# THE DEVELOPMENT OF AN ARTIFICIAL INTELLIGENCE ADOPTION FRAMEWORK FOR FOOD RETAIL MARKETING IN SOUTH AFRICA.


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A Thesis submitted to the Faculty of Commerce, Law and Management,
The University of the Witwatersrand, in partial fulfilment of the requirements for the Degree of
PhD in Management.

**JOHANNESBURG, 2023**

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## DEDICATION

*Without any doubt and hesitation, dedicate this work to me, YES; TO ME, Sinenhlanhla Mpunzi. I worked hard for this. I deserve it! Sine Mpunzi, this is for you.*

*Equally so, mummy, this achievement is for you, Dr Priscilla Ndebele (Tjibelu)!*

*My siblings (Chelesani, Collen-Fish, and Sinobuhle-Sinkwa), cheers to another Dr!*

*To my dad, your boy has done it.*

*Batshana bami, umalume sesebenzile: Sandile, Noxolo, Thandisiwe, Luthando, Thamsanqa and Myles.*

**ACKNOWLEDGEMENTS**

Completing this write-up was made possible through the sacrifices of several individuals. The researcher would like to extend their gratitude to these individuals, as without their help, the thesis would not have been finished:

- ⇒ To God Almighty, thank you for your guidance. With you, nothing is impossible.
- ⇒ To aboko-Mpunzi and labako-Ndebele, ngyabonga.
- ⇒ My supervisor, mentor, brother and friend, Dr Fanny Saruchera, thank you for your guidance, mentorship, help, financial support, and appreciation. I gained so much from you, and I am no longer the same since I met you. You supported me in many ways, through hard times and when it was rosy.
- ⇒ Prof Asante-Darko and Prof Mafini, thank you for being part of my journey. Your contribution is greatly appreciated.
- ⇒ To the Fish family, Memo, thank you so much for the support. I know what you did for me cannot be equated to anything. You're a blessing to my life.
- ⇒ Nokuthula Sibanda, thank you so much; words can't describe your support.
- ⇒ Thanks for your continued support and assistance, Lina bakoMhlanga (Shakes and Myles).
- ⇒ Thandisiwe, my daughter, thank you for your continued harassment and encouragement – "*Ncanez, go and do your schoolwork*" can't be forgotten.
- ⇒ My family, friends and colleagues, I thank you.
- ⇒ Zibani Ndebele Mzala, thank you for your support and dragging me into this academic world.
- ⇒ As for Amajita hanti, Zakhe, Madiba, Figo, Zibusiso, Knowledge, Bling, Bazel, Khotso, Muzi, Dlundu, Mathuthu, JB, Pride and Mpho, Dankoe!
- ⇒ All research institutes and respondents who consented to participate in this study for the sacrifices they made to respond to the research questions.

**ABSTRACT**

Industry 4.0 has taken the world by storm and impacted how we live, work, and behave. Focused on business transformation and revolution, industry 