	AI7: We have strong leadership to support AI initiatives.

	AI8: Our managers demonstrate ownership of and commitment to AI projects.
	AI9: Our managers demonstrate an exemplary attitude to the use of AI.
Part C: Organisational Activities	
Process Automation	PA1: The use of AI has enabled us to automate back office administrative tasks
	PA2: The use of AI has allowed us to automate financial activities
	PA3: The use of AI has helped us automate structured tasks (e.g. transferring of data, updating records)
	PA4: The use of AI has helped us automate complex human processes for our employees
	PA5: The use of AI has enabled us to free up employees in tasks that are now automated
	PA6: The use of AI has optimised our information systems itself (e.g. optimising processes, machine learning)
Cognitive Insights	COI1: We have access to large, unstructured, or fast-moving data for analysis
	COI2: We integrate data from multiple internal sources into a data warehouse or mart for easy access
	COI3: We integrate external data with internal to facilitate high-value analysis of our retail organisational environment
	COI4: We have the capacity to share our data across organisational units and organisational boundaries.
	COI5: We can prepare and cleanse AI data efficiently and assess data for errors
	COI6: We can obtain data at the right level of granularity to produce meaningful insights
Cognitive Engagements	COE1: We have explored or adopted cloud-based services for processing data and performing AI and machine learning
	COE2: We have the necessary processing power to support AI applications (e.g., CPUs, GPUs)

	COE3: We have invested in networking infrastructure (e.g., enterprise networks) that supports efficiency and scale of applications (scalability, high bandwidth, and low latency)
	COE4: We have explored or adopted parallel computing approaches for AI data processing
	COE5: We have invested in advanced cloud services to allow complex AI abilities on simple API calls (e.g., Microsoft Cognitive Services, Google Cloud Vision)
	COE6: We have invested in scalable data storage infrastructures
	COE7: We have explored AI infrastructure to ensure that data is secured from to end to end with state-of-the-art technology
Innovativeness	INO1: Our organisation has access to internal talent with the right technical skills to support AI work
	INO2: Our organisation has access to external talent with the right technical skills to support AI work
	INO3: Our data scientists are very capable of using AI technologies (e.g. machine learning, natural language processing, deep learning)
	INO4: Our data scientists have the right skills to accomplish their jobs successfully
	INO5: Our data scientists are effective in data analysis, processing, and security
	INO6: Our data scientists are provided with the required training to deal with AI applications
	INO7: We hire data scientists that have the AI skills we are looking for
	INO8: Our data scientists have suitable work experience to fulfil their jobs
Part D: Organisational Performance	
Compared with how your organisation was performing 1 year ago, please indicate how much you agree or disagree with the following statements.	
	OP1: We have been able to reduce operating costs.
	OP2: We have been able to increase efficiency.
	OP3: We have been able to generate more knowledge.
	OP4: We have been able to increase the quality of our services.
	OP5: We have been able to increase the level of innovation output.

	OP6: We have been able to improve the speed to which we respond to requests.
	OP7: We have been able to serve more customers.
	OP8: We have been able to increase agility in changing the way we do things.
	OP9: We have been able to reduce bottlenecks.
	OP10: We have been able to improve the speed to which we develop innovative solutions for our customers.
	OP11: We have been able to improve the reliability of our IT systems.