THE NEXUS BETWEEN CRM CAPABILITIES AND SUSTAINABLE COMPETITIVE ADVANTAGE IN THE SOUTH AFRICAN RETAIL SECTOR: THE MODERATING ROLE OF AI

Sharnè Motala

Student number: 689937

Supervisor: Dr Emmanuel S. Quaye

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DECLARATION

I, Sharné Motala, declare that this research article 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 Strategic Marketing at Wits Business School, University of Witwatersrand. It has not been submitted before for any degree or examination in this or any other university.

Name: Sharné Motala

Signature:

Signed at Johannesburg

On the 26th of February 2025

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ABSTRACT

Purpose: Despite the growing importance of customer relationship management CRM capabilities in attaining a sustainable competitive advantage (SCA), limited research exists on their relationship with artificial intelligence (AI) in the South African retail sector. This study examines the connection between CRM capabilities and SCA, with AI as a moderating factor. It explores how AI-driven CRM capabilities enhance SCA.

Theoretical approach: Grounded in the relationship marketing theory, the resource-based view (RBV) and the dynamic capabilities view (DCV), the study investigates CRM capabilities, customer interaction management (CIMC), customer relationship upgrading (CRUC), customer win-back (CWBC) and AI's moderating role.

Design/Methodology/Analysis: A quantitative approach was used, with data collected from 286 South African retail sector employees via self-administered online surveys. Structural equation modelling (SEM) assessed relationships between CRM capabilities, AI and SCA.

Findings: CRM capabilities significantly impact SCA, with CIMC and CRUC showing the strongest influence. AI moderates these relationships, enhancing organisations' customer retention and operational efficiency. AI-powered CRM capabilities help organisations adapt to market changes and strengthen SCA.

Originality/Value: This study fills a gap in South African retail research by exploring AI-enhanced CRM capabilities role in SCA. Findings offer insights for organisations aiming to leverage AI in CRM capabilities and strategies for sustained growth.

Keywords: CRM Capabilities, Sustainable Competitive Advantage, AI, Retail, South Africa.

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CHAPTER 1: INTRODUCTION

1.1 Introduction

While CRM capabilities have been widely studied in developed markets, limited empirical evidence exists on their role in driving sustainable competitive advantage (SCA) within the South African retail sector. This study situates the discussion within the context of South Africa's dynamic retail industry. Customer relationship management (CRM) encompasses the strategies and activities employed by organisations to understand, manage and enhance their relationships with customers. The main objective of CRM is to drive an organisation's profitability and sustainability by deeply understanding customers' behaviour and priorities (Alqershi et al., 2020). To compete efficiently and effectively in today's intensively competitive business environment, CRM capability and Sustainable Competitive Advantage (SCA) is critical (Thongrawd et al., 2020). Sofi et al. (2020) argue that in the competitive marketplace, organisations that build their business with current clients rather than bringing in new customers will be more profitable and long-lasting.

Therefore, to succeed, South African retail organisations must achieve competitive advantage by effectively leveraging their resources and capabilities to differentiate themselves from competitors and peers. Augmenting CRM capabilities with accurate data and superior intelligence to effectively identify and meet customers' needs is crucial to South African retail organisations' quest to improve customer relationships, promoting loyalty and gaining competitive edge. Artificial Intelligence (AI) employs adaptive computer algorithms that progressively evolve or learn through collection and rapid processing of large volumes of computer-generated data that is gathered from various computer and communication systems, tools, applications and social media platforms (Buchanan, 2005). It could, therefore, be argued that the effectiveness of CRM is dictated by a combination of the strength of the CRM capabilities that underpin it and the robustness of the AI applied. This chapter aims to introduce the purpose and problem statement of the study, provide definitions to enhance conceptual clarity, discuss the major problem and research questions and establish the study's objectives.

1.2 Purpose of the study

The purpose of the study is to investigate the intricate relationships among CRM capabilities, AI technology application and SCA within the South African retail sector. This study aims to provide valuable insights for organisations by exploring how CRM capabilities are associated with SCA and how the application of AI technologies moderates this relationship. The study intends to add to the body of knowledge in the fields of CRM, AI and SCA by investigating their interplay in the retail sector.

1.3 Context of the study

South Africa is a country of about 63 million individuals (Statistics South Africa, 2024) with a wide range of racial backgrounds, cultural practises and income levels, which are characterised by intricate and ever-changing dynamics. Its retail sector, therefore, exhibits a broad spectrum of consumer needs and expectations, which are influenced by distinct political and socio-economic factors that have given rise to a diverse retail landscape with various types of establishments (Masojada, 2021). Being the second largest employment source after Government, South Africa's retail sector contributes close to 20 percent of the country's gross domestic product (GDP) (LRS, 2023). Retailers are classified in various categories, including general dealers; food, beverages and tobacco in specialised stores; pharmaceuticals and medical goods, cosmetics and toiletries; textiles, clothing, footwear and leather goods; household furniture, appliances and equipment; hardware, paint and glass; and all other retailers. Table 1 depicts the year-on-year retail trade sales and changes per category.

Table 1 Retail Trade Sales

Type of retailer	May – Jul 2022 (R million)	Weight (%)	May – Jul 2023 (R million)	% change between May – Jul 2022 and May – Jul 2023	Contribution (% points) to the total % change
General dealers	123 633	44,1	117 884	-4,7	-2,1
Food, beverages and tobacco in specialised stores	21 523	7,7	21 156	-1,7	-0,1
Pharmaceuticals and medical goods, cosmetics and toiletries	21 147	7,5	20 649	-2,4	-0,2
Textiles, clothing, footwear and leather goods	47 156	16,8	50 373	6,8	1,1
Household furniture, appliances and equipment	12 346	4,4	12 311	-0,3	0,0
Hardware, paint and glass	23 918	8,5	22 198	-7,2	-0,6
All other retailers	30 598	10,9	29 695	-3,0	-0,3
Total	**280 321**	**100,0**	**274 266**	**-2,2**	**-2,2**

Source: Statistics South Africa (2023)

In the three months to July 2023 retail trade sales decreased by 2.2% compared to the three months for the same period in 2022, mainly due to decreases in the sales of paint, glass and hardware. However, retailers of textiles, clothing, footwear and leather goods (CTFL) contributed a positive increase of 6.8%. It has been observed that economic conditions significantly influence consumer shopping behaviours and noted that during challenging economic times, consumers tend to shop less frequently, opt for smaller basket sizes and prioritise essential items such as groceries (SyndiGate Media Inc, 2023). This shift reflects a heightened focus on value and necessity, with consumers becoming more selective in their purchases to manage financial constraints. The pressures of high inflation, rising interest rates and increased load shedding in South Africa, in the post-COVID-19 era have clearly left consumers feeling the crunch from all angles. Retailers must be strategic with their promotions, assortment and online presence to draw in new customers and hold onto existing ones.

CRM is the strongest and the most efficient approach in maintaining and creating relationships with customers (Khodakarami & Chan, 2014, Baran & Galka, 2013) and is not only purely about business but also about building strong personal bonding between people. This aligns with Maslow's concept of addressing fundamental human needs, particularly in the retail sector where the focus lies on fulfilling such needs (Maslow, 1943). In the contemporary market setting, which is characterised by intense competition and rapid changes, organisations must employ innovative strategies to establish a SCA (Mukonza & Swarts, 2020). Understanding consumer demands and leveraging information processing innovations (Myllylä, 2023), becomes paramount for retailers striving to gain an edge in this dynamic landscape. Thus, CRM emerges not only as a business tactic but as an essential driver for retailers navigating today's multifaceted market challenges.

Focusing organisational activities and strategies on customer satisfaction with products or services has transformed into a fundamental management philosophy. In their quest to become leaner, more agile (Goworek, 2014) and innovate their value chains, retailers have increasingly adopted new technologies, of which AI has become the most transformative (Kietzmann et al., 2018; Lee et al., 2018; Silva et al., 2019). However, despite the great excitement about AI, it is not fully exploited (Ransbotham et al., 2017) because its application is yet to be fully understood (Xu et al., 2020). It is therefore crucial that the retail industry evolves with new digital technologies to transform (Fiorito et al., 2010; Romero & Martínez-Román, 2015; Hagberg et al., 2016; Xu et al., 2020). According to Rehman (2019), research is necessary to determine how CRM capabilities relates to the achievement of corporate goals and competitive edge. However, notwithstanding that South African business managers and marketers embrace the immense power of AI, there is limited knowledge on how applying AI into CRM capabilities would elevate the interplay between CRM capabilities in the retail sector and enhance competitive advantage (Ledro et al., 2023).

1.4 Problem statement

South African retailers face challenges in effectively leveraging CRM capabilities to achieve sustainable competitive advantage, particularly given the underexplored moderating role of AI technologies (Bhat & Darzi, 2018; El Daly, 2020). In today's extremely competitive economy, developing and keeping a SCA has become increasingly important (Torres et al., 2018) for retaining current and acquiring new customers, which in turn underpins sustainability and growth. However, many organisations are unaware of the strategies that can help them operate more efficiently and gain a competitive edge (Shafiee, 2021). CRM is a multifaceted concept, defined variously as a strategy, a process, or an information system, as noted by Bhat and Darzi (2016). These diverse perspectives contribute to the richness and complexity found in the existing literature. Loureiro et al. (2021) underscore the necessity for more comprehensive databases in CRM research. This call for enhanced data repositories aligns with the viewpoint of Ledro et al. (2022), who advocate for the systematic organisation of the CRM literature into a well-structured body of knowledge. Acknowledging the differing viewpoints on CRM and its potential advantages for academic and business fields, there is a mutual appreciation for the significance of advancing and systemising the literature into a structured body of knowledge.

CRM capabilities, which outline an organisation's aptitudes, competencies and expertise, are ingrained in CRM activities. Consistent with the resource-based view (RBV) theory, Kaleka (2002) asserts that an organisation's resources, in the form of assets acquired, can yield a competitive advantage. Day (1994) asserts that value creation and competitive advantage are achieved through the utilisation of capabilities, which take the form of acquired skills and expertise. Although the role of CRM in improving customer-centric strategies and practices is well researched globally, Bhat and Darzi (2018, p. 163) state that *"very little literature is available that investigates the relationship between CRM capabilities variables and SCA"*. Although there has been significant discussion in the literature about the concept of SCA, which is essential to a firm's performance, there has been little empirical research on the topic and "there are few frameworks that reflect the divergence of perspectives on the matter*"* (El Daly, 2020, p. 299).

Diverse viewpoints exist regarding the factors that determine competitive advantage. These include industry-based explanations put forth by industrial economists like Porter (1989), resource-based explanations favoured by authors like Barney (1991) and more market-oriented perspectives (De Wit & Meyer 2005). Different perspectives related to these factors lead to the formation of discrete knowledge domains, which means that research advances inside isolated fields with little cross-disciplinary exchange.

Management scholars have not delved deeply into the role of AI over the past two decades despite its growing relevance in managerial settings (Raisch & Krakowski, 2021). Beyond its business applications, some academics suggest that AI can offer a novel approach to customer relationship management (Kumar et al., 2021; Logkue et al., 2020; Vignesh & Vasantha, 2019). Since much of the existing literature remains theoretical (Laaksonen, 2020) there is a crucial need for further research, particularly from a practical perspective, as interest in AI continues to grow. This knowledge gap prevents organisations from developing CRM capabilities that enable them to effectively stand out amongst their competitors, improve customer interactions and assume leading positions in their markets. In-depth research to examine the relationship between CRM capabilities and SCA and the moderating effect of AI technology application in the South African retail sector is therefore required to offer practical insights and recommendations that could inform strategic decision-making, improve performance and achieve SCA. This research paper examines the nexus between CRM capabilities and SCA and the influence of AI technology application on the strength of this interplay, in the South African retail sector. The main question that research addresses is how do CRM capabilities influence SCA in the South African retail sector and what role does AI play in this relationship?

1.5 Objectives

The objectives of the research are:

- To examine the influence of customer interaction management capability (CIMC) on sustainable competitive advantage in the retail sector.
- To examine the influence of customer relationship upgrading capability (CRUC) on sustainable competitive advantage in the retail sector.
- To examine the influence of customer win-back capability (CWBC) on sustainable competitive advantage in the retail sector.
- To determine whether artificial intelligence (AI) technology application moderates the relationship between customer interaction management capability (CIMC) and sustainable competitive advantage.
- To determine whether artificial intelligence (AI) technology application moderates the relationship between customer relationship upgrading capability (CRUC) and sustainable competitive advantage.

- To determine whether artificial intelligence (AI) technology application moderates the relationship between customer win-back capability (CWBC) and sustainable competitive advantage.

1.6 Intended contributions of the study

The significance of this study stems in its potential contribution to advancing both academic theoretical knowledge and to generate practical knowledge and insights that could help South African retail organisations to achieve SCA by leveraging CRM capabilities and AI technology application.

1.6.1 Theoretical contributions

The existing literature reveals notable gaps that underscore the need for the current study. First, Rehman (2019) highlights the necessity to investigate how CRM capabilities impact the achievement of corporate goals, indicating a gap in understanding this critical relationship. Additionally, the connection between SCA and CRM capabilities remains underexplored (Bhat & Darzi, 2018) highlighting a gap in research regarding the competitive dynamics within customer relationship management. The lack of practical empirical studies on AI, predominantly theoretical in nature, as mentioned by Laaksonen (2020), indicates a need for research that bridges the gap between theory and practical application. Furthermore, despite the increasing prevalence of AI in managerial contexts, a dearth of insights into AI has persisted over the past two decades (Raisch & Krakowski, 2021). Lastly, Monod et al. (2023) underscore the urgency of investigating the application of AI technology's effects on CRM procedures, given the widespread integration of AI in CRM practices. The identified gaps collectively highlight the importance for a comprehensive study that addresses these nuanced relationships and contributes to filling these critical voids in the literature.

Examining the precise connection between CRM capabilities and SCA within the South African retail sector will address the research gap discussed above. Drawing on relevant theories, such as relationship marketing (RM), resource-based view (RBV), dynamic capabilities (DC), along with AI applications, will provide theoretical insights into the mechanisms through which AI-enabled CRM capabilities can elevate SCA, thus enriching the existing body of knowledge.

1.6.2 Practical contributions

The findings of this study provide practical and strategic insights for South African retail organisations by highlighting the transformative role of AI-enhanced CRM capabilities in achieving SCA. The integration of AI technologies enables retailers to address inefficiencies in their value chains, optimise customer satisfaction and create personalised shopping experiences. This aligns with the Retail-Clothing, Textile, Footwear and Leather (R-CTFL) Master Plan, which emphasises technology adoption to enhance competitiveness, localisation and job creation within the South African retail sector (The DTIC, 2020; 2022). AI's moderating role is identified as crucial for transforming CRM systems into adaptive, data-driven platforms. AI technologies not only enhance operational efficiency but also enable predictive consumer behaviour modelling, real-time inventory management and streamlined marketing strategies. These advancements empower organisations to remain agile and competitive in a market disrupted by digital innovation and globalisation (Heins, 2023; Oosthuizen et al., 2021).

The findings provide South African retail organisations with practical insights into which CRM capabilities are most effective in achieving SCA, which will assist managers and executives in making informed strategic decisions regarding CRM capabilities and resource allocation. By leveraging AI-enhanced CRM capabilities, retailers can improve customer loyalty, boost sales and achieve strategic objectives outlined in national frameworks, contributing to the growth and sustainability of South Africa’s retail sector (Tshivhase, 2023). Furthermore, understanding the link between CRM capabilities, SCA and AI's role enables organisations to optimise their CRM initiatives. This leads to improved customer satisfaction, increased customer loyalty and ultimately enhanced business performance. These insights ensure that organisations are better positioned to meet evolving market demands while contributing to the broader goals of economic growth and technological advancement in South Africa.

1.7 Delimitations of the study

Acknowledging the delimitations listed below helped maintain the focus and scope, while ensuring a realistic, feasible and meaningful study:

- The study specifically focused on the retail sector. Findings and conclusions drawn from this research and recommendations presented may not be directly applicable to other industries or sectors.
- The study was limited to the context of the South African retail industry. Therefore, the findings may not be generalisable to other countries or regions with different business environments, cultural factors, or market dynamics.

- While efforts were made to obtain a diverse sample of South African retail organisations, the sample size and representativeness may be subject to limitations due to resource constraints and accessibility issues. The findings may reflect the characteristics and perspectives of the organisations included in the study but may not capture the entire spectrum of the retail industry in South Africa.

1.8 Definition of terms

Retail Sector: the retail sector in South Africa includes the following sub-sectors/industries: General dealers; food, beverages and tobacco in specialised stores; pharmaceuticals and medical goods, cosmetics and toiletries; textiles, clothing, footwear and leather goods; household furniture, appliances and equipment; hardware, paint and glass; and all other retailers.

CRM Capability: embedded in CRM activities and it refers to an organisation's abilities, skill and knowledge to regularly establish, maintain, upgrade and re-establish beneficial relationships with customers.

Sustainable Competitive Advantage: a sustained advantage over competitors that is attained by offering customers higher value, over time.

Artificial Intelligence: encompasses computer programmes and machines that possess the capacity to learn.

1.9 Assumptions

The following assumptions were made:

- The selected sample of retail organisations in South Africa was representative of the broader retail sector in the country.
- The participants identified in the sample selection were available within the timeframe of the study.
- The participants offered in-depth and substantive responses that were comprehensive and complete.
- A sample size of 250-300 respondents were used to adequately validate or refute the hypothesis.

1.10 Chapter Summary

This chapter introduced the study and outlined its purpose, which was to explore how CRM capabilities influence SCA and how the application of AI technology enhances this relationship. Contextual background on the South African retail industry was provided, highlighting its economic significance and the impact of evolving consumer behaviours. The problem statement was presented, identifying gaps in understanding the interplay between CRM, AI and SCA and the research objectives were framed, focusing on specific CRM capabilities and AI's moderating effect. Additionally, the chapter discussed the intended theoretical and practical contributions of the study, defined key terms and clarified the study's scope and assumptions.

CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

This chapter provides a comprehensive review of the theoretical and empirical foundations of this research, beginning with an exploration of three key theoretical perspectives. These theories offer critical insights into how CRM capabilities can be leveraged to achieve and sustain a competitive advantage. Furthermore, it explores how AI technologies enhance CRM capabilities, influencing their effectiveness in fostering SCA.

2.2 Theoretical foundation

The three key theories considered in examining the nexus between CRM capabilities, SCA with AI as a moderator are the theory of relationship marketing (RM), the resource-based view (RBV) and the dynamic capabilities (DC) view.

2.2.1 Theory of relationship marketing

Möller and Halinen (2000) found that four marketing traditions, namely business marketing, services marketing, marketing channels, and database and direct marketing contributed significantly to the shift from business transactions to business relationships (particularly customer relationships) as the main objective of marketing strategy. Relationship Marketing (RM) is the overarching theory from which Customer Relationship Management (CRM) strategy and practices are derived. CRM is a strategic approach that focuses on effectively identifying and meeting customers' needs to enhance customer relationships, promote loyalty and ultimately achieve a competitive advantage in the market. More recent research has reaffirmed that relationship marketing is central to business performance, with trust and commitment serving as key mediators in successful long-term business relationships (Jain et al., 2024).

Luck and Lancaster (2013) define CRM as the strategies or activities that organisations employ to outdo or have an edge over competitors. CRM helps the organisation to strengthen the trust and commitment bonds with customers to enhance long-term patronage and loyalty (Kamal et al., 2022; Zeithaml et al., 1996). While CRM enables organisations to obtain a thorough understanding of client needs and quickly address those needs through product creation or upselling (Rehman, 2019), it operates within the broader RM paradigm. Successful relationship marketing strategies, particularly those enhanced by AI and digital tools, lead to higher levels of engagement and stronger stakeholder relationships (Jain et al., 2024). The adoption of AI-powered CRM solutions has accelerated the transition from traditional customer engagement to data-driven, predictive RM, reinforcing the strategic importance of relationship marketing activities (Badrinarayanan & Ramachandran, 2024).

2.2.2 Resource-based view

The Resource-Based View (RBV) exemplifies the role of capabilities in enhancing business performance and creating a competitive advantage (Barney, 1991). It describes the strategic and philosophical perspective through which an organisation transforms and manages its skills and resources to maintain an edge over competitors (Ofori & Appiah-Nimo, 2022). RBV posits that organisations achieve SCA by leveraging resources that meet the VRIN criteria: valuable, rare, imperfectly imitable and non-substitutable (Barney, 1991). The body of research on RBV shows that achieving SCA stems from possessing heterogeneous resources, such as relational assets like customer relationships or intellectual assets such as knowledge of client preferences (Barney, 1991; Srivastava et al., 1998). Lubis (2022) emphasises the importance of intangible resources such as brand reputation, knowledge management and customer relationships as key sources of SCA.

CRM is considered a critical resource that can be leveraged to improve business performance (Rafiki et al., 2019). Research suggests that organisations with unique CRM capabilities, such as AI-driven customer analytics, gain a competitive edge that is difficult to imitate (Lubis, 2022). Strategic resource bundling plays a crucial role in maximising the benefits of CRM capabilities. By integrating AI-driven CRM tools with existing business capabilities, organisations can enhance customer engagement and retention, ultimately leading to superior business performance (Kabue & Kilika, 2016). This strategic bundling of resources aligns with the RBV perspective, reinforcing the notion that a firm's ability to effectively combine and deploy its resources determines its long-term success in achieving a SCA.

2.2.3 Dynamic capabilities view

The dynamic capabilities (DC) view posits that organisations achieve SCA by continuously sensing, seizing and transforming resources in response to environmental changes (Teece, 2018). An organisation's ability to acquire and deploy resources in response to dynamic market conditions, thereby achieving advantage, is known as dynamic capability (Eisenhardt and Martin, 2000; Makadok, 2001). Within the context of CRM capabilities, dynamic capabilities enable organisations to adapt their customer management strategies in response to shifting consumer demands, technological advancements and competitive pressures (Laaksonen &

Peltoniemi, 2018).

Day and van den Bulte (2002) determined that some organisations failed because they did not utilise the CRM resources at their disposal to build superior capabilities in managing customer relationships and achieving competitive advantage. CRM capabilities are embedded in CRM activities and are more challenging to comprehend and replicate than other organisational competencies because they depend on the intricate interplay of auxiliary resources and are mostly based on tacit knowledge and interpersonal skills (Hooley et al., 2005). The interplay between business model innovation and dynamic capabilities is particularly relevant to CRM-driven strategies, as organisations must continually refine their ability to leverage customer data, personalise experiences and optimise engagement mechanisms (Teece, 2018). By embedding AI into CRM capabilities, organisations can better anticipate customer needs, customise service delivery and foster deeper customer relationships, ultimately driving SCA.

Recent empirical studies validate the role of AI-integrated CRM in strengthening dynamic capabilities, particularly in volatile retail environments. Chatterjee et al. (2022) argue that AI-enhanced CRM capabilities improve organisations' ability to sense market shifts and rapidly reconfigure customer engagement strategies. Similarly, Rahman et al. (2023) emphasise that AI-based CRM capabilities in B2B and B2C settings facilitate superior customer relationship performance, reinforcing organisations' adaptive capacity in the face of technological turbulence. CRM capabilities help organisations maintain large customer bases and deliver greater value to customers, thus securing a competitive advantage (Day, 2003). In the South African retail sector, where competitive advantage hinges on responsiveness to customer behaviour and market fluctuations, the ability to dynamically adjust CRM capabilities using AI offers a powerful mechanism for SCA and market leadership.

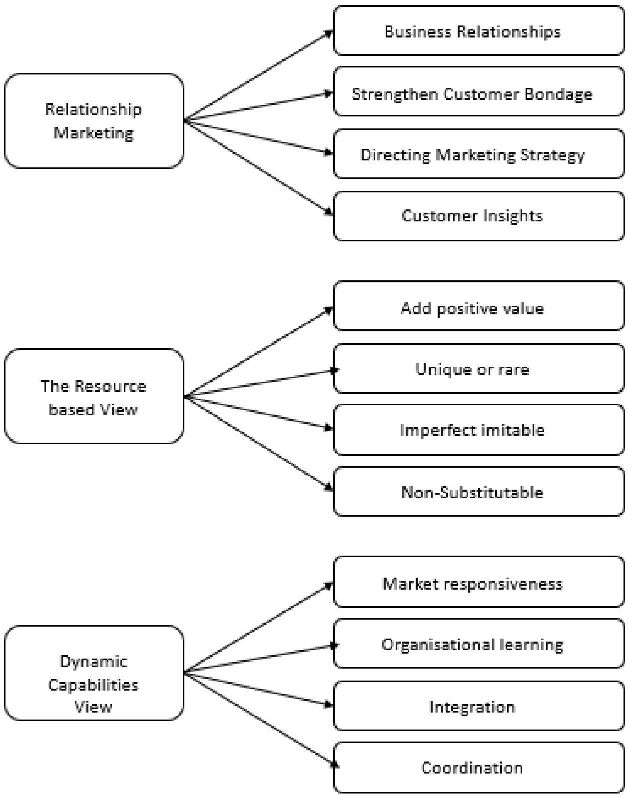

Figure 1 Applicable Theories

Adapted from Vinayan et al. (2012)

2.3 Empirical literature review

2.3.1 Customer relationship management capability

CRM is widely recognized as a strategic marketing approach that enables organisations to strengthen their competitive position in today's dynamic market landscape (Bhat & Darzi, 2018). By incorporating organisations' people, processes and technology to deepen the understanding and delivery of the customers' needs and priorities, CRM remains as a crucial component of business (Buttle & Maklan, 2019). CRM capability describes an organisation's abilities, skill and knowledge to regularly establish, maintain, upgrade and re-establish beneficial relationships with customers (Wang & Feng, 2012). CRM capability refers to an organisation's ability to cultivate and sustain long-term profitable customer relationships while enhancing its competitive standing (Bhat & Darzi, 2018). According to Morgan et al. (2009), these capabilities reflect an organisation's capacity to identify attractive customers and prospects, initiate and maintain relationships with attractive customers and leverage relationships into customer level profits, all of which contribute to superior performance and, ultimately, competitive advantage.

Wang and Feng (2008) consider CRM capability as a multi-dimensional construct comprising four key dimensions: customer knowledge management capability, customer interaction management capability, customer relationship upgrading capability and customer win-back capability. Sofi et al. (2013) provide a slightly different perspective, focusing on five key capabilities: customer interaction capability, customer relationship upgrading capability, customer win-back strategies, CRM technology updating and customer orientation. In their 2012 study, Wang and Feng refine their earlier model, proposing three key capabilities: interaction management, relationship upgrading and win-back. Wang and Kim (2017) broaden the scope of CRM capabilities, introducing three new dimensions: customer attraction capability, customer conversion capability and customer retention capability. Chatterjee et al. (2022) introduce a unique perspective on CRM capabilities, focusing on two main dimensions: customer interactivity capability and customer retention capability.

This research adopts the CRM capabilities framework proposed by Wang and Feng (2012), which categorises CRM into three essential dimensions: interaction management, relationship upgrading and win-back. This framework is particularly suitable as it provides a comprehensive yet streamlined structure for examining CRM capabilities, aligning closely with the research objectives. Unlike other models that include additional or overlapping capabilities, the Wang and Feng (2012) framework offers a focused lens on core CRM functions that are directly linked to SCA. By selecting this framework, the study can effectively address the identified gaps in understanding the impact of these CRM capabilities on competitive positioning within the retail sector, making it a compelling choice for this research.

2.3.2 Sustainable competitive advantage

Organisations strive to obtain and maintain a competitive advantage in the hypercompetitive era (Kennedy & King, 2004). According to Al Karim and Habiba (2020), a competitive advantage is a benefit over rival organisations that is obtained by providing clients with greater value. Sustainable competitive advantage (SCA) is different from competitive advantage, as conceptualised by Barney (1991), it is characterised by its distinction as a long-term advantage derived from unique value creation processes. Organisations that adeptly nurture and uphold sustainable competitive advantages gain a strategic edge, ensuring their viability in the dynamic business environment. Studies, including the works of Abdul Rahim and Abdul Rahman (2013), underscore the importance of accumulating both resources and capabilities as fundamental prerequisites for achieving SCA. This holistic approach aligns with the idea that a combination of unique resources and distinctive capabilities is essential for building a competitive advantage that stands the test of time.

SCA is a concept widely debated in organisational studies, yet there exist no universally accepted criteria for its measurement. Bandaranayake and Pushpakumari (2021) acknowledge that SCA is an organisational-level construct. This has led to various approaches to measuring SCA, with researchers frequently focusing on financial and market-based outcomes. Several authors have proposed using financial and market indicators to assess SCA. For instance, Bromiley and Rau (2016) identifies profitability measures like return on assets (ROA), return on investment (ROI) and return on sales (ROS) as common indicators. Additionally, other financial performance metrics, such as sales volume, sales growth, market share and changes in market share, can be utilised (Powell & Dent-Micallef, 1997; Zhu, 2004). In the context of retail supermarkets, Ngila and Muturi (2016) suggest that increases in profits, customer base and revenue could serve as indicators of SCA. However, the reliance on financial performance as an SCA measure has faced criticism, particularly from a RBV perspective. This critique arises because financial success might not necessarily equate to SCA, as competitive advantage could be a precursor to improved financial outcomes rather than the other way around (Powell, 2001). Organisations might possess valuable resources that have not yet translated into superior financial performance.

An alternative to financial indicators is process performance, which aligns more closely with the RBV approach (Ray et al., 2004). Business processes are classified into managerial, operational and supportive processes (Cao & Duan, 2014). Among these, operational and supportive processes are linked to current performance, while managerial processes are associated with sustaining future performance (Bititci et al., 2011). Given this framework, process performance can be seen as an alternative method to assess SCA, as it addresses both the foundations of RBV and acknowledges the fundamental value in business processes themselves (Abideen et al., 2018). Additionally, organisational resources and capabilities are considered important factors in measuring SCA (Almuslamani & Duad, 2022). This aligns with RBV, which suggests that a firm's unique resources and capabilities can lead to SCA. To ensure the sustainability aspect, Bandaranayake and Pushpakumari (2021) recommend that measurements be taken over time, allowing for more robust data validation and capturing the evolving nature of SCA.

2.3.3 Artificial intelligence

The term artificial intelligence (AI) encompasses computer programmes and machines that possess the capacity to learn (Kiruthika & Khaddaj, 2017). The objective of AI is to advance the capabilities of machines in a manner that emulates human intelligence (Ertel, 2018). In the business context, Kaplan and Haenlein (2019) describe AI technology as the capacity of a technological system to accurately interpret external data, learn from that information and demonstrate adaptive flexibility. In a retail context, AI technology pertains to programs, algorithms, systems and machines exhibiting intelligent capabilities (Shankar, 2018).

The emergence of AI has had a profound impact on the operational environment of the modern business environment. According to Thiraviyam (2018), AI facilitates informed decision-making and the implementation of strategies that were previously impractical for organisations by effectively analysing extensive datasets and bridging the gap between data science and practical application. Although the technology in question has a long history, it has gained significant attention in recent times due to its transformative capabilities in data analytics, potential to enhance operational effectiveness and demonstrated capacity to generate predominantly favourable outcomes in various domains.

During this era of increasing emphasis on digitalisation, there have been notable developments in the role of technology in CRM. Academia claims that AI represents the next step in effectively managing customer relations (Kumar et al., 2021; Lokuge et al., 2020; Vingesh & Vasantha, 2019). This assertion underscores the transformative potential of AI technologies in revolutionising customer-centric practices across various industries. AI technology is a significant contributor to many innovations that are fundamentally reshaping the retail industry (Shankar et al., 2021). By leveraging AI technology, organisations can gain deeper insights into customer preferences and behaviours, predict future trends and proactively address their needs, thereby fostering stronger relationships and driving sustainable growth. In the realm of CRM, the adoption of AI technology solutions has become indispensable for organisational survival (Pearson, 2019). Thus, the synergy of diverse AI technologies propels customer relationship management into a new era of efficiency and effectiveness, marking a significant milestone in the evolution of business practices. Specifically, adhering to the RBV, the incorporation of AI technologies ought to be executed internally when it is deemed a foundational capability for cultivating knowledge in the management of customer relationships and sustaining a competitive advantage (Grover et al., 2018; Zerbino et al., 2018).

2.3.4 Relationship quality

Relationship quality (RQ) is a fundamental construct in inter-organisational and customer relationships, representing the strength and depth of interactions between parties. High-quality relationships foster stronger and more intimate partnerships, enhancing the effectiveness of organisational networks (Griffith & Harvey, 2001). Within the relationship marketing (RM) literature, RQ is recognised as a crucial determinant of the longevity and robustness of exchange partnerships (Hennig-Thurau et al., 2002). It is also closely linked to relationship performance and overall business performance, demonstrating its role in driving long-term success (Palmatier et al., 2007).

The role of RM in shaping RQ is well-documented, with studies highlighting its contribution to building sustainable relationships between organisations and their customers. Effective RM strategies enhance customer loyalty, satisfaction and ultimately, business revenues (Evans & Laskin, 1994; Quach et al., 2020). Palmatier et al. (2006) further identify RM as an antecedent of RQ, suggesting that the implementation of RM practices directly influences the perceived quality of business relationships. Key dimensions of RQ include satisfaction, trust and commitment, all of which play a pivotal role in maintaining long-term relationships. Satisfaction, for instance, is particularly crucial in service industries such as hospitality and retail, where customers assess their experiences based on factors like service quality, personalisation and overall atmosphere (Sanchez-Franco et al., 2019). Higher satisfaction levels contribute to positive business outcomes, including increased customer loyalty, repeat visits and favourable word-of-mouth recommendations. Trust and commitment further reinforce RQ by fostering a sense of reliability and long-term engagement between exchange partners. Narteh et al. (2013) found that trust enhances both customer loyalty and RQ, ultimately improving customer lifetime value metrics (Dlačić et al., 2018).

RQ has been increasingly acknowledged as a key determinant of business success, influencing both customer retention and organisational competitiveness. Putri and Rahayu (2023) define RQ as a continuous effort to maintain positive customer relationships, which is critical for ensuring sustained business growth. The literature emphasises that RQ acts as an outcome variable in RM, reflecting the effectiveness of relationship-building efforts (Smith, 1998). Additionally, Rauyruen & Miller (2007) argue that RQ plays a vital role in fostering customer loyalty and deepening business relationships. As organisations strive for competitive advantage, fostering high RQ becomes an essential strategy for sustaining long-term success.

By embedding RM practices that enhance satisfaction, trust and commitment, organisations can create resilient and mutually beneficial relationships with customers and stakeholders. As organisations continue to seek sustainable competitive advantages in evolving markets, RQ will remain central to both strategic decision-making and operational success.

2.4 Conceptual model and hypotheses development

2.4.1 Conceptual framework

Drawing from the reviewed literature, the conceptual framework was developed to visually represent the research variables and their interrelationships. This model serves as a foundation for understanding how the variables interact, offering a structured approach to examine the proposed relationships within the study. In this conceptualised research model, CRM capabilities are hypothesised to influence SCA while being moderated by AI technology application. Thus, the CRM capabilities are the predictor variables while SCA is the sole outcome variable and AI technology application is the moderating variable. The hypothesised relationships between the research variables are underlined in Figure 2.

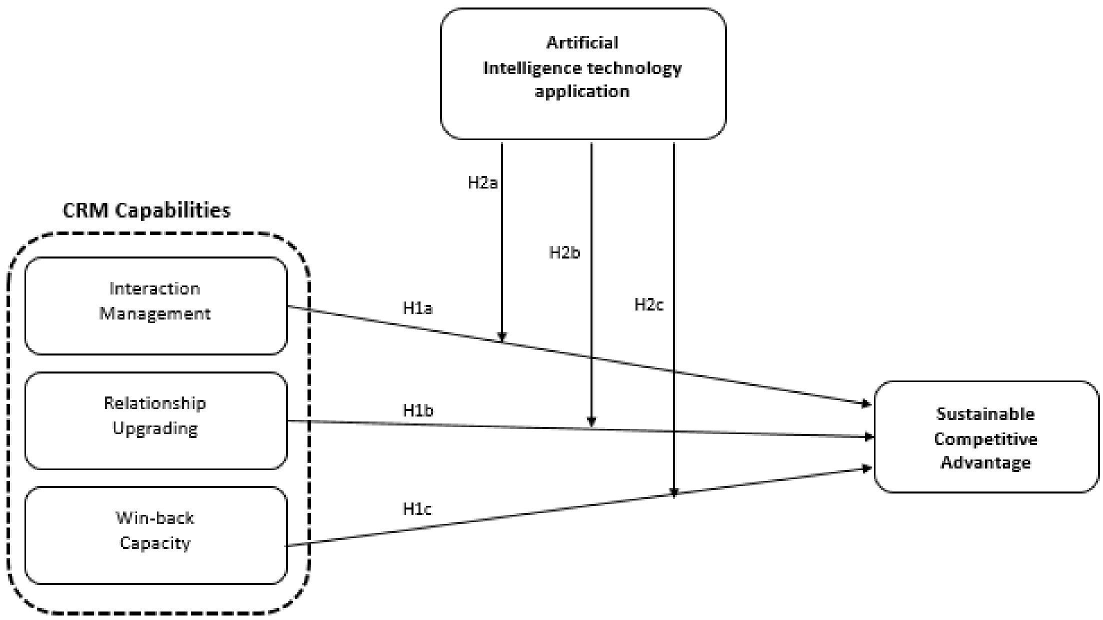

Figure 2 Proposed Conceptual Framework

Author's compilation (2024)

2.4.2 Customer interaction management capability and SCA

Customer interaction management capability (CIMC) refers to an organisation's capacity and expertise in identifying, acquiring and retaining profitable customers (Wang & Feng, 2012; Guerola-Navarro et al., 2021). CIMC involves the systematic collection, collation and use of customer information from multiple contact points to generate valuable customer insights and devise targeted marketing responses (Payne & Frow, 2005). Research has shown that organisations with high CIMC tend to exhibit superior sales performance and greater customer satisfaction (Rapp et al., 2010; Abdullateef et al., 2010). Through consistent and meaningful interactions, organisations can strengthen customer loyalty and foster a user-friendly environment that encourages repeat business (Sheth & Parvatiyar, 1994).

Empirical studies highlight that a robust CIMC can lead to increased sales performance and long-term competitive advantage. As organisations improve their interaction capabilities, they can leverage customer data to create tailored marketing campaigns, which in turn enhances cross-selling and upselling opportunities (Kamakura et al., 2003). By maintaining open and effective communication channels, organisations can build trust with their customers, ultimately leading to greater customer retention and an elevated competitive edge in the retail sector (Morgan et al., 2009). Organisations with superior CIMC demonstrate stronger customer retention and loyalty, leading to increased profitability and market differentiation (Al-Zyadat & Al-Zyadat, 2018). High-performing organisations utilise CIMC to translate customer insights into tailored marketing strategies and product innovations, thereby strengthening their competitive position (Nurhayati & Hendar, 2017). The empirical evidence underscores that a strong CIMC plays a critical role in achieving sustainable competitive advantage by fostering enduring relationships and driving consistent business growth. Based on the above, the following is hypothesised:

> *H1a: Customer interaction management capability has a positive influence on sustainable competitive advantage in the retail sector.*

2.4.3 Customer relationship upgrading capability and SCA

Organisations' abilities and skills to upsell (sell more expensive items, upgrades) and/or cross-sell (sell additional products and services) to existing customers, thereby increasing the share of customer spend through effective customer data analysis, can be described as customer relationship upgrading capability (CRUC) (Reinartz et al., 2004; Wang & Feng, 2012). Outstanding CRUC enhances customer loyalty, thereby strengthening organisational sustainability and competitive positioning (Day, 2003). By offering additional services or enticing upgrades, organisations can significantly increase revenue while improving customer retention (Caroll, 2024). This approach aligns with the intention to capture missed revenue opportunities and foster client loyalty.

Studies by Harrigan et al. (2012) underscore the significance of CRM capabilities, including CRUC, in enhancing perceived sales in small and medium-sized enterprises (SMEs), highlighting its importance across different organisational contexts. Similarly, research by Alshura (2018) further emphasises the pivotal role of CRUC in improving organisational performance. The importance of nurturing long-term relationships with clients is also evident in the work of Kusnadi et al. (2024), who stress the necessity of ensuring effective communication and addressing evolving customer needs (Rane et al., 2023). CRUC's influence on SCA is manifested through its focus on customer relationship enhancement and revenue generation. By effectively upselling and cross-selling products, organisations can not only increase sales but also enhance customer satisfaction, retention, commitment and loyalty (Anderson et al., 1994).

> *H1b: Customer relationship upgrading capability has a positive influence on sustainable competitive advantage in the retail sector.*

2.4.4 Customer Win-Back Capability and SCA

Customer win-back capability (CWBC) describes organisations' abilities and skills to re-establish desired profitable customer relationships that had been lost (Wang & Feng, 2012). Since re-establishing customer relations often hinges on organisations addressing customer dissatisfactions and/or deficiencies in products or services, CWBC is tantamount to developing superior products, services and customer relationships, which in turn improves profitability and sustainability (Ryals, 2005). CWBC plays a crucial role in SCA by restoring relationships with lost customers, thereby bolstering customer satisfaction, loyalty and retention. CRM capabilities, such as CWBC, can contribute to SCA by targeting key customers, enhancing the experience for existing customers and attracting new ones (Demlehner et al., 2021). Organisations that prioritise CWBC can differentiate themselves in highly competitive markets by leveraging customer insights to address dissatisfaction, refine service offerings and foster stronger brand relationships (Foltean et al., 2019). Research by Plakoyiannaki and Tzokas (2002) supports the significant impact of CRM capabilities, including CWBC, on organisational performance, reinforcing the notion that customer win-back strategies are critical for business success. Moreover, Vomberg et al., (2020) emphasise that organisations with structured CWBC strategies, supported by proactive organisational policies, experienced significantly higher customer reacquisition success rates.

H1c: Customer win-back capability has a positive influence on sustainable competitive advantage in retail sector.

2.4.5 CRM capability, SCA and AI

AI technology's application into CRM activities can amplify or alter the influence of CIMC, CRUC and CWBC on SCA. AI has a transformative effect on CIMC by allowing organisations to process vast amounts of customer data quickly, leading to real-time insights and improved customer interactions (Libai et al., 2020). AI-powered CRM tools such as chatbots and personalised marketing can help organisations engage with customers more effectively, facilitating the identification, acquisition and retention of profitable customers (Wang & Feng, 2012). This approach not only boosts customer satisfaction but also enhances retention, both of which are key contributors to SCA (Coltman, 2006).

H2a: Artificial intelligence technology application moderates the relationship between customer interaction management capability and sustainable competitive advantage.

In the context of CRUC, AI supports organisations in conducting in-depth customer analysis, enabling more precise cross-selling and upselling strategies (Guerola Navarro et al., 2021). By utilising AI to understand customer behaviour and purchasing patterns, organisations can offer personalised product recommendations, leading to increased sales and customer loyalty (Chiang et al., 2010). This capability strengthens a firm's market position, driving additional sales from existing customers and contributing to SCA.

H2b: Artificial intelligence technology application moderates the relationship between customer relationship upgrading capability and sustainable competitive advantage.

AI also plays a crucial role in CWBC by aiding organisations in re-establishing relationships with lost or inactive but profitable customers. Through AI-based analytics, organisations can identify the reasons for customer churn and devise targeted win-back strategies (Li et al., 2023). AI can automate and personalise customer re-engagement, increasing the chances of rebuilding relationships, thus reducing customer acquisition costs and solidifying a firm's SCA (Wang & Feng, 2012).

H2c: Artificial intelligence technology application moderates the relationship between customer win-back capability and sustainable competitive advantage.

Overall, AI technology moderates the relationship between CRM capabilities and SCA in the retail sector. By integrating AI into CRM processes, organisations can significantly enhance customer interaction, relationship upgrading and win-back strategies, leading to improved customer satisfaction, higher sales and a stronger competitive position in the market. This underscores the crucial role of AI in shaping CRM capabilities into strategic assets that enable organisations to achieve and sustain a competitive advantage in the retail sector.

2.5 Chapter Summary

The literature review investigated CRM theories and concepts, its capabilities and its effects on the retail sector's SCA, as well as the moderating role of application of AI technologies. The theory of relationship marketing (RM), the resource-based view (RBV) and the dynamic capabilities (DC) view were three important theories that were taken into consideration. These theories shed light on how CRM capabilities influence SCA and AI's moderating role.

CRM capabilities are essential for organisations to effectively manage customer relationships. These capabilities enable organisations to acquire, retain and re-establish profitable customer relationships, leading to SCA. In conclusion, the literature review establishes the foundation for understanding CRM capabilities and its relationship to SCA, as well as the role of AI technology application in the retail sector. The subsequent chapters will further explore this relationship.

CHAPTER 3: RESEARCH METHODOLOGY

3.1 Introduction

This chapter outlines the research methodology employed in this study, detailing the approach used to investigate the relationship between CRM capabilities, AI and SCA in the South African retail sector. It provides a structured framework for data collection and analysis, ensuring the study's reliability and validity. Furthermore, the chapter discusses the research design, target population, sampling techniques, data collection methods and ethical considerations.

3.2 Research approach

The research approach is a systematic approach employed to address research problems, which encompasses an organised process for conducting research (Goundar, 2012). According to Kumar (1999), quantitative study designs possess distinct characteristics such as specificity, well-structured frameworks, established validity and reliability and explicit definitions and recognition. In contrast, qualitative study designs are characterised by lower specificity and precision due to their subjective interpretivist philosophy approach which facilitates the interpretation of data (Saunders et al., 2019; Rahi, 2017). The chosen methodology for this study is the quantitative approach, which is commonly employed to examine the correlations between variables, producing results that are predictive, explanatory, or confirmatory (Williams, 2011). The goal of quantitative approaches is to explain a set of data by gathering information from a wide sample of people in a scientific manner. Given its effectiveness in identifying relationships, trends, or patterns, this approach is highly suitable for addressing the research question.

3.3 Research philosophy

The research philosophy is a system of beliefs and assumptions about the development of knowledge and allows the researcher to consider their own position (Saunders et al., 2019). The present study adopts a positivist approach, which aligns with the principles of positivism that advocate for the scientific examination of empirical evidence and the exploration of causal relationships using quantitative data analysis (Tashakkori & Creswell, 2007).

3.4 Research design

Considering that research design is the solid foundation of the entire research project and has a significant impact on the validity of the conclusions drawn, it must be carefully considered.

According to Kothari (2004), the utilisation of research design is essential as it enables the seamless execution of many research procedures, thereby optimising research efficiency and maximising the acquisition of information while minimising the utilisation of resources such as effort, time and finances.

Surveys were used in this study to collect participant data. A survey questionnaire is one of the traditional ways to gather primary data. Despite lacking the in-depth nature of interviews, surveys are considered a valuable instrument for data collection (Dalati & Marx Gomez, 2018). The advantages of utilising surveys for this study include efficiency, standardisation and anonymity. Questionnaires are an efficient way to gather a large amount of participant data at once. The structured format reduced the possibility of interviewer bias by guaranteeing consistency in data collection. By preserving participants' anonymity, more honest and impartial responses are promoted. The disadvantages of utilising surveys for this study include response dishonesty, interpretation challenges and survey fatigue. These challenges were overcome by ensuring questions were well designed.

3.5 Population and sample

3.5.1 Population

The population for this study included employees working in South Africa's retail sector focused on clothing, textile, footwear and leather goods (CTFL) category. The CTFL industry plays a pivotal role in the South African retail sector, driving a significant portion of the industry's growth and economic activity. According to Statistics South Africa (2024), CTFL retailers are among the most influential contributors to the retail sector, impacting not only sales revenue but also employment opportunities and consumer trends. The study's population included a diverse range of CTFL retail employees, including those in customer-facing roles, sales and marketing, CRM specialists, IT/Technology specialists and management, to capture a comprehensive view of CRM capabilities and AI technology use.

3.5.2 Sampling method

A target population describes the complete group of people that the study will focus on; the ideal approach would be to investigate the problem in the entire population (Rahi, 2017). However, since this is not practically possible, a sample is used. A sample refers to a smaller group that is chosen from a larger population with the intention of accurately representing the characteristics of the entire population (Acharya et al., 2013). To determine an appropriate sample size for this study, the Raosoft sample size calculator was used (Appendix C). Given the total population of 210,071 employees in the South African Retail-CTFL sector (The DTIC, 2020), sample sizes were calculated based on two commonly used confidence levels: 90% and 95%.

At a 90% confidence level, with a 5% margin of error, Raosoft suggested a minimum sample size of 271 respondents (Appendix C). This confidence level allows for a slightly lower sample requirement while still providing a reasonable degree of accuracy in representing the broader population's characteristics. At a 95% confidence level, also with a 5% margin of error, the calculator recommended a sample size of 384 respondents. This higher confidence level offers increased reliability in reflecting the population's true attributes but requires a larger sample size to achieve that statistical rigor. For this study, considering practical limitations, a target sample size of between 250 and 300 respondents was selected. This size is slightly below the ideal sample for a 95% confidence level but aligns more closely with the 90% confidence level recommendation, balancing feasibility with representativeness.

Non-probability sampling methods involve selecting participants based on their availability or the researcher's discretion, meaning that not all individuals have an equal chance of being included in the final sample (Naderifar et al., 2017). This approach was chosen due to its practicality and efficiency in reaching specific subgroups (CTFL) within the retail sector. Although snowball sampling is typically associated with qualitative research, academic literature indicates that it aligns with two distinct epistemological perspectives and has also been applied in quantitative research (Parker et al., 2019). As a form of convenience sampling, snowball sampling is particularly valuable for identifying individuals with specific target characteristics that may be difficult to reach (Naderifar et al., 2017). In this method, existing study participants were requested to recruit future participants from within their social or professional networks. Recruitment was conducted through a combination of email invitations and direct outreach to CTFL retail organisations. The email invitations were sent to department heads and HR managers, providing information about the study's purpose and requesting their assistance in disseminating the invitation to relevant employees. Additionally, the researcher reached out to industry associations as well as social and professional networks to increase awareness and encourage participation.

3.6 Instrument design

3.6.1 The research instrument

In selecting a data collection tool, the variables that this study seeks to analyse play a crucial role in determining the most appropriate method. Considering the goals of the study, a fully structured online questionnaire was identified as the most effective tool for gathering the necessary data. Questionnaires, when carefully designed, can generate significant and practical data, achieving commendable response rates (Williams, 2003). Furthermore, a questionnaire offers several advantages, including cost-effectiveness and the assurance of respondent confidentiality, which makes it a valuable method for large-scale data collection (Jack & Clarke, 1998). Likert scales were used in the questionnaire to gauge respondents' views, attitudes and perceptions of important factors. These ratings ranging from ‘strongly disagree’ to ‘strongly agree’ scales made it easier to quantify participants' opinions and enable statistical analysis to find trends, correlations and patterns. The standardised nature of scales ensures consistency in responses, contributing to the validity of the study's findings. The key variables in this study include customer interaction management capability, customer relationship upgrading capability, customer win-back capability, AI technology application and SCA. RQ was incorporated into the questionnaire as a supplementary construct. The measurement items were crafted to cover the variables using literature and modifying it to the retail sector context.

3.7 Measurement of variables

The operationalisation of the research constructs was done in accordance with earlier studies and the necessary adjustments were made to meet the current study context and goal. In this study, CRM Capabilities are the independent variables, SCA is the dependent variable while AI technology application is the moderating variable. The variables were measured utilising the seven-point Likert scale ranging from ‘strongly disagree’ to ‘strongly agree’. This scale provides more granularity than shorter scales, allowing for more nuanced responses and greater variability in data analysis.

3.7.1 CRM capabilities

CRM capabilities describe an organisation’s abilities, skill and knowledge to regularly establish, maintain, upgrade and re-establish beneficial relationships with customers (Wang & Feng, 2012). The CRM capabilities framework employed in this study divides CRM into three main capabilities: customer interaction management capability (CIMC), customer relationship upgrading capability (CRUC) and customer win-back capability (CWBC). The researcher utilised previous research (Wang & Feng, 2012; Alushra, 2018; Foltean et al., 2019) to measure CRM capabilities. The five items used to measure CIMC cover various aspects of a retail organisation's capacity to manage and maintain strong relationships with customers. The five

CRUC questions assessed the extent to which organisations employed strategies to deepen and broaden relationships with customers, focusing on enhancing customer satisfaction, upselling, cross-selling and maximising customer value. Lastly, the five CWBC questions were designed to evaluate an organisation's strategies and processes for re-engaging with lost or inactive customers, managing customer complaints and taking corrective actions to address customer dissatisfaction.

3.7.2 SCA

SCA is characterised by its distinction as a long-term advantage derived from unique value creation processes (Barney, 1991). The researcher utilised five items based on previous research (Bagram, 2010; Keshvari, 2012; Martin et al., 1995) to measure SCA. The questions evaluated the relative strengths of the organisation compared to its competitors, with a focus on customer care, service quality and staff training for CRM.

3.7.3 AI technology application

AI technology is defined as the capacity of a technological system to accurately interpret external data, learn from that information and demonstrate adaptive flexibility (Kaplan & Haenlein, 2019). The researcher used five items from past research (Shankar et al., 2018; Libai et al., 2020) to measure AI technology application.

3.7.4 Relationship quality

Relationship Quality (RQ), a key element of relationship marketing, influencing customer retention, loyalty and business performance (Rauyruen & Miller, 2007) was assessed through five items based on established literature, measuring trust, commitment and investment in customer relationships (Sanchez-Franco et al., 2019; Narteh et al., 2013; Dlačić et al., 2018).

3.8 Data collection technique

CTFL retail organisations were identified through various methods such as; Retail Association of South Africa which is an industry association and directory; conducting online research to identify retailers; reviewing Department of Trade and Industry reports and CTFL Master Plans; and leveraging professional networks and LinkedIn. Email addresses were obtained through organisation websites, business databases and by reaching out to HR and/or administrative departments directly. An invitation via email and instant messaging at times, were sent to relevant HR departments detailing the purpose of the study, highlighting the confidentiality and requesting distribution of questionnaire or email addresses. Participants received an invitation via email or instant messaging, containing a URL link to the questionnaire. After being informed about the study's purpose and giving their consent, participants were provided a link which they could click on to access the online survey.

The survey primarily consisted of closed-ended questions with responses recorded on a rating scale, allowing for quantitative analysis of feedback. The questionnaire was designed in Qualtrics, which provides a flexible platform for customising questions, implementing logic and ensuring a seamless respondent experience. The responses were securely stored in Qualtrics which enabled efficient data collection, while maintaining respondent confidentiality and facilitating broad distribution across various retail organisations.

3.9 Pilot testing

Conducting a pilot test is essential to identify and address potential challenges that may otherwise impede data collection, participant engagement and instrument effectiveness (Thabane et al., 2010). By pre-emptively addressing these issues, researchers can mitigate risks associated with recruitment difficulties, data collection inconsistencies and resource constraints (Arain et al., 2010; Leon et al., 2011). The pilot data will also inform refinements in question phrasing, response formats and the online survey's accessibility and user experience (van Teijlingen & Hundley, 2002).

To enhance the reliability and validity of the data collection process, a pilot study of the questionnaire was conducted prior to the main survey. This step is crucial to ensure that the questionnaire is user-friendly and effective in gathering valid data, ultimately contributing to the study’s robustness. The pilot participants were approached to represent the broader target population within the South African retail sector. Feedback from the 29 pilot participants were invaluable in refining the final questionnaire. Minor adjustments were made to improve question clarity, relevance and overall comprehension. Through this structured piloting process, the research aimed to enhance the reliability of the data collection instrument, ensuring a robust foundation for the main study.

3.10 Data analysis approach

Data analysis is a critical process in research, involving the cleaning, transformation and modification of data to uncover valuable insights that contribute to the study's objectives (Hancock et al., 2016). In this research, descriptive statistics were employed to examine the demographic distribution of respondents, with the results presented in tables and graphs where appropriate. To facilitate this process, the collected data was cleansed and coded using Microsoft Excel spreadsheets. The data was then analysed using the IBM Statistical Package for Social Sciences (SPSS) and Smart PLS, facilitating the computation of descriptive statistics, data interpretation, and the derivation of precise, actionable insights. The data analysis aimed to test the research hypotheses and evaluate the model. The researcher ensured clarity of hypotheses and a solid grasp of the theoretical framework to preserve study's objectives and avoid external influence.

3.10.1 Structural equation modelling (SEM)

For the data analysis, structural equation modelling (SEM) was employed to examine the structural relationships between variables and model causal relationships. SEM is a theory-driven analytical approach used to test pre-specified hypotheses about causal connections among both measured and latent variables (Mueller & Hancock, 2018). It is considered a general model that encompasses several commonly used statistical methods, such as multiple regression, factor analysis, path analysis, econometric models of simultaneous equations and latent growth curve modelling (Bowen & Guo, 2011). SEM is often seen as similar to regression analysis, but it offers an important advantage by assessing the correlations between variables while accounting for measurement error (Sarstedt et al., 2014).

According to Nusair and Hua (2010), SEM is typically conducted in a two-step process. The first step involves evaluating the measurement model to assess its adequacy by examining construct reliability and item reliability. Once the reliability of the scale has been confirmed, the next step is to evaluate construct validity, which involves assessing both convergent and discriminant validity. After finalising the measurement model, the structural model is then analysed in the second step. The overall model fit for both the measurement and structural models is assessed using goodness-of-fit indices. Confirmatory factor analysis (CFA) is utilised in the first stage to determine how well the latent variables are measured by the observable variables, while multiple regression and path analysis are used in the second stage to examine the relationships between variables (Chen et al., 2011). Unlike path analysis, which focuses on relationships between unobserved variables, CFA is primarily concerned with evaluating the fit between latent variables and their indicators (Chen et al., 2011; Nusair & Hua, 2010). Additionally, this study utilised the PROCESS macro (Hayes, 2015) to conduct moderation and conditional process analyses. This tool enhanced the strength and reliability of the results by enabling a detailed investigation of both direct and indirect effects, as well as interactions between variables. Consequently, it provided a comprehensive understanding of the complex relationships within the research framework. For the implementation of SEM, this study employed the SmartPLS (Version 4) statistical software, which was particularly well-suited for analysing structural equation models.

3.11 Measurement model assessment

3.11.1 Reliability

According to Middleton (2019), reliability refers to the consistency of a measurement and reflects how trustworthy the test scores are. To assess the reliability of the data in this study, the internal consistency procedure was utilised. This will involve the calculation of Cronbach's alpha and the composite reliability value using statistical software. Cronbach's alpha is a widely accepted measure of internal consistency, indicating how closely related a set of items are within a test or scale (Kiliç, 2016). It is commonly used in research to evaluate the reliability of scales and tests developed for specific projects. A Cronbach's alpha score above 0.7, along with a composite reliability value of 0.7, is generally considered acceptable for most research objectives (Nunnally & Bernstein, 1994).

3.11.2 Validity

Research validity in surveys refers to the extent to which the survey accurately measures the intended elements (Middleton, 2019). In simpler terms, validity determines how well an instrument captures what it is supposed to measure. In this study, two types of validity were evaluated: convergent validity and discriminant validity. Convergent validity was assessed using outer loadings and the average variance extracted (AVE). This ensures that the items intended to measure a particular construct are strongly related. Discriminant validity, on the other hand, was assessed using the Fornell-Larcker Criteria, heterotrait-monotrait (HTMT) ratio and cross-loading criteria. These methods helped confirm that each construct is distinct and not measuring overlapping concepts.

Additionally, the survey questionnaire included demographic qualifying questions to ensure that respondents meet the necessary criteria for participation (Kolb, 2018). Ensuring internal validity involves implementing controls to minimise potential biases, thereby strengthening the causal relationship between variables (Shadish et al., 2002). Internal validity was ensured by setting clear, unbiased objectives. The internal validity of the study was further strengthened through rigorous data analysis.

3.12 Limitations of the study

Limitations are defined as factors that are outside the researcher's control in the study. The following limitations were identified:

- The survey questionnaire was accessible and open to South African Retail Sector business representatives.
- The survey was open to retail organisations who have CRM capabilities and who utilise any form of AI technology and/or applications.

3.13 Ethical considerations

The researcher upheld ethical standards in data collection, ensuring respondent safety, privacy and voluntary participation. Mlambo and Msosa (2020) emphasise that participation must be free from coercion, allowing individuals to withdraw at any time without consequence. Additionally, the research design incorporated safeguards to maintain data confidentiality, protecting participants' responses, records and documents. The researcher provided clear information on the study’s purpose and obtained informed consent from participants before their involvement. Ethical clearance was obtained from the University of the Witwatersrand’s ethics committee (Appendix B), confirming adherence to established ethical standards. By following these guidelines, the researcher aimed to uphold professional research standards. Given the study’s focus on a real-life business problem, compliance with ethical protocols set by both the academic institution and participating organisations was essential. To maintain ethical integrity, participants were informed of their voluntary participation, assured of anonymity and granted the right to withdraw without explanation. These measures ensured the protection of participants' rights, anonymity and confidentiality throughout the study.

3.14 Chapter summary

This chapter outlined the research methodology used to investigate the relationship between CRM capabilities, AI technology application and SCA in the South African retail sector. A quantitative research approach with a positivist philosophy was adopted, utilising a structured online questionnaire for data collection. The target population comprised employees from the Retail Clothing, Textile, Footwear and Leather (R-CTFL) sector. Data analysis was conducted using SEM via SmartPLS and SPSS, with measurement model assessments performed to ensure reliability and validity. Additionally, the chapter covered the pilot testing process and ethical considerations, emphasising participant confidentiality and research integrity.

CHAPTER 4: DATA ANALYSIS AND RESULTS

4.1. Introduction

This chapter presents the research findings derived from the data analysis. The first section covers the descriptive statistical results, highlighting demographic information and the descriptive statistics of the measurement instruments. The second section delves into structural equation modelling, with an initial evaluation of the measurement instruments. The third section focuses on the hypothesis testing and lastly, a post hoc analysis is discussed.

4.2. Response rate analysis

A total of 384 questionnaires were distributed, with the aim of gathering responses from a target sample of 250 to 300 participants. The survey achieved strong engagement, yielding 354 responses, however, 41 respondents only completed the consent question, 6 respondents answered only one question, 15 provided demographic data only (Part A) and 6 completed the demographic section but had incomplete responses on the constructs. As a result, 68 responses were discarded. This left 286 fully completed and usable responses, yielding a response success rate of 74.48%. This far exceeds the minimum benchmarks established in academic literature. For instance, Richardson (2005), regards a 50% response rate as acceptable for social research, while Baruch (1999) observed an average response rate of 55.6% in management studies.

While no universal benchmark exists for an acceptable response rate, the representativeness of the sample is crucial (Layne et al., 1999; Porter, 2004; Coates et al., 2006). Excluding incomplete responses ensured the integrity and reliability of the dataset, aligning with ethical research practices. The final dataset of 286 responses offers a reliable and substantial foundation for analysis and supports meaningful insights and generalisations within the research parameters.

4.3. Descriptive statistics for demographics

Hahs-Vaughn and Lomax (2013) describe descriptive statistics as methods used to tabulate and summarise the characteristics of research subjects within a study. The following section presents a concise overview of the respondents' profiles, adhering to Collis and Hussey’s (2014) recommendation that descriptive statistics be summarised for clarity, ease of interpretation and effective presentation of the data.

4.3.1. Demographic profile of respondents

The demographic profile of the survey respondents, drawn from Part A of the research questionnaire, highlights the diverse backgrounds of the participants. Table 2 provides a detailed summary of this information. The demographic profile of respondents highlights a diverse representation of roles and organisational characteristics. Many respondents (44.1%) were within the Sales function, followed by 25.5% classified as Other and 18.5% in Customer Service Manager roles. Smaller proportions of participants included Marketing Managers, Managing Directors and Executive Directors. In terms of organisational revenue, many (31.5%) of respondents worked for organisations with annual revenues exceeding R201 million, while 22.0% were associated with organisations earning less than R20 million.

Regarding professional experience, most respondents (64.3%) reported having less than five years of experience at their current organisation, with only 1% indicating tenure exceeding 25 years. Organisational longevity showed a significant portion (49.0%) of respondents working in well-established organisations operating for over 25 years, whereas newer organisations (less than five years) accounted for 11.2% of the sample. Additionally, workforce size varied significantly, with 43.0% of respondents working in organisations with fewer than 1 000 employees, while 15.4% were in organisations employing over 50 000 people.

Table 2 Demographic Profile of Respondents

Variable	Category	Percentage	Cumulative Percent
Job Title	Customer Service Manager	18,5	18,5
	Executive Director	2,1	20,6
	Managing Director	4,2	24,8
	Marketing Manager	4,2	29,0
	Sales	44,1	73,1
	Technology Manager	1,4	74,5
	Other	25,5	100
	Total	**100**	
Annual revenue	<R20m	22,0	22,0
	R21-R50 m	15,0	37,1
	R51-R100m	10,8	47,9
	R101-R150m	12,9	60,8
	R151-R200m	7,7	68,5
	>R201m	31,5	100
	Total	**100**	
Years of Experience at Current Retail Organisation	<5 years	64,3	64,3
	6-10 years	21,7	86,0
	11-15 years	7,3	93,4
	16-20 years	4,5	97,9
	21-25 years	1,0	99,0
	>25 years	1,0	100
	Total	**100**	
Organisation Years of Operation	<5 years	11,2	11,2
	6-10 years	8,7	19,9
	11-15 years	7,7	27,6
	16-20 years	13,3	40,9
	21-25 years	10,1	51,0
	>25 years	49,0	100
	Total	**100**	
Number of Employees in the Retail Organisation	<1000 employees	43,0	43,0
	1 001-4 999 employees	17,5	60,5
	5 000-9 999 employees	12,6	73,1
	10 000-49 999 employees	11,5	84,6
	> 50 000	15,4	100,0
	Total	**100**	

4.3.2. Organisation's use of AI technology

Tables 3 and 4 present the profile of respondents regarding their organisations' use of AI technology. These tables provide detailed statistics on the duration of AI adoption within organisations and the various AI technologies currently in use.

Table 3 Duration of AI usage

Variable	Category	Percentage	Cumulative Percent
Duration of AI Usage	<5 years	65,4	65,4
	6- 10 years	21,3	86,7
	11-15 years	4,2	90,9
	16- 20 years	5,2	96,2
	21-25 years	1,4	97,6
	>25 years	2,4	100,0
	Total	**100**	

The data also revealed that AI adoption in the retail sector is relatively recent, with many organisations (65.4%) having implemented AI technologies within the last five years. This profile reflects both the professional diversity of participants and the evolving technological landscape within the sector.

Table 4 AI technology type

Variable	Category	Percentage
Type of AI Technology	Chatbots	43,4
	Customer Relationship Management (CRM) systems	57,0
	Predictive Analytics	14,7
	Personalisation Engines	16,1
	Sentiment Analysis Tools	7,3
	Voice Assistants	22,7
	Recommendation Systems	26,9
	Email Marketing Automation	60,5
	Social Media Analytics	65,4
	Other	2,1

The survey responses provided an overview of the types of AI technologies utilised by organisations in the South African retail sector. Among the respondents, the most widely adopted technologies were social media analytics, utilised by 65.4% of organisations and email marketing automation, implemented by 60.5%. CRM systems also featured prominently, with 57.0% of respondents indicating their usage. Chatbots were another significant technology, with 43.4% of respondents reporting their use. Recommendation systems, while moderately adopted at 26.9%, were also noteworthy and voice assistants, used by 22.7% of respondents. Adoption of advanced analytical tools such as personalisation engines and predictive analytics was less widespread, with usage rates of 16.1% and 14.7%, respectively. Sentiment analysis tools were employed by only 7.3% of organisations and a small fraction of respondents (2.1%) indicated the use of other AI technologies. These findings highlight varying degrees of AI integration, with some organisations focusing on foundational tools, while others are beginning to explore more sophisticated applications.

4.4. Descriptive statistics for the measure of variables

Participants were asked to indicate their level of agreement with clusters of statements related to various constructs, including CIMC, CRUC, CWBC, SC and AI technology application. Responses were captured on a seven-point Likert scale, ranging from 1 (Strongly Disagree) to 7 (Strongly Agree). The descriptive findings for each construct are summarised in their respective sections.

4.4.1. Customer interaction management capability

The CIMC construct comprises five items evaluating organisational efforts to engage with and understand customer needs effectively. Table 5 shows the mean and standard deviation for CIMC. CIMC 2 ("Our organisation is good at creating relationships with key customers") recorded the highest mean (5.97, SD = 1.27), suggesting that respondents perceive their organisation as effective in developing relationships with key customers. CIMC 4 ("Our organisation has a continual dialogue with each customer and uses well-developed methods to improve our relationships") had the lowest mean (5.48, SD = 1.44), indicating room for improvement in continuous engagement and relationship-building strategies.

Table 5 CIMC

Customer Interaction Management Capability (CIMC)		Mean	Standard Deviation
CIMC 1	Our organisation regularly meets customers by learning their current and potential needs for new products.	5,83	1,24
CIMC 2	Our organisation is good at creating relationships with key customers.	5,97	1,27
CIMC 3	Our organisation maintains interactive two-way communication with our customers.	5,81	1,25
CIMC 4	Our organisation has a continual dialogue with each customer and uses well developed methods to improve our relationships.	5,48	1,44
CIMC 5	Our organisation is good at maintaining relationships with key customers.	5,93	1,21

4.4.2. Customer relationship upgrading capability

CRUC assesses the organisation's ability to systematically enhance customer satisfaction and loyalty through practices like upselling and cross-selling. Mean scores for this construct range from 5.59 to 6.03 as shown in Table 6. CRUC 5 ("Our organisation has procedures designed to enhance customer satisfaction and loyalty") had the highest mean (6.03, SD = 1.09), highlighting strong efforts in ensuring customer satisfaction and loyalty. CRUC 3 ("Our organisation has formalised procedures for cross-selling to valuable customers") recorded the lowest mean (5.59, SD = 1.31), suggesting that structured cross-selling strategies may require further enhancement.

Table 6 CRUC

Customer Relationship Upgrading Capability (CRUC)		Mean	Standard Deviation
CRUC 1	Our organisation measures customer satisfaction systematically and frequently.	5,73	1,37
CRUC 2	Our organisation has formalised procedures for upselling to valuable customers.	5,67	1,31
CRUC 3	Our organisation has formalised procedures for cross-selling to valuable customers.	5,59	1,31
CRUC 4	Our organisation tries to systematically extend our share of customers with high value.	5,62	1,27
CRUC 5	Our organisation has procedures designed to enhance customer satisfaction and loyalty.	6,03	1,09

4.4.3. Customer win back capability

The CWBC construct evaluates how effectively organisations regain lost or dissatisfied customers. The mean scores range from 5.40 to 6.19 as shown in Table 7. CWBC 5 ("In our organisation, retaining customers is considered to be a key priority") had the highest mean (6.19, SD = 1.09), indicating a strong organisational focus on customer retention. CWBC 1 ("Our organisation has a systematic process/approach to re-establish relationships with valued lost customers and inactive customers") recorded the lowest mean (5.40, SD = 1.32), suggesting that more structured approaches may be required to re-engage lost customers.

Table 7 CWBC

Customer Win Back Capability (CWBC)		Mean	Standard Deviation
CWBC 1	Our organisation has a systematic process/approach to re-establish relationships with valued lost customers and inactive customers.	5,40	1,32
CWBC 2	When our organisation finds that customers are unhappy with the appropriateness of our product or service, corrective action is taken immediately.	5,99	1,20
CWBC 3	Our organisation maintains positive relationships with migrating or less frequent/less profitable customers on a regular basis.	5,53	1,20
CWBC 4	Our organisation apologises or quickly remedies for any inconvenience or loss that it brings to customers.	6,07	1,18
CWBC 5	In our organisation, retaining customers is considered to be a key priority.	6,19	1,09

4.4.4. AI technology application

This construct explores the extent of AI integration within CRM systems and its impact on operational efficiency. The mean scores range from 4.96 to 5.26, as shown in Table 8. AI 5 ("Our organisation's AI is integrated with CRM systems to improve operational efficiency") achieved the highest mean (5.26, SD = 1.37), suggesting that AI is contributing to operational improvements. AI 2 ("Our organisation uses AI to simplify the decision-making process") recorded the lowest mean (4.96, SD = 1.45), highlighting a potential gap in AI-driven decision-making support.

Table 8 AI Application

Artificial Intelligence (AI) Technology Application		Mean	Standard Deviation
AI 1	Our organisation uses AI to build personalised recommendations.	4,97	1,42
AI 2	Our organisation uses AI to simplify the decision-making process.	4,96	1,45
AI 3	Our organisation uses AI to communicate with customers at any time.	5,03	1,46
AI 4	Our organisation uses AI to enhance effective customer relationships.	5,19	1,43
AI 5	Our organisation's AI is integrated with CRM systems improves operational efficiency of the organisation.	5,26	1,37

4.4.5. Sustainable competitive advantage

SCA measures the organisation's ability to outperform competitors through customer care, service delivery and financial performance. Table 9 depicts the mean scores which range from 5.38 to 5.71. SCA 1 ("Our organisation is more customer caring than its competitors") had the highest mean (5.71, SD = 1.30), indicating that respondents believe their organisations excel in customer care compared to competitors. SCA 5 ("Our organisation has consistently outperformed its competitors in services, processes and financial performance in the past three years") recorded the lowest mean (5.38, SD = 1.40), suggesting that consistent outperforming of competitors remains a challenge.

Table 9 SCA

Sustainable Competitive Advantage (SCA)		Mean	Standard Deviation
SCA 1	Our organisation is more customer caring than its competitors.	5,71	1,30
SCA 2	Our organisation provides superior services than its competitors.	5,67	1,33
SCA 3	Our organisation has better trained staff for delivering CRM than its competitors.	5,51	1,34
SCA 4	Our organisation has had a higher increase in revenue and customer base compared to its competitors	5,54	1,32
SCA 5	Our organisation has consistently outperformed its competitors in services, processes and financial performance in the past 3 years.	5,38	1,40

4.5. Additional analysis

Before conducting factor analysis in this study, it is essential to evaluate the data's appropriateness for identifying underlying structures. The following sections outline the tests performed to confirm the appropriateness of the data for factor analysis.

4.5.1. Normality test

The normality of the data was assessed using skewness and kurtosis values for each construct measured in the study. The results of the assessment are summarised in Table 10. According to Kline (2023), skewness values should remain within ±3 and kurtosis values should not exceed ±10. These thresholds were used as benchmarks to interpret the results. An analysis of the skewness and kurtosis values obtained in this study revealed that skewness ranged from -1.457 to -0.437, while kurtosis values ranged from -0.724 to 2.354. Based on the skewness and kurtosis results of the study, the data conforms to the assumptions of univariate normality, supporting its suitability for further statistical analysis.

4.5.2. Collinearity statistics

The variance inflation factor (VIF) is a statistical measure used to detect collinearity among indicators (Zornata et al., 2023). As per Sarstedt et al. (2016), collinearity is not considered a significant concern when VIF values remain below the threshold of 5. Table 11 presents the VIF values for the indicators in this study ranging from 1.492 to 3.141, confirming that all indicators exhibit VIF values well within the acceptable range.

Table 10 Normality tests

	Excess Kurtosis	Skewness
Customer Interaction Management Capability		
CIMC 1	1.824	-1.123
CIMC 2	2.354	-1.457
CIMC 3	1.015	-0.990
CIMC 4	0.437	-0.917
CIMC 5	2.149	-1.267
Customer Relationship Upgrading Capability		
CRUC 1	2.162	-1.354
CRUC 2	1.242	-1.014
CRUC 3	0.984	-0.915
CRUC 4	0.600	-0.777
CRUC 5	1.043	-1.084
Customer Win Back Capability		
CWBC 1	0.119	-0.666
CWBC 2	1.602	-1.253
CWBC 3	0.028	-0.526
CWBC 4	2.055	-1.376
CWBC 5	2.058	-1.410
Artificial Intelligence (AI) Technology Application		
AI 1	0.168	-0.541
AI 2	-0.259	-0.437
AI 3	0.012	-0.543
AI 4	0.246	-0.645
AI 5	0.512	-0.636
Sustainable Competitive Advantage		
SCA 1	0.260	-0.829
SCA 2	-0.462	-0.699
SCA 3	-0.724	-0.492
SCA 4	-0.404	-0.605
SCA 5	-0.509	-0.455

Table 11 Collinearity statistics (VIF)

	Customer Interaction Management Capability	Customer Relationship Upgrading Capability	Customer Win Back Capability	AI Technology Application	Sustainable Competitive Advantage
Customer Interaction Management Capability					3.141
Customer Relationship Upgrading Capability					2.684
Customer Win Back Capability					2.777
AI Technology Application					1.492

4.6. Factor analysis

Factor analysis is a statistical technique used to identify underlying patterns within large datasets by reducing them into smaller, more meaningful factors or components (Pallant et al., 2016). It serves as a crucial preliminary step before conducting higher-order inferential analysis. This study applied principal component analysis (PCA) as the chosen factor extraction method. An exploratory factor analysis (EFA) approach was initially employed to examine the underlying structure of the constructs.

4.6.1. Exploratory factor analysis

The Kaiser-Meyer-Olkin (KMO) test is a widely used statistical measure that assesses the adequacy of a dataset for factor analysis (Jere & Ngidi, 2020). Similarly, Bartlett's test of sphericity evaluates whether the collected data is appropriate for factor analysis by determining the presence of sufficient correlations among variables (Saravanan & Dharani, 2020). A KMO value above 0.7 is considered the minimum threshold for factor analysis to proceed effectively (Jere & Ngidi, 2020).

The results of the KMO test and Bartlett's test of sphericity confirm the suitability of the dataset for factor analysis, as shown in Table 12. The KMO value of 0.929, which exceeds the recommended threshold of 0.7, indicates excellent sampling adequacy. Additionally, Bartlett's test is statistically significant ($p < 0.000$, Chi-Square = 4578.87, df = 300), confirming that the variables exhibit sufficient correlations for meaningful factor extraction. These findings validate the appropriateness of the dataset for further analysis, ensuring that the constructs align with the intended theoretical framework.

Table 12 KMO and bartlett's test

KMO and Bartlett's test		
Kaiser-Meyer-Olkin measure of sampling adequacy		0.929
Bartlett's test of sphericity	Approx. chi-square	4578.865
	df	300
	Sig.	0.000

4.7. Structural equation modelling data analysis

This study adopted Structural Equation Modelling (SEM) as the primary technique for data analysis, utilising the Partial Least Squares (PLS-SEM) approach. SEM is a multivariate statistical technique widely used for examining complex relationships between latent variables and their indicators, as well as for testing hypothesised causal relationships between constructs (Karakaya-Ozyer & Aksu-Dunya, 2018; Thakkar, 2020). There are two main types of SEM: covariance-based SEM (CB-SEM) and partial least squares SEM (PLS-SEM). While CB-SEM is suitable for validating, testing, or comparing theories, PLS-SEM is often employed to determine or forecast essential driver constructs, particularly in exploratory or predictive research (Sarstedt et al., 2021).

By employing PLS-SEM, this study benefits from a method tailored for predictive modelling and exploratory research. The flexibility and efficiency of SmartPLS enable the analysis of the intricate relationships between CRM capabilities, SCA and the moderating role of AI. This methodological approach ensures that the findings are statistically robust and aligned with the study's theoretical framework. The subsequent sections provide a detailed account of the SEM analysis results and discussion.

4.7.1. Measurement Model Assessment

SEM consists of two interconnected models: the measurement model and the structural model (Petko et al., 2018). The measurement model, also referred to as Confirmatory Factor Analysis (CFA), identifies latent variables (constructs) within the model and assigns observed variables to each. In contrast, the structural model, also known as path analysis, examines the hypothesised causal relationships between the latent variables (Zhang, 2022). Yu et al. (2021)

recommend a two-step approach when using SEM. The initial step involves evaluating the measurement model for one-dimensionality, reliability, and validity, including both convergent and discriminant validity. This ensures that the observed variables accurately represent their respective constructs. The second step involves evaluating the structural model to test the hypothesised relationships among constructs by assessing the path significance.

4.7.1.1. Reliability

Reliability refers to the extent to which the variance of an item can be attributed to its underlying construct rather than random error (Sürücü & Maslakci, 2020) and the extent to which data collection techniques or analysis procedures will yield consistent findings (Saunders et al., 2019). The reliability of the constructs was assessed using Cronbach's alpha, which measures the internal consistency of the items within each scale. All constructs demonstrated excellent reliability, exceeding the commonly accepted threshold of 0.70, as shown in Table 13. Specifically, CIMC achieved a Cronbach's alpha of 0.893, CRUC scored 0.839 and CWBC recorded 0.836, indicating strong consistency among these constructs. Similarly, SCA exhibited a high level of reliability with a value of 0.868, while AI showed exceptional reliability with a Cronbach's alpha value 0.904. These results confirm that the scales used in this study are highly reliable and suitable for further analysis.

Table 13 Cronbach's alpha

Construct	No. of Items	Cronbach's alpha
Customer Interaction Management Capability	5	0.893
Customer Relationship Management Capability	5	0.839
Customer Win Back Capability	5	0.836
AI Technology Application	5	0.904
Sustainable Competitive Advantage	5	0.868

4.7.1.2. Validity

Construct validity was evaluated statistically using Partial Least Squares Structural Equation Modelling (PLS-SEM). Construct validity is confirmed when both convergent and discriminant validity are present. In this study, factor loadings, average variance extracted (AVE), Fornell and Larcker criterion and the Heterotrait-Monotrait (HTMT) ratio were utilised to assess the validity of the instruments. Each of these methods provides insights into different aspects of validity, ensuring that the constructs are appropriately measured by their respective indicators. The results and interpretations of these measures are presented and discussed in the subsequent sections.

4.7.1.2.1. Convergent Validity

In this study, convergent validity was assessed using outer loadings and AVE. Table 14 presents the outer loading values along with AVE scores obtained from the analysis. According to Chin and Yao (2024), outer loadings should exceed 0.5 to ensure that each item captures at least 50% of the variance in the intended construct. The findings confirm that the instruments used in the study effectively measure their respective constructs, establishing strong convergent validity for the model.

Table 14 Convergent Validity

	Factor Loading	AVE
Customer Interaction Management Capability (CIMC)		0.703
CIMC 1	0,741	
CIMC 2	0,832	
CIMC 3	0,882	
CIMC 4	0,844	
CIMC 5	0,885	
Customer Relationship Upgrade Capability (CRUC)		0.610
CRUC 1	0,685	
CRUC 2	0,803	
CRUC 3	0,813	
CRUC 4	0,824	
CRUC 5	0,772	
Customer Win-Back Capability (CWBC)		0.604
CWBC 1	0,748	
CWBC 2	0,810	
CWBC 3	0,802	
CWBC 4	0,739	
CWBC 5	0,784	
Artificial Intelligence Technology Application (AI)		0.722
AI 1	0,821	
AI 2	0,811	
AI 3	0,847	
AI 4	0,894	
AI 5	0,874	
Sustainable Competitive Advantage (SCA)		0.655
SCA 1	0,784	
SCA 2	0,825	
SCA 3	0,811	
SCA 4	0,816	
SCA 5	0,811	

4.7.1.2.2. Discriminant validity

Discriminant validity refers to the extent to which distinct constructs are measured by distinct instruments. As Sarstedt et al., (2016) and Rönkkö and Cho (2022) explain, if two or more constructs are truly distinct, the measures designed to capture each construct should not exhibit significant correlations. This ensures that the constructs are not only conceptually distinct but also empirically separable, which is essential for establishing the validity of the measurement model. Discriminant validity was assessed using the Fornell and Larcker Criterion and the HTMT ratio.

The Fornell-Larcker criterion was applied following the guidelines provided by Ab Hamid et al. (2017) and Fornell and Larcker (1981). As per this criterion, discriminant validity is confirmed when the square root of the AVE for each construct surpasses its correlation with all other constructs. In this study, the square root of AVE (emphasised in bold and italics) for each construct was greater than its correlation with other constructs, as illustrated in Table 15. This finding provides strong evidence supporting the discriminant validity of the measurement model.

Table 15 Fornell and Larcker criterion

	AI	CIMC	CRUC	CWBC	SCA
AI	***0.850***				
CIMC	0.448	***0.838***			
CRUC	0.539	0.639	***0.781***		
CWBC	0.426	0.677	0.661	***0.777***	
SCA	0.452	0.629	0.614	0.694	***0.809***

Note: Each diagonal value (in bold and italics) represents the square root of the AVE for its respective construct.

CIMC= Customer Interaction Management Capability; CRUC= Customer Relationship Upgrading Capability; CWBC = Customer Win-Back Capability; AI= Artificial Intelligence technology application; and SCA = Sustainable Competitive Advantage

In addition, discriminant validity was further evaluated using the HTMT ratio, as recommended by Roemer et al. (2021). This method assesses the extent to which constructs are distinct by comparing the average correlations of indicators across constructs (heterotrait) to the average correlations within the same construct (monotrait). As demonstrated in Table 16, all inter construct correlations remained below the threshold of 0.90, as recommended by Cheung et al. (2024). This confirms that the constructs are empirically distinct and that discriminant validity is established in this study.

Table 16 HTMT Ratio

	CIMC	CRUC	CWBC	AI	SCA
CIMC				0.495	
CRUC	0.733			0.611	
CWBC	0.782	0.784		0.490	
AI					
SCA	0.709	0.712	0.815	0.503	

Note: CIMC= Customer Interaction Management Capability; CRUC= Customer Relationship Upgrading Capability; CWBC = Customer Win-Back Capability; AI= Artificial Intelligence technology application; and SCA = Sustainable Competitive Advantage

4.8. Model explanatory power

The coefficient of determination (R^2) measures the proportion of variance in the dependent variable explained by independent variables, indicating a model's explanatory power (Shmueli & Koppius, 2011). Hair et al. (2011, 2013) classify R^2 values as follows: 0.75 as substantial, 0.50 as moderate and 0.25 as weak, while adjusted R^2 accounts for model complexity to prevent overestimation (Chin, 1998). In this study, the SCA values for R^2 of 0.573 and adjusted R^2 of 0.562 suggest a moderate explanatory power, indicating meaningful predictor contributions.

Following the framework outlined by Hair et al. (2017), the predictive power of the model was assessed, as presented in Table 17. Predictive relevance was evaluated using Q^2, which determines the model's ability to predict outcomes (Zhang, 2022). Specifically, Q^2 evaluates the predictive significance of the endogenous constructs. A Q^2 value greater than zero signifies that the model is well-structured and has predictive relevance (Hair et al., 2013). In this study, the Q^2 values exceeded zero, confirming the model's predictive capability.

Table 17 Q-Square

Construct	Q^2predict	RMSE	MAE
Sustainable Competitive Advantage	0.542	0.682	0.530

This study evaluated the model's predictive capability using Smart-PLS predict (PLS-predict) to address out-of-sample prediction challenges (Shmueli et al., 2016). PLS-predict applies a split-sample approach, typically using a 70% training sample and a 30% predictor sample, to estimate model accuracy and performance (Shmueli et al., 2019). Predictive power was evaluated by analysing prediction error statistics, where lower residual values (the difference between actual and predicted values) indicated higher accuracy (Hair et al., 2017). The study used Root-Mean-Square Error (RMSE) as the primary prediction error metric, while Mean Absolute Error (MAE) was recommended for non-symmetric error distributions (Danks & Ray, 2018). According to Shmueli et al. (2019), high predictive power is achieved when all indicators have lower RMSE or MAE values than the naive linear model (LM) benchmark, moderate power when most indicators show lower errors and low power when only a few indicators record lower errors. Given the study's findings shown in Table 18, the model demonstrates high predictive power, validating its accuracy and reliability.

Table 18 Model Predictive Power: Q^2, RMSE and MAE

Construct	Q^2predict	PLS-SEM_RMSE	PLS-SEM_MAE	LM_RMSE	LM_MAE	IA_RMSE	IA_MAE
SCA_1	0.348	1.049	0.801	1.059	0.820	1.299	1.098
SCA_2	0.364	1.062	0.836	1.081	0.859	1.332	1.141
SCA_3	0.391	1.052	0.843	1.100	0.866	1.348	1.175
SCA_4	0.295	1.113	0.871	1.167	0.918	1.326	1.137
SCA_5	0.369	1.111	0.892	1.153	0.915	1.399	1.202

Besides improving the model's predictive power, a model fit test was also performed. Model fit was examined using SmartPLS 4, using key fit indices including the Standardised Root Mean Square Residual (SRMR), d_ULS (squared Euclidean distance), d_G (Geodesic Distance), Chi-Square and Normed Fit Index (NFI), as shown in Table 19.

Table 19 Model Fit

	Saturated model	Estimated model
SRMR	0.064	0.064
d_ULS	1.312	1.321
d_G	0.523	0.522
Chi-square	892.148	893.005
NFI	0.811	0.811

PLS-SEM does not have an established goodness-of-fit measure, as it primarily follows a causal-predictive modelling perspective that aims to maximise explained variance rather than minimise the divergence between empirical and model-implied covariance matrices (Hair et al., 2016). While some researchers question its suitability for theory testing, recent studies explored alternative fit measures, including the standardized root mean square residual (SRMR), root mean square residual covariance (RMS_theta) and exact fit tests, though their effectiveness in detecting model misspecifications remains debated (Henseler et al., 2015). The SRMR value of 0.064 falls within acceptable thresholds, supporting model adequacy despite an NFI below the conventional 0.90 threshold (Dijkstra & Henseler, 2015). The literature suggests that traditional fit indices like NFI should not be overemphasised in PLS-SEM, as the approach focuses on predictive relevance rather than covariance-based fit (Hair et al., 2018). Having confirmed the model's goodness-of-fit and predictive power, all results are substantiated with confidence.

4.9. Structural model assessment

As the measurement model assessment successfully met all required thresholds, the next step involved evaluating the structural model. To achieve this, a path analysis was conducted to examine the relationships between the constructs. Path coefficients were computed for each proposed hypothesis, while bootstrapping was employed to generate t-statistics and p-values, enabling the assessment of statistical significance.

4.9.1. Path modelling

Following the successful assessment of the measurement model, the structural model was evaluated through path analysis, a key step in SEM-based data analysis (Beran et al., 2010; Cepeda-Carrion et al., 2019). Path modelling not only establishes relationships between observed variables and theoretical constructs (Sarstedt et al., 2021), it also examines the structural paths within the conceptualised research model. The primary objective of this step was to validate the theoretical framework of the study and assess the significance of relationships between model constructs (Jenatabadi et al., 2014). The structural model was analysed by evaluating standardised regression coefficients and p-values to determine statistical significance (Held & Ott, 2018). Given that path modelling requires both an explanation of regression coefficients and an assessment of the model's predictive power (Sarstedt et al., 2021), these factors were critically examined. Figure 3 presents the structural model outcomes for the proposed hypotheses.

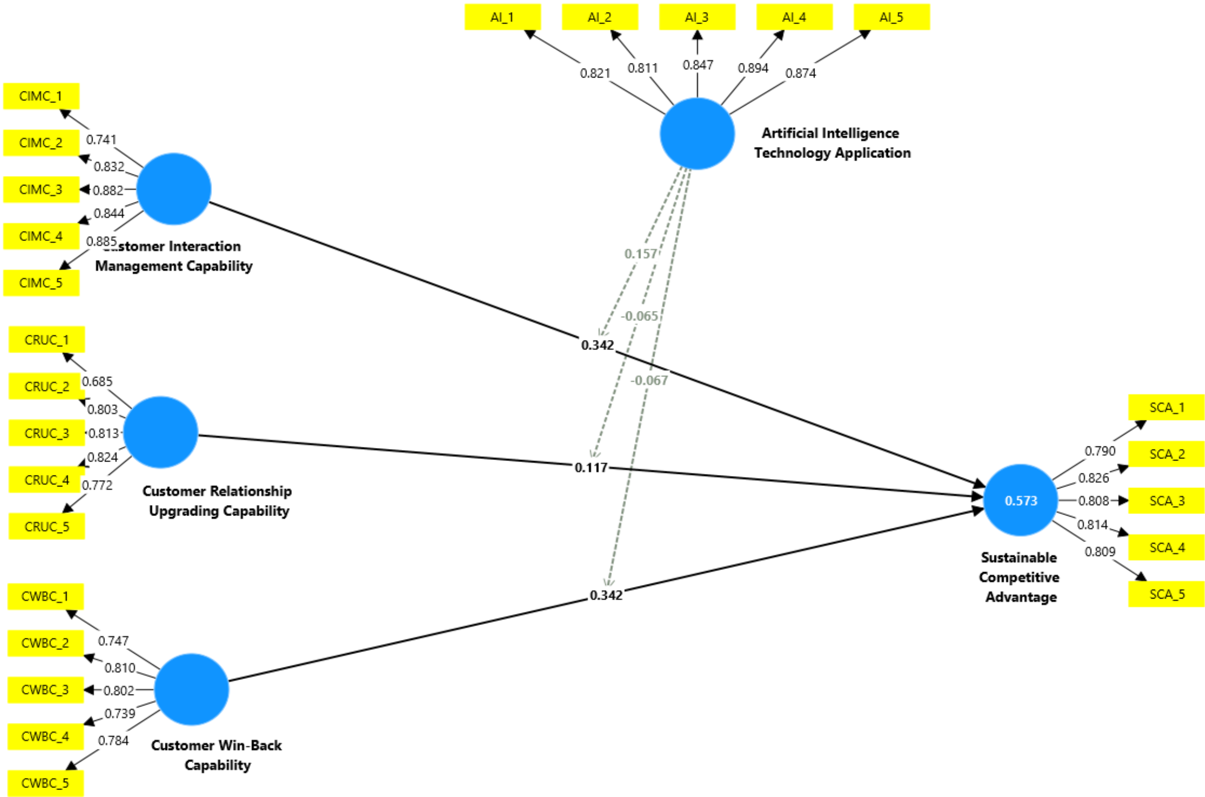

Figure 3 Structural Model

4.10. Hypothesis testing

Following the evaluation and finalisation of the measurement and structural models, path analysis was conducted to investigate the causal relationships between latent variables (Mueller & Hancock, 2018). According to Nusair et al. (2010), SEM posits that certain latent variables exert either a direct or indirect influence on other variables within the model, with estimation results illustrating these relationships. The existing literature suggests that a t-value greater than 1.96 indicates a statistically significant relationship, while path coefficients exceeding 1 denote a strong association between latent variables (Zhang, 2022).

4.10.1. Construct results

The construct hypothesis testing results for this study are presented in Table 20, which outlines the proposed hypotheses, corresponding path coefficients, t-statistics and p values.

Table 20 Hypothesis Testing Results

Hypothesised Relationship	Hypothesis	Path Coefficient (β)	T-Statistics (t)	P Value
CIMC -> SCA	H1a	0.341	4.313	0.000
CRUC -> SCA	H1b	0.118	1.597	0.055
CWBC -> SCA	H1c	0.341	4.533	0.000

Note: CIMC= Customer Interaction Management Capability; CRUC= Customer Relationship Upgrading Capability; CWBC = Customer Win-Back Capability; AI= Artificial Intelligence technology application; and SCA = Sustainable Competitive Advantage

H1a: Customer interaction management capability and sustainable competitive advantage

The relationship between CIMC and SCA was assessed. A path coefficient of 0.341 was realised after testing the hypothesis, indicating a positive relationship between the two variables. furthermore, the results indicate a significant positive relationship between customer interaction management capability and sustainable competitive advantage ($\beta = 0.341$, $t= 4.313$, $p= 0.000$). As a result of the positive association revealed by the results, hypothesis H1a was supported.

H1b: Customer relationship upgrading capability and sustainable competitive advantage

The effect of CRUC on SCA was also investigated. The findings indicate a positive but weak relationship, with a path coefficient of 0.118. The t-statistic ($t = 1.597$) and p value ($p = 0.055$) suggests that while the relationship does not meet the conventional threshold for statistical significance, it is marginally significant at the 10% level ($p < 0.10$). Consequently, H1b is supported at a marginal level, indicating that CRUC exhibits a weak but marginally significant influence on SCA in the South African CTFL retail sector.

H1c: Customer win-back capability and sustainable competitive advantage

The results confirm a positive and statistically significant relationship between CWBC and SCA, with a path coefficient of 0.341. The t-statistic ($t = 4.533$) and p-value ($p < 0.001$) further validate this relationship. These findings suggest that effective customer win-back strategies can enhance sustainable competitive advantage, reinforcing the importance of retaining and re-engaging previous customers. As a result, H1c is supported.

4.10.2. Moderation results

Moderation analysis examines whether the strength or direction of the relationship between predictor and outcome variables changes when influenced by a third variable (Hair, et al., 2021). In the context of this study, AI technology application is introduced as a moderating variable, influencing the relationships between CIMC, CRUC, CWBC and SCA, using PROCESS macro (SPSS) and SmartPLS (Version 4). The results from both methodologies provide complementary insights into the extent to which AI influences the CRM-SCA relationship.

Using Process Model 1, the PROCESS macro (SPSS) results examined whether AI moderates the relationship between Customer Relationship Management (CRM) Capabilities and Sustainable Competitive Advantage (SCA). The model explained 53.91% of the variance in SCA ($R^2 = 0.5391$, $p < 0.001$), confirming a strong relationship between CRM and SCA. CRM Capabilities had a significant positive effect on SCA ($\beta = 0.6631$, $p = 0.0001$), indicating that organisations with stronger CRM Capabilities achieve a greater competitive advantage. However, AI did not have a significant direct effect on SCA ($p = 0.4014$), nor did it significantly moderate the CRM-SCA relationship (interaction term $\beta = 0.0412$, $p = 0.2173$). The moderation effect was minimal, with an R^2 change of only 0.0025 (0.25%), suggesting that AI does not substantially alter the impact of CRM Capabilities on SCA.

A more granular analysis was conducted in SmartPLS, examining how AI moderates specific CRM capabilities. Table 21 presents the results of the moderation analysis, detailing how AI technology influences the relationship between CRM capabilities and SCA.

Table 21 Moderation results

Hypothesised Relationship	Hypothesis	Path Coefficient (β)	T-Statistics (t)	P Value
AI x CIMC -> SCA	H2a	0,156	2.359	0.009
AI x CRUC -> SCA	H2b	-0,066	1.188	0.117
AI x CWBC -> SCA	H2c	-0,065	1.173	0.120

Note: CIMC= Customer Interaction Management Capability; CRUC= Customer Relationship Upgrading Capability; CWBC = Customer Win-Back Capability; AI= Artificial Intelligence technology application; and SCA = Sustainable Competitive Advantage

H2a: Artificial intelligence technology application moderates the relationship between customer interaction management capability and sustainable competitive advantage.

The results indicate that AI technology application significantly moderates the relationship between CIMC and SCA, with a path coefficient of 0.156. The t-statistic (t = 2.359) and p-value (p = 0.009) confirm statistical significance, supporting H2a. This suggests that AI enhances the impact of customer interaction management capability on sustainable competitive advantage. The slope analysis (Figure 4) further reinforces this finding, as the interaction effect illustrates that as AI adoption increases, the positive impact of CIMC on SCA becomes stronger.

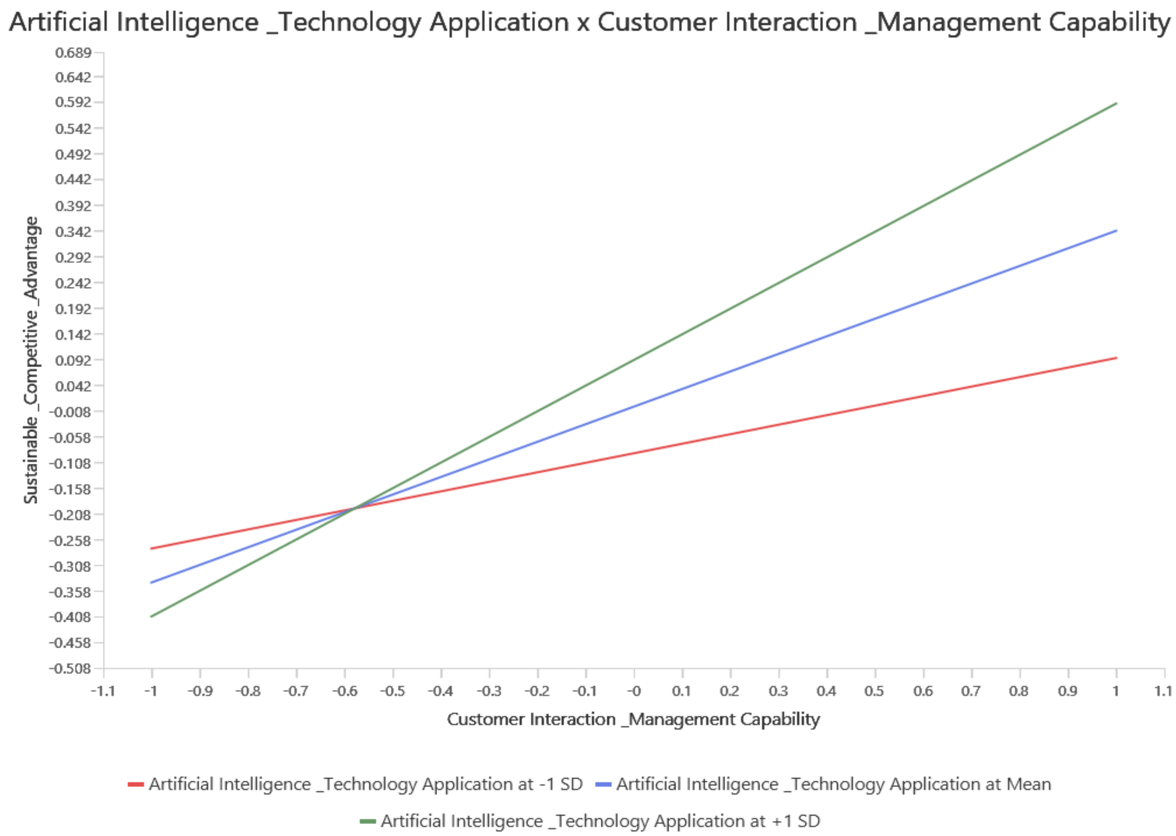

Figure 4 Moderating effect of AI on CIMC and SCA

H2b: Artificial intelligence technology application moderates the relationship between customer relationship upgrading capability and sustainable competitive advantage.

The moderation analysis for the relationship between CRUC and SCA produced a negative but statistically insignificant interaction effect (β = -0.066, t = 1.188, p = 0.117). Given that the p-value exceeds 0.05, hypothesis H2b is not supported. This suggests that AI technology application does not significantly influence the relationship between CRUC and SCA. The slope analysis supports this conclusion, showing a minimal variation in the impact of CRUC on SCA as AI application increases, as seen in Figure 5.

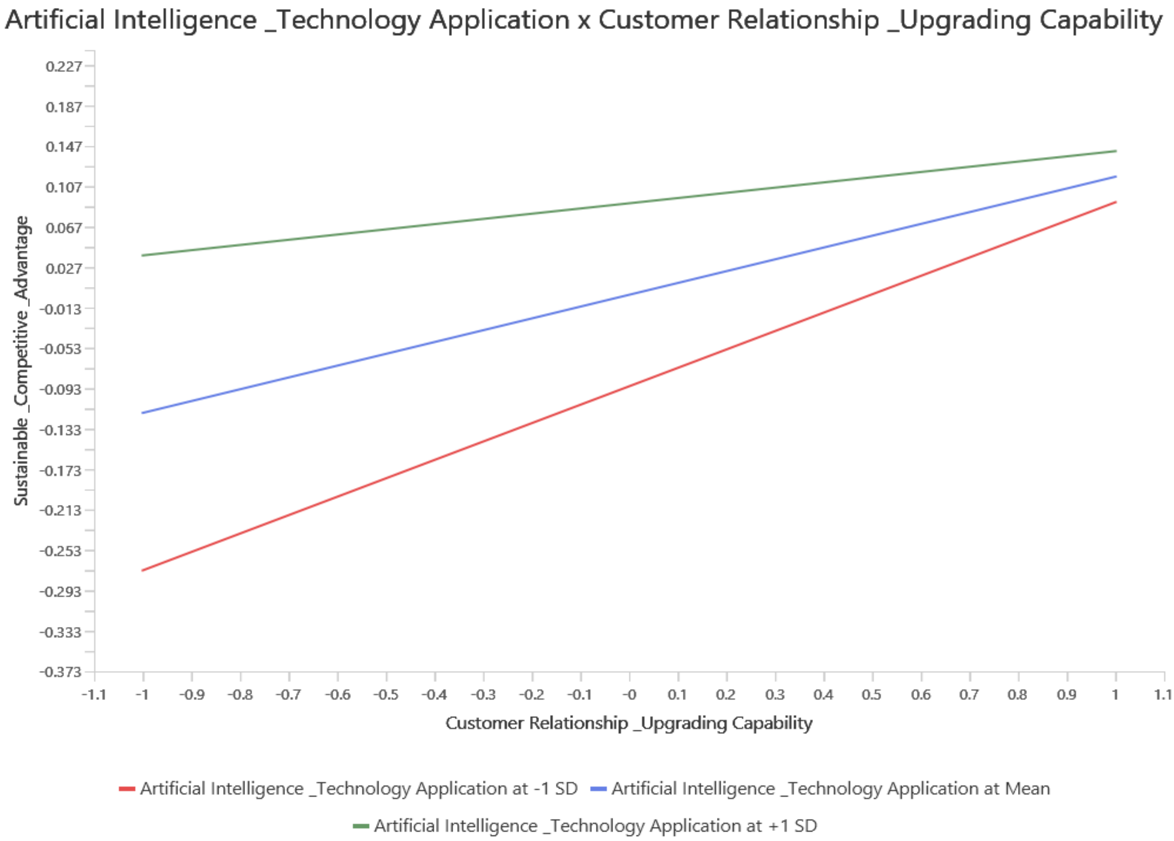

Figure 5 Moderating effect of AI on CRUC and SCA

H2c Artificial Intelligence technology application moderates the relationship between Customer Win-Back Capability and Sustainable Competitive Advantage.

The results reveal a negative but statistically insignificant interaction effect (β = -0.065, t = 1.173, p = 0.120), indicating that H2c is not supported. This suggests that AI technology application does not significantly moderate the relationship between CWBC and SCA. The slope analysis shown in Figure 6 further corroborates this finding, as there is little variation in the impact of CWBC on SCA across different levels of AI application.

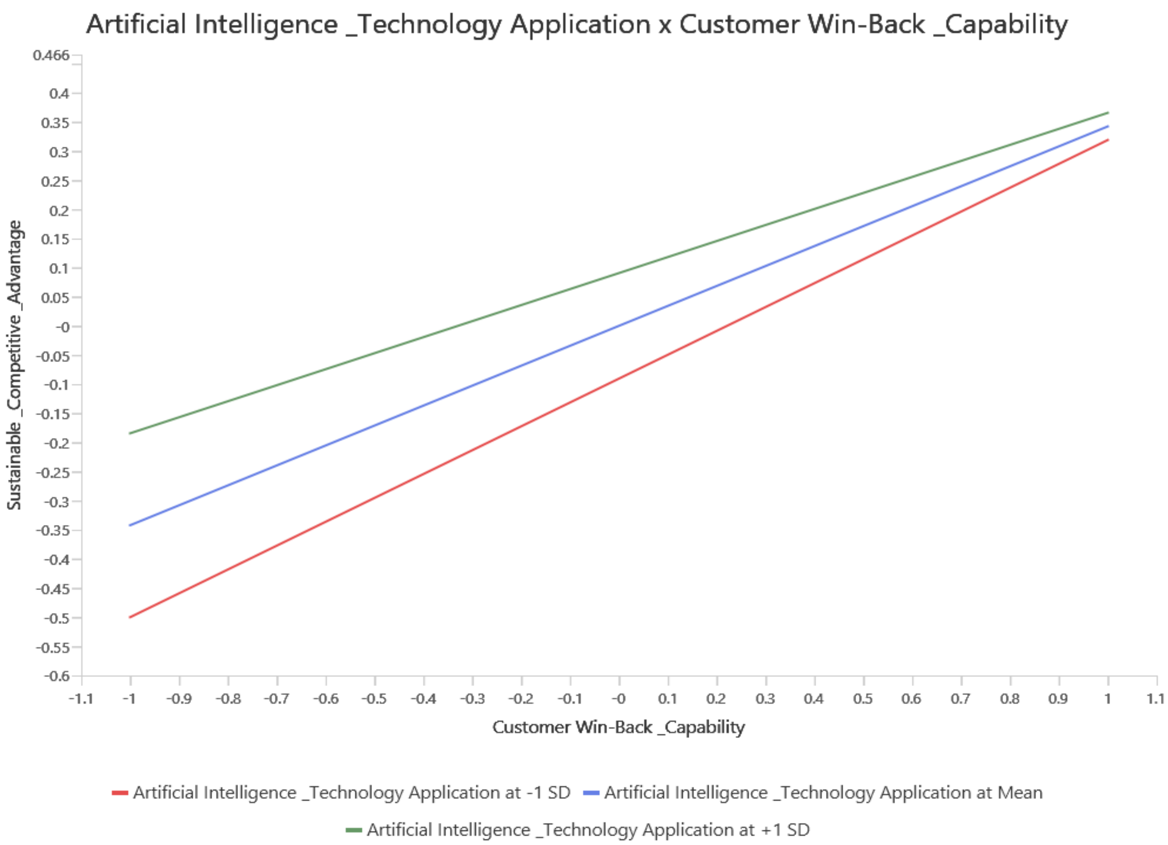

Figure 6 Moderating effect of AI on CWBC and SCA

4.11. Post hoc analysis

Following the primary analysis, a post hoc analysis was conducted to further explore the role of AI in the relationship between CRM capabilities and SCA, introducing relationship quality (RQ) as an intermediary variable within the framework (Figure 7). This analysis aimed to refine the understanding of AI's influence on CRM Capabilities and its downstream effects on SCA (Table 22). The post hoc analysis examined the revised model, incorporating RQ as an intermediary factor in the relationship between AI-enabled CRM capabilities and SCA. The statistical results indicate significant relationships across multiple pathways, supporting the inclusion of RQ in the model.

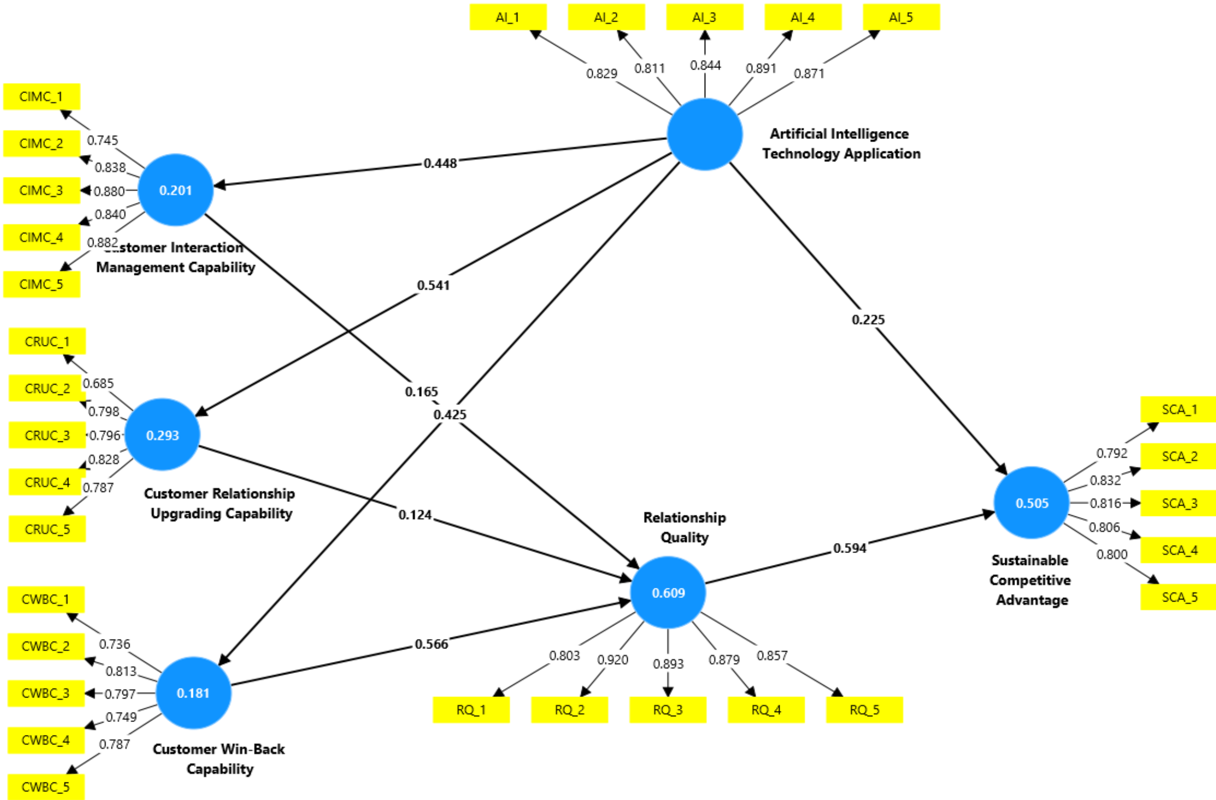

Figure 7 Post Hoc Analysis Model

Table 22 Post Hoc Analysis Hypothesis

Hypothesised Relationship	**Post Hoc Hypothesis**	**Path Coefficient (β)**	**T-Statistics (t)**	**P Value**
CIMC -> RQ	PH1a	0,165	2.315	0.021
CRUC -> RQ	PH1b	0,124	1.996	0.046
CWBC -> RQ	PH1c	0,566	8.830	0.000
AI -> CIMC	PH2a	0,448	7.544	0.000
AI -> CRUC	PH2b	0,541	10.336	0.000
AI -> CWBC	PH2c	0,425	8.546	0.000
AI-> SCA	PH3	0,225	4.026	0.000
RQ -> SCA	PH4	0.594	13.113	0.000

Note: CIMC= Customer Interaction Management Capability; CRUC= Customer Relationship Upgrading Capability; CWBC = Customer Win-Back Capability; AI= Artificial Intelligence technology application; and SCA = Sustainable Competitive Advantage

PH1a -c: CRM capabilities and relationship quality

CIMC positively influences RQ (coefficient = 0.165, t-statistic = 2.315, p-value = 0.021), confirming that effective customer interactions build stronger relationships. CRUC efforts also contribute to improved RQ, though at a lower significance level (coefficient = 0.124, t-statistic = 1.996, p-value = 0.046). Strong evidence supports the assertion that CWBC significantly enhances RQ (coefficient = 0.566, t-statistic = 8.830, p-value = 0.000).

PH2a -c: AI and CRM capabilities

The findings reveal that AI significantly enhances CIMC, as indicated by a coefficient of 0.448 and a t-statistic of 7.544, with a p-value of 0.000. This confirms that AI-driven solutions enable better customer engagement and responsiveness. AI also positively influences CRUC (coefficient = 0.541, t-statistic = 10.336, p-value = 0.000), emphasising AI's role in fostering personalised experiences and deeper customer engagement. Furthermore, AI-driven CWBC strategies are effective in reclaiming lost customers through predictive analytics and targeted interventions, as evidenced by a coefficient of 0.425, t-statistic of 8.546 and p-value of 0.000.

PH3: AI and SCA

The statistical results indicated that AI technology application directly contributes to SCA, with a path coefficient (β) of 0.225, a t-value of 4.026 and a p-value of 0.000. The path coefficient of 0.221, demonstrates that AI plays a notable role in enhancing SCA. The t-value of 4.026, which exceeds the threshold of 1.96 for statistical significance at the 95% confidence level, further reinforces the robustness of this finding. Additionally, the p-value of 0.000 indicates that the observed effect is unlikely to be due to chance. While the effect size is smaller compared to indirect effects mediated through RQ, it remains statistically significant. These findings underscore AI's role as a key enabler of SCA within the South African retail sector.

PH4: RQ and SCA

The statistical analysis confirms a strong positive relationship between Relationship Quality (RQ) and SCA ($\beta = 0.594$, $t = 13.113$, $p = 0.000$), indicating that organisations with higher-quality customer relationships are more likely to achieve a sustainable edge over competitors. This substantial effect size suggests that fostering strong, trust-based relationships with customers is a key driver of long-term business success in the South African retail sector.

The post hoc analysis provides critical insights into the role of AI in enhancing CRM capabilities and its subsequent influence on SCA within the South African retail sector. By introducing RQ as an intermediary variable, this analysis refines the understanding of AI's impact on customer relationships and business competitiveness. The key takeaway is that while AI directly contributes to SCA, its strongest influence is exerted indirectly, by enhancing CRM capabilities, which improve RQ, ultimately driving SCA.

4.12. Chapter Summary

This chapter presented the research findings obtained through data analysis, beginning with descriptive statistics that detailed the demographic profiles of respondents and the use of AI technology within their organisations. Structural equation modelling (SEM) was then conducted, including an evaluation of the measurement model to assess reliability and validity, followed by hypothesis testing to determine relationships between CRM capabilities, AI technology application and SCA. The moderation analysis revealed that AI significantly enhances the impact of CIMC on SCA but did not moderate the effects of other CRM capabilities. Finally, a post hoc analysis introduced relationship quality as an intermediary variable, highlighting AI's role in improving CRM capabilities, which in turn contributed to stronger customer relationships and SCA.

CHAPTER 5: DISCUSSION OF FINDINGS

5.1. Introduction

This chapter provides a comprehensive interpretation of the findings presented in the previous chapter, placing them within the context of the existing literature and the broader research objectives. It critically examines how the results align with or diverge from prior studies and integrates recent empirical findings. Finally, the researcher will relate the findings to the proposed framework, highlighting its theoretical implications and limitations.

5.2. Research objectives

The study was designed to examine the influence of various CRM capabilities on SCA within the South African retail sector. Specifically, the research aimed to explore whether Customer Interaction Management Capability, Customer Relationship Upgrading Capability and Customer Win-Back Capability each have a significant impact on SCA. Additionally, the study sought to assess the moderating role of AI technology applications in shaping the relationship between these CRM capabilities and SCA.

5.3. CIMC and SCA

In this study, it was hypothesised that Customer Interaction Management Capability (CIMC) would positively influence Sustainable Competitive Advantage (SCA) in the retail sector. The findings confirm this hypothesis, demonstrating that CIMC exerts a statistically significant positive effect on SCA in the South African retail sector. The SEM analysis indicated a robust relationship between CIMC and SCA, supporting the assertion that organisations with enhanced CIMC are better positioned to foster SCAs. This aligns with existing literature such as Payne and Frow (2005) and Rapp et al. (2010), highlighting the role of effective customer interaction in driving superior sales performance and customer satisfaction. Additionally, Kamal et al. (2020) highlight that strategic customer engagement strengthens long-term customer relationships, enhancing SCA.

Among CIMC components, creating relationships with key customers achieved the highest mean score, underscoring its importance in securing competitive advantages. Conversely, maintaining continuous dialogue with each customer recorded the lowest mean, suggesting potential areas for improvement. These results are supported by the theory of relationship marketing (RM) (Möller & Halinen, 2000; Kamal et al., 2022), the resource-based view (RBV) (Barney, 1991; Ofori & Appiah-Nimo, 2022) and the dynamic capabilities (DC) framework

(Eisenhardt & Martin, 2000; Teece, 2018), which collectively emphasise the strategic value of strong customer engagement, valuable resources and adaptability in sustaining competitive advantage. The empirical evidence from this study reinforces the pivotal role of CIMC in achieving SCA within the South African retail sector. Organisations that invest in enhancing their customer interaction capabilities are likely to experience improved customer relationships, higher satisfaction levels and ultimately, a SCA in the market.

5.4. CRUC and SCA

In this study, it was hypothesised that customer relationship upgrading capability (CRUC) would positively influence sustainable competitive advantage (SCA) in the retail sector. The results provide marginal support for this hypothesis, indicating that CRUC exerts some influence on SCA in the South African retail sector. While RM theory suggests that upselling and cross-selling foster customer loyalty (Luck & Lancaster, 2013), the marginal support implies that CRUC practices may not be fully optimised or integrated into broader strategies to yield robust SCA. The weak effect suggests that CRUC capabilities may not fully meet the RBV criteria of being valuable, rare, inimitable and non-substitutable (VRIN) in the South African retail context, where many competitors may be employing similar strategies. Moreover, the diversity of customer relationships and preferences in this sector may constrain the effectiveness of standardised CRUC practices, limiting their potential to create a distinctive, sustainable competitive position.

The DC framework extends the RBV by highlighting the need for CRM capabilities to be adaptable to evolving market conditions (Teece, 2018; Chatterjee et al., 2022). It emphasises a firm's ability to adapt, integrate and reconfigure both internal and external competencies in response to rapidly changing environments (Eisenhardt & Martin, 2000). However, many organisations struggle to transform CRM resources into a SCA due to a lack of superior capabilities for managing customer relationships dynamically (Day & van den Bulte, 2002). In this study, the marginal influence of CRUC on SCA suggests that while organisations may possess foundational CRM resources, they often lack the strategic agility to refine and optimise customer relationships effectively. This limitation may stem from an absence of dynamic capabilities required to continuously adapt and enhance these resources in response to market fluctuations (Rahman et al., 2023).

5.5. CWBC and SCA

In this study, it was hypothesised that Customer Win-Back Capability (CWBC) would positively influence Sustainable Competitive Advantage (SCA) in the retail sector. The findings reveal a significant positive relationship between CWBC and SCA, suggesting that organisations proficient in re-engaging previously lost customers experience enhanced customer retention, loyalty and overall profitability, which are critical drivers of SCA. The literature corroborates these findings, emphasising the pivotal role of CWBC in organisational performance and SCA. Wang and Feng (2012) identify CWBC as a core CRM capability that directly impacts customer loyalty and retention, key contributors to SCA. Demlehner et al. (2021) assert that win-back strategies enhance SCA by targeting previously lost high-value customers, thereby improving customer lifetime value and reducing acquisition costs. Foltean et al. (2019) find that effective CWBC initiatives differentiate organisations by addressing prior service gaps, restoring customer trust and commitment. Vomberg et al. (2020) report that structured CWBC strategies, such as targeted campaigns and proactive follow-ups, increase customer reacquisition success rates, leading to sustained profitability.

Empirical data highlights that while organisations prioritise customer retention, systematic win-back processes are less developed, indicating areas for improvement. The positive influence of CWBC on SCA is supported by RM (Möller & Halinen, 2000; Jain et al., 2024), which highlights the importance of re-establishing customer relationships as central to CRM strategies; the RBV (Barney, 1991; Lubis, 2022), which suggests that CWBC, as an organisational capability, provides a source of SCA when it meets the VRIN criteria; and the DC framework (Eisenhardt & Martin, 2000; Laaksonen & Peltoniemi, 2018), which emphasises the strategic importance of strong customer relationships, valuable resources and organisational agility in sustaining competitive advantage. The study affirms that robust CWBC mechanisms contribute to SCA by enhancing customer loyalty, satisfaction and retention. Organisations that systematically address customer grievances and proactively re-engage lost customers are better positioned to maintain a SCA in the dynamic retail sector.

5.6. CRM Capabilities, SCA and AI

This study hypothesised that AI technology application moderates the relationship between Customer Relationship Management (CRM) capabilities and Sustainable Competitive Advantage (SCA).

5.6.1. AI and customer interaction management capability (CIMC)

It was hypothesised that AI technology enhances the relationship between Customer Interaction Management Capability (CIMC) and SCA. The results confirmed a significant positive moderating effect, supporting this hypothesis. This outcome suggests that AI enhances the influence of CIMC on SCA within the South African retail sector. AI tools such as chatbots, predictive analytics and personalised marketing facilitate real-time customer engagement, enabling organisations to process vast amounts of customer data efficiently (Libai et al., 2020; Wang & Feng, 2012). According to relationship marketing (RM) theory (Möller & Halinen, 2000; Kamal et al., 2022), AI facilitates more personalised interactions, strengthening customer relationships. The resource-based view (RBV) perspective (Barney, 1991; Ofori & Appiah-Nimo, 2022) identifies AI-driven analytics as a valuable resource for enhancing customer engagement strategies. Additionally, the dynamic capabilities (DC) framework (Eisenhardt & Martin, 2000; Teece, 2018) highlights that AI fosters organisational agility, enabling organisations to adapt customer interactions to evolving preferences. By rapidly processing and responding to customer inputs, AI fosters agility in customer engagement, enabling organisations to align more effectively with evolving customer needs and preferences. Thus, the findings affirm that AI not only supports but significantly enhances the role of CIMC in driving SCA.

5.6.2. AI and customer relationship upgrading capability (CRUC)

It was hypothesised that AI technology strengthens the relationship between Customer Relationship Upgrading Capability (CRUC) and SCA. The results did not support this hypothesis, with a negative and statistically insignificant interaction effect. The lack of a significant moderating effect can be contextualised using the theoretical frameworks. RM theory suggests that upgrading customer relationships through cross-selling, upselling and personalisation should strengthen loyalty and customer lifetime value (Luck & Lancaster, 2013). However, the results suggest that AI applications in these areas may not be as effective in strengthening relational bonds as anticipated. From an RBV standpoint, while CRUC is a valuable capability, its effectiveness may depend on how well AI tools are integrated and aligned with organisational resources (Ofori & Appiah-Nimo, 2022). If AI systems are not fully embedded or if organisations lack the complementary skills to leverage AI insights effectively, the resource's potential may not translate into a SCA. The DC view highlights the necessity of agility and the ability to reconfigure resources in response to environmental changes (Day & van den Bulte, 2002; Teece, 2018). The lack of a significant moderating effect suggests that successful AI integration in CRUC requires more than technology—it demands organisational agility and strategic alignment. Thus, while AI holds theoretical potential to enhance CRUC, its practical application may be limited by integration challenges, organisational readiness, or customer receptiveness.

5.6.3. AI and customer win-back capability (CWBC)

It was hypothesised that AI technology enhances the relationship between Customer Win-Back Capability (CWBC) and SCA. This hypothesis was not supported, as the moderation effect was negative and statistically insignificant. The theoretical frameworks offer insights into this unexpected outcome. RM theory posits that re-engaging lost customers can restore trust and loyalty, contributing to long-term profitability (Rehman, 2019; Jain et al., 2024). However, the findings suggest that AI-driven win-back strategies may lack the personal touch or nuanced understanding necessary to rebuild fractured relationships. From an RBV perspective, while CWBC can be considered a strategic resource, the mere application of AI might not enhance its value if organisations do not possess the requisite data quality or analytical sophistication to identify and address the root causes of customer churn (Barney, 1991; Lubis, 2022). Additionally, the DC framework (Hooley et al., 2005; Laaksonen & Peltoniemi, 2018) highlights that many organisations struggle to use AI dynamically for win-back campaigns, limiting its impact on SCA. The insignificant moderation effect indicates that many organisations may struggle to use AI dynamically in this context, perhaps relying too heavily on automated processes that fail to address the complexities of customer re-engagement.

5.7. Post hoc: introducing relationship quality

The original hypotheses proposed direct relationships between CRM capabilities, AI and SCA, suggesting that AI would moderate the impact of CRM on SCA. However, the post hoc findings revealed that Relationship Quality (RQ) plays a critical mediating role in this relationship. While AI and CRM capabilities positively influence SCA, their strongest impact occurs indirectly by enhancing RQ, which in turn drives SCA. This refinement indicates that the quality of customer relationships is a more significant driver of SCA than initially hypothesised.

Empirical research supports the significance of RQ as a multidimensional construct encompassing trust, commitment, satisfaction, communication and cooperation (De Wulf et al., 2001; Palmatier et al., 2007). These elements play a crucial role in the effectiveness of CRM strategies, which in turn enhance business performance and customer retention (Rauyruen & Miller, 2007; Narteh et al., 2013). Given the competitive nature of the South African retail sector, organisations that successfully cultivate high RQ are more likely to sustain competitive advantage by fostering stronger customer relationships and driving long-term business success (Wong & Sohal, 2002).

Overall, the post hoc analysis highlights the pivotal role of RQ in the nexus between CRM capabilities and SCA. While AI directly contributes to SCA (Kaplan & Haenlein, 2019; Shankar et al., 2021), its most significant impact is mediated through its enhancement of CRM capabilities, which improve RQ and in turn, drive SCA. These findings underscore the importance of integrating AI technological advancements with strategic relationship management to achieve and sustain a competitive advantage in the South African retail sector. By situating the post hoc findings within established theoretical frameworks, this study provides a comprehensive understanding of the factors contributing to long-term business success. It affirms that the combination of AI-enabled CRM capabilities and strong RQ is essential for achieving and maintaining SCA.

5.8. Chapter summary

This chapter interpreted the research findings within the context of the existing literature and research objectives, examining how CRM capabilities and AI technology application influence SCA in the South African R-CTFL sector. The results confirmed that Customer Interaction Management Capability (CIMC) and Customer Win-Back Capability (CWBC) significantly contributed to SCA, while Customer Relationship Upgrading Capability (CRUC) showed only a marginal effect. AI technology application significantly enhanced the impact of CIMC on SCA but did not moderate the relationships for CRUC or CWBC. Additionally, a post hoc analysis introduced Relationship Quality (RQ) as a key mediator, revealing that while AI directly influenced SCA, its strongest impact occurred indirectly through its enhancement of CRM capabilities, which improved RQ and consequently, SCA.

CHAPTER 6: CONCLUSION AND RECOMMENDATIONS

6.1 Introduction

In this chapter, the researcher presents conclusions derived from the findings discussed in Chapter 5 and provides recommendations aligned with the study's objectives. The theoretical contributions to existing knowledge are highlighted, along with managerial implications for the South African R-CTFL sector, offering practical insights into enhancing CRM capabilities and leveraging AI for sustainable competitive advantage. The chapter concludes with suggestions for future research, identifying areas for further exploration to expand academic and practical discussions within the South African retail sector and beyond.

6.2 Overview of the study

This study examined the relationship between customer relationship management (CRM) capabilities and sustainable competitive advantage (SCA) in the South African retail sector, with a particular focus on the moderating role of AI technology. Grounded in theoretical frameworks such as relationship marketing (RM) theory, the resource-based view (RBV) and dynamic capabilities (DC), the research explored how CRM capabilities, including customer interaction management, customer relationship upgrading and customer win-back capabilities, contribute to SCA and how ai influences these dynamics.

A quantitative methodology was employed, with data collected through a structured survey from professionals in the South African retail clothing, textile, footwear and leather (R-CTFL) sector. Structural Equation Modelling (SEM) using SmartPLS and SPSS software was utilised to analyse the data and test the hypotheses outlined in Chapter 1. This analytical approach validated the relationships between CRM capabilities, AI application and SCA. Additionally, a post-hoc analysis was conducted, introducing Relationship Quality (RQ) as a mediating variable to refine the understanding of AI's impact on CRM capabilities and its downstream effects on SCA. The findings discussed in Chapter 5 underscore the critical role of CRM capabilities in driving SCA, demonstrating AI's moderating effect on this relationship. Moreover, the post-hoc analysis revealed that while AI directly contributes to SCA, its most significant influence is indirect, enhancing CRM capabilities, which, in turn, improve RQ and ultimately drive SCA.

6.3 Practical implications of the study

The South African retail sector spans a wide range of consumer needs and expectations, shaped by distinct political and socio-economic factors. This has resulted in a diverse retail landscape comprising various types of establishments (Masojada, 2021). The sector is characterised by complex and evolving dynamics, influenced by the country's estimated 63 million citizens, who represent a broad range of racial backgrounds, cultural practices and income levels (Statistics South Africa, 2024). As the second-largest employer after the government, the South African retail sector contributes nearly 20% of the country’s GDP (LRS, 2023). Retailers in South Africa fall into several categories, including general dealers; food, beverages and tobacco in specialised stores; pharmaceuticals, medical goods, cosmetics and toiletries; textiles, clothing, footwear and leather goods; household furniture, appliances and equipment; hardware, paint and glass; and other retail segments. Examining how CRM capabilities drive SCA within this retail landscape—and how AI technology enhances this relationship—underscores the study’s economic significance. It also highlights the impact of shifting consumer behaviours on the sector’s sustainability and competitive positioning.

6.3.1 Theoretical implications

This study offers meaningful contributions to the academic literature and the body of knowledge by closing key research gaps identified in Chapter 1. Specifically, it advances understanding of how CRM capabilities (CIMC, CRUC and CWBC) influence SCA and how AI Technology Application moderates these relationships. The research empirically extends the RBV and DC theories, demonstrating how AI integration transforms firm-specific capabilities into drivers of competitive advantage. Additionally, the study introduces RQ as a crucial mediating factor, enriching theoretical discourse on customer loyalty and engagement within CRM frameworks. By linking AI-driven CRM capabilities with SCA outcomes, the study offers future researchers a robust framework to explore digital transformation strategies within customer relationship management.

6.3.2 Managerial implications

The study provides actionable recommendations to help retail managers translate research insights into strategic advantage. Managers are advised to prioritise the development of CIMC, CRUC and CWBC, with a strong focus on leveraging AI Technology Application to optimise customer engagement and loyalty. The findings suggest that deploying AI tools, such as predictive analytics, personalised marketing and automated customer interactions can significantly enhance CRM outcomes. Additionally, enhancing RQ through AI-enabled personalised experiences can drive customer retention and trust. The research also emphasises the importance of upskilling staff to effectively use AI-powered CRM systems, ensuring that technological investments yield measurable improvements. These practical strategies empower managers to make data-driven decisions, optimise CRM processes and achieve Sustainable Competitive Advantage (SCA) in the competitive South African retail market.

6.4 Objectives and conclusions

6.4.1 Objective 1

The role of customer interaction management capability in predicting sustainable competitive advantage.

Customer interaction management capability (CIMC) is a crucial component of CRM, focusing on managing customer interactions to enhance satisfaction and loyalty. CIMC are particularly significant in the competitive South African retail sector and organisations with superior CIMC capabilities experience enhanced customer retention and loyalty, which translates into increased profitability and distinct market positioning, both vital components of SCA (Al-Zyadat & Al-Zyadat 2018). Respondents acknowledged strong CIMC within their organisations, particularly in building relationships with key customers, although continuous engagement and relationship-building strategies were identified as areas for improvement. Statistical analysis supported H1a, showing a significant relationship between CIMC and SCA (p-value [0.000] < 0.05), indicating that effective CIMC contribute directly to SCA.

6.4.2 Objective 2

The role of customer relationship upgrading capability in predicting sustainable competitive advantage.

Customer relationship upgrading capability (CRUC) refers to the ability to advance relationships with existing customers through personalised services, value-added offerings and cross-selling strategies. Alshura (2018) and Kusnadi et al. (2024) highlight that CRUC enhances organisational performance and strengthens long-term client relationships, supporting its critical role in driving SCA through customer relationship enhancement and revenue generation. The results indicate that organisations excel in enhancing customer satisfaction and loyalty, although opportunities remain to strengthen formalised cross-selling strategies. The study results showed that organisations with strong CRUC experienced a marginally significant positive relationship with SCA, supporting H1b at a marginal level.

6.4.3 Objective 3

The role of customer win-back capability in predicting sustainable competitive advantage.

Customer win-back capability (CWBC) involves strategies to re-engage and recover lapsed customers, which can be crucial for maintaining market share and reducing acquisition costs. Research by Demlehner et al. (2021), Foltean et al. (2019) and Vomberg et al. (2020) highlights that CWBC plays a crucial role in driving SCA by enabling organisations to leverage customer insights, address dissatisfaction and implement structured win-back strategies that enhance customer reacquisition and strengthen brand relationships. The results indicate a strong organisational focus on customer retention, although there is a need to develop more structured approaches for re-engaging lost and inactive customers. The study revealed that organisations with strong CWBC demonstrated a significant relationship with SCA (p-value [0.001] < 0.05), supporting H1c and indicating that CWBC contributes directly to SCA.

6.4.4 Objective 4

The role of artificial intelligence technology in moderating the relationship between customer relationship upgrading capability and sustainable competitive advantage.

According to Libai et al. (2020) and Wang & Feng (2012), the literature highlights AI's potential to enhance CRM outcomes through real-time insights, personalised engagement and predictive analytics. Moderation analysis found that AI significantly enhances the CIMC-SCA relationship ($p = 0.009$) but had no significant effect on CRUC ($p = 0.117$) or CWBC ($p = 0.120$), indicating challenges in leveraging AI for customer relationship upgrades and win-backs. These findings highlight AI’s capacity to amplify CIMC’s contribution to SCA while underscoring the need for better AI integration and organisational alignment within CRUC and CWBC processes.

6.4.5 Post-hoc objective

Investigate the mediating effect of Relationship Quality (RQ) on the interplay between CRM capabilities, AI technology application and Sustainable Competitive Advantage (SCA).

RQ plays a pivotal role in relationship marketing (RM), where trust, commitment and satisfaction foster customer loyalty and drive business performance (Quach et al., 2020; Putri & Rahayu, 2023). The statistical results confirm that AI enhances CRM capabilities, which significantly strengthens RQ, ultimately leading to improved SCA. Notably, RQ exhibits a direct and robust impact on SCA ($\beta=0.594$, $p=0.000$), highlighting its central role. The post hoc analysis further reveals that AI's most substantial contribution to SCA is through its enhancement of CRM capabilities, which, in turn, boosts RQ, underscoring the importance of integrating AI-driven CRM capabilities for SCA.

6.5 Recommendations

6.5.1. Adopt AI-driven customer engagement tools

To maximise the impact of CIMC on SCA, organisations should adopt AI-driven customer engagement tools such as chatbots, virtual assistants and predictive analytics to personalise interactions and anticipate customer needs (Ledro et al., 2022). AI-powered sentiment analysis should also be leveraged to assess customer feedback and enhance response strategies in real time (Li et al., 2023). Furthermore, organisations should implement omnichannel CRM strategies that integrate AI across multiple customer touchpoints, including social media, email and in-store experiences, ensuring seamless interactions and brand consistency. These initiatives will improve customer satisfaction and retention, ultimately SCA.

6.5.2. Use AI-driven recommendation and relationship building strategies

Given the marginal significance of CRUC's impact on SCA, organisations should refine their relationship-building strategies. AI-driven recommendation engines can be used to offer personalised cross-selling and upselling opportunities based on customer preferences and purchase history (Wang & Feng, 2012). AI-based loyalty programs that dynamically adjust rewards based on customer behaviour will also enhance customer engagement and retention (Badaru et al., 2023). By deepening customer relationships through AI-driven insights, organisations can improve customer lifetime value and strengthen their SCA.

6.5.3. Employ AI-driven predictive models and win-back strategies

CWBC showed a significant influence on SCA, organisations should implement structured win-back strategies supported by AI-driven predictive models. AI-powered churn prediction models can help identify at-risk customers, enabling organisations to engage them proactively before they lapse (Shahbaz et al., 2020). Automated re-engagement campaigns using AI-driven personalised messages and incentives can further encourage customer return. Moreover, AI-driven customer profiling should be leveraged to understand why customers disengage and to tailor recovery strategies accordingly. These approaches will enable proactive customer retention efforts, reducing churn and reinforcing brand loyalty in a competitive retail landscape.

6.5.4. Adopt AI-driven analytics, automation, intelligence and integration

To enhance AI's role across all CRM capabilities, organisations should employ AI-driven CRM platforms with seamless AI integration across all CRM capabilities. Investing in AI-driven CRM platforms that incorporate advanced analytics, automation and customer intelligence will ensure that AI's potential is fully realised (Libai et al., 2020). Furthermore, organisations must enhance AI literacy by providing employee training programs that enable staff to effectively utilise AI-powered CRM tools (Krakowski et al., 2023).

6.5.5. Improve ethical practices through AI Governance Frameworks

Given the ethical concerns surrounding AI, such as data privacy, algorithmic bias and transparency, organisations should also establish AI governance frameworks to mitigate these risks. By ensuring responsible AI use, organisations can strengthen customer trust and long-term engagement.

6.5.6. Enhance customer trust, experience and interaction using AI tools

A particularly important finding was the mediating role of Relationship Quality (RQ) in the AI-CRM-SCA relationship, indicating that organisations should prioritise trust-building strategies. AI-powered personalisation tools should be implemented to enhance customer trust and satisfaction through tailored interactions (Demlehner et al., 2021). AI-enabled customer service solutions, such as real-time issue resolution and proactive engagement, should also be deployed to improve customer experience (Heins, 2023). Moreover, AI-driven sentiment analysis can provide valuable insights into customer emotions, allowing organisations to refine engagement strategies accordingly. Strengthening RQ will amplify AI's indirect contribution to SCA, reinforcing customer commitment and brand loyalty.

6.6 Limitations and future research

This study offers significant contributions to both theory and managerial practice; however, it is important to acknowledge certain limitations and propose directions for future research. One key limitation is the use of a non-probability sampling method, which may restrict the generalisability of findings to the broader South African retail sector. Additionally, due to financial and time constraints, the research was confined to the Clothing, Textile, Footwear and Leather (CTFL) retail category, potentially limiting the applicability of the findings to other retail sectors. Another constraint lies in the study's cross-sectional research design, which captured data on CRM capabilities, AI integration and their impact on sustainable competitive advantage (SCA) at a single point in time. Consequently, the study does not account for potential changes or trends that may emerge over time. As AI technologies continue to evolve, future research should explore their long-term impact on CRM capabilities and their role in shaping competitive strategies.

Building on these limitations, several avenues for future research are proposed. First, a similar study could be conducted with a larger sample size to obtain a broader range of responses. Additionally, alternative sampling methods could be employed to enhance the representativeness of the findings. Given the rapidly evolving technological landscape, future research could adopt a longitudinal approach to examine how consumer behaviour in the South African retail sector adapts over time in response to advancements in CRM capabilities and AI integration. This approach would provide deeper insights into long-term trends and shifts in customer engagement and competitive advantage. Furthermore, future studies could explore additional factors, such as digital transformation maturity, organisational culture, or customer experience management, to better understand their influence on the relationship between CRM capabilities, AI and SCA.

6.7 Conclusion

The study's findings offer South African retail organisations practical insights into the most effective CRM capabilities for achieving SCA, equipping managers and executives with the knowledge to make informed strategic decisions regarding CRM investments and resource allocation. By leveraging AI-enhanced CRM capabilities, retailers can strengthen customer loyalty, increase sales and align with strategic objectives outlined in national frameworks, thereby contributing to the growth and sustainability of the country's retail sector (Tshivhase, 2023). Understanding the relationship between CRM capabilities, SCA and AI's role enables organisations to optimise their CRM initiatives, leading to improved customer satisfaction, increased loyalty and enhanced business performance. These insights position organisations to better adapt to evolving market demands while supporting broader economic growth and technological advancement in South Africa. It can thus be argued that CRM effectiveness is shaped by both the strength of its underlying capabilities and the robustness of the AI technologies applied. The study contributes to theory by addressing gaps in the literature on CRM and AI within the South African retail context, while also providing practical recommendations for retailers to optimise AI-enhanced CRM capabilities, strengthen customer relationships and drive SCA. Specifically, it offers valuable insights for South African R-CTFL organisations by examining the link between CRM capabilities and SCA, and the moderating influence of AI technologies on this relationship.

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Appendix A: Research Instrument

Dear Participant

My name is Sharnè Motala, I am a Master of Management: Strategic Marketing student at the University of Witwatersrand. I am conducting a research study on the nexus between CRM Capabilities and Sustainable Competitive Advantage (SCA) in the South African retail sector, the moderating role of Artificial Intelligence (AI).

The purpose of this study is to explore how CRM capabilities are linked to SCA and to understand how the application of AI technologies may influence this relationship. Given your organisation's prominence and expertise in the retail industry, your participation will contribute significantly to the understanding of these critical dynamics.

The questionnaire consists of demographic information about your organisation and statements related to your perceptions of CRM Capabilities, SCA and AI. It should take approximately 10 to 20 minutes to complete.

Participation is entirely voluntary, and you may choose to withdraw at any point without any consequences. The information you provide will be kept confidential and used solely for academic purposes. Any data shared in our research publications will be anonymised to ensure your organisation's privacy.

For any enquiries during or after the study, do not hesitate to contact me directly at 689937@students.wits.ac.za or my supervisor Dr Emmanuel Quaye at Emmanuel.quaye@wits.ac.za. Thank you for considering participating in this research study.

I look forward to your response and appreciate your valuable contribution to this research.

Regards,
Sharnè Motala
689937@students.wits.ac.za

QUESTIONNAIRE

Consent

To voluntarily participate in this research, kindly Accept.

YES	NO
I am interested in participating in this study	I am not interested in participating in this study

Part A: Demographic Information

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

A1: Please select the number of years that your organisation has been using AI.

<5 years	6- 10 years	11-15 years	16- 20 years	21-25 years	>25 years
1	2	3	4	5	6

A2: Please indicate the revenue that your organisation generates per year. (R million).

<R20m	R21- R50 m	R51- R100m	R101- R150m	R151- R200m	>R201m
1	2	3	4	5	6

A3: Please select your job title.

Customer Service Manager	Marketing Manager	Technology Manager	Managing Director	Executive Director	Sales Consultant	Other
1	2	3	4	5	6	7

If other, please specify_____________

A4: Please select your years of experience in the organisation.

<5 years	6- 10 years	11-15 years	16- 20 years	21-25 years	>25 years
1	2	3	4	5	6

A5: 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	>25 years
1	2	3	4	5	6

A6: Please indicate the number of years that your organisation has been in operation.

<1000 employees	1001- 4999 employees	5000- 9999 employees	10 000 - 49999 employees	> 50 000 employees
1	2	3	4	5

A7: Please indicate which AI Technology your organisation uses to build relationships with customers. (select as many as applicable)

Chatbots	Customer Relationship Management (CRM) systems	Predictive Analytics	Personalisation Engines	Sentiment Analysis Tools
Voice Assistants	Recommendation Systems	Email Marketing Automation	Social Media Analytics	Other

If other, please specify_____________

Part B: CRM Capability, SCA, AI and RQ

Please indicate your level of agreement with the following statements regarding your organisation's customer relationship management capability, sustainable competitive advantage and AI application., by using a 7-point Likert scale. With 1 stating that you do not agree and 7 stating that you agree fully.

Table 1: Customer Interaction Management Capability (CIMC)
Wang & Feng, 2012; Alshura, 2018; Foltean et al., 2019

Customer Interaction Management Capability	**Statement**	**Strongly Disagree**	**Mostly Disagree**	**Disagree**	**Neutral**	**Agree**	**Mostly Agree**	**Strongly Agree**
CIMC 1	Our organisation regularly meets customers by learning their current and potential needs for new products.	1	2	3	4	5	6	7
CIMC 2	Our organisation is good at creating relationships with key customers.	1	2	3	4	5	6	7
CIMC 3	Our organisation maintains interactive two-way communication with our customers.	1	2	3	4	5	6	7
CIMC 4	Our organisation has a continual dialogue with each customer and uses well developed methods to improve our relationships.	1	2	3	4	5	6	7
CIMC 5	Our organisation is good at maintaining relationships with key customers.	1	2	3	4	5	6	7

Table 2: Customer Relationship Upgrading Capability (CRUC)
Wang & Feng, 2012; Alshura, 2018; Foltean et al., 2019

Customer Relationship Upgrading Capability	**Statement**	**Strongly Disagree**	**Mostly Disagree**	**Disagree**	**Neutral**	**Agree**	**Mostly Agree**	**Strongly Agree**
CRUC 1	Our organisation measures customer satisfaction systematically and frequently.	1	2	3	4	5	6	7
CRUC 2	Our organisation has formalised procedures for upselling to valuable customers.	1	2	3	4	5	6	7

CRUC 3	Our organisation has formalised procedures for cross-selling to valuable customers.	1	2	3	4	5	6	7
CRUC 4	Our organisation tries to systematically extend our share of customers with high value.	1	2	3	4	5	6	7
CRUC 5	Our organisation has procedures designed to enhance customer satisfaction and loyalty.	1	2	3	4	5	6	7

Table 3: Customer Win-Back Capability (CWBC)
Wang & Feng, 2012; Alshura, 2018; Foltean et al., 2019

Customer Relationship Upgrading Capability	Statement	Strongly Disagree	Mostly Disagree	Disagree	Neutral	Agree	Mostly Agree	Strongly Agree
CWBC 1	Our organisation has a systematic process/approach to re-establish relationships with valued lost customers and inactive customers.	1	2	3	4	5	6	7
CWBC 2	When our organisation finds that customers are unhappy with the appropriateness of our product or service, corrective action is taken immediately.	1	2	3	4	5	6	7
CWBC 3	Our organisation maintains positive relationships with migrating or unattractive customers on a regular basis.	1	2	3	4	5	6	7
CWBC 4	Our organisation apologises or compensates in time for the inconvenience or loss that it brings to customers.	1	2	3	4	5	6	7
CWBC 5	In our organisation, retaining customers is considered to be a key priority.	1	2	3	4	5	6	7

Table 4: Sustainable Competitive Advantage
Bagram, 2010; Keshvari, 2012; Bandaranayake and Pushpakumari, 2021

Sustainable Competitive Advantage	Statement	**Strongly Disagree**	**Mostly Disagree**	**Disagree**	**Neutral**	**Agree**	**Mostly Agree**	**Strongly Agree**
SCA 1	Our organisation is more customer caring than its competitors.	1	2	3	4	5	6	7
SCA 2	Our organisation provides superior services than its competitors.	1	2	3	4	5	6	7
SCA 3	Our organisation has well trained staff for delivering CRM than its competitors.	1	2	3	4	5	6	7
SCA 4	Our organisation has had an increase in revenue and customer base compared to its competitors	1	2	3	4	5	6	7
SCA 5	Our organisation has been consistently outperforming competitors in services, processes and financial performance in the past 3 years.	1	2	3	4	5	6	7

Table 5: Artificial Intelligence

Shankar, 2018; Libai et al., 2020

Artificial Intelligence	Statement	**Strongly Disagree**	**Mostly Disagree**	**Disagree**	**Neutral**	**Agree**	**Mostly Agree**	**Strongly Agree**
AI 1	Our organisation uses AI to build personalised recommendations.	1	2	3	4	5	6	7
AI 2	Our organisation uses AI to simplify the decision-making process.	1	2	3	4	5	6	7
AI 3	Our organisation uses AI to communicate with customers at any time.	1	2	3	4	5	6	7
AI 4	Our organisation uses AI to enhance effective customer relationships.	1	2	3	4	5	6	7
AI 5	Our organisation's AI integrated with CRM systems improves operational efficiency of the organisation.	1	2	3	4	5	6	7

Table 6: Relationship Quality

Sanchez-Franco et al., 2019; Narteh et al., 2013; Dlačić et al., 2018

Relationship Quality	Statement	**Strongly Disagree**	**Mostly Disagree**	**Disagree**	**Neutral**	**Agree**	**Mostly Agree**	**Strongly Agree**
RQ 1	Our organisation is trustworthy	1	2	3	4	5	6	7
RQ 2	Our organisation is committed to its relationships with customers.	1	2	3	4	5	6	7
RQ 3	Our organisation is willing to invest in maintaining relationships with its customers.	1	2	3	4	5	6	7
RQ 4	Our organisation is committed to improving customer experience.	1	2	3	4	5	6	7
RQ 5	Our organisation is committed to resolving customer queries speedily.	1	2	3	4	5	6	7

Thank you for taking time to participate in my questionnaire.

Appendix B: Ethics Clearance Certificate

Graduate School of Business Administration
University of the Witwatersrand, Johannesburg

Wits Business School

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

Ethics Clearance Certificate

Ethics protocol number: WBS/SM689937/437

This certificate is only valid with a legitimate ethics protocol number and signed by the Researcher (below).

Project title	The nexus between CRM capabilities and sustainable competitive advantage in the South African Retail sector: the moderating role of AI
Investigator / Researcher	Mrs Sharne Motala
Nature of Project	MM (Strategic Marketing)
Decision of the Committee	Approved, provided stakeholders and participants are guaranteed anonymity and confidentiality.
Issue Date of Certificate	05/09/2024
Expiry date	Date of submission of the project / research report
Chairperson	Dr Ayanda Magida ☎ +27 11 717 3953 ayanda.magida@wits.ac.za

Declaration by Researcher

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

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

Signature

9 October 2024
Date:

Appendix C: Raosoft Sample Size Calculator

Raosoft — **Sample size calculator**

What margin of error can you accept? 5% is a common choice	5 %	The margin of error is the amount of error that you can tolerate. If 90% of respondents answer *yes*, while 10% answer *no*, you may be able to tolerate a larger amount of error than if the respondents are split 50-50 or 45-55. Lower margin of error requires a larger sample size.
What confidence level do you need? Typical choices are 90%, 95%, or 99%	95 %	The confidence level is the amount of uncertainty you can tolerate. Suppose that you have 20 yes-no questions in your survey. With a confidence level of 95%, you would expect that for one of the questions (1 in 20), the percentage of people who answer *yes* would be more than the margin of error away from the true answer. The true answer is the percentage you would get if you exhaustively interviewed everyone. Higher confidence level requires a larger sample size.
What is the population size? If you don't know, use 20000	210071	How many people are there to choose your random sample from? The sample size doesn't change much for populations larger than 20,000.
What is the response distribution? Leave this as 50%	50 %	For each question, what do you expect the results will be? If the sample is skewed highly one way or the other,the population probably is, too. If you don't know, use 50%, which gives the largest sample size. See below under **More information** if this is confusing.
Your recommended sample size is	**384**	This is the minimum recommended size of your survey. If you create a sample of this many people and get responses from everyone, you're more likely to get a correct answer than you would from a large sample where only a small percentage of the sample responds to your survey.

Online surveys with Vovici have completion rates of 66%!

Alternate scenarios

With a sample size of	100	200	300
Your margin of error would be	**9.80%**	**6.93%**	**5.65%**

With a confidence level of	90	95	99
Your sample size would need to be	**271**	**384**	**662**

Appendix D: Turnitin Report

turnitin

Digital Receipt

This receipt acknowledges that Turnitin received your paper. Below you will find the receipt information regarding your submission.

The first page of your submissions is displayed below.

Submission author:	Sharne Motala
Assignment title:	BUSA7076A Research Report Class of 23/24
Submission title:	S Motala 689937_Research_2025 Final.docx
File name:	S_Motala_689937_Research_2025_Final.docx
File size:	1.36M
Page count:	109
Word count:	28,267
Character count:	173,508
Submission date:	27-Feb-2025 09:29AM (UTC+0200)
Submission ID:	2600125444

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Sculpting global leaders

THE NEXUS BETWEEN CRM CAPABILITIES AND SUSTAINABLE COMPETITIVE ADVANTAGE IN THE SOUTH AFRICAN RETAIL SECTOR: THE MODERATING ROLE OF AI

Sharnè Motala

Student number: 689937

Supervisor: Dr Emmanuel S. Quaye

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 Strategic Marketing

Johannesburg, 2025

Appendix E: Language Editing Confirmation

LINDA SCOTT DEVELOPMENTS
PROMOTING LINGUISTIC & CULTURAL INCLUSIVITY

Dr Linda Scott
083 654 4156
lindascott1984@gmail.com
www.justedit.co.za

15 Shannon Close
The Circus
Three Rivers
1929

English language editing
SATI membership number: 1002595

25 February 2025

To whom it may concern

This is to confirm that I, the undersigned, have language edited the **dissertation** of

Sharnè Motala

Entitled:

THE NEXUS BETWEEN CRM CAPABILITIES AND SUSTAINABLE COMPETITIVE ADVANTAGE IN THE SOUTH AFRICAN RETAIL SECTOR: THE MODERATING ROLE OF AI

The responsibility of implementing the recommended language changes rests with the author of the document.

Yours truly,

Dr Linda Scott

SATI membership number: 1002595
SACE membership number: 1096643
ORCID ID.: 0000-0003-2049-0732

PhD: Language Practice
MA: Intercultural Communication
BA (Hons): Language Practice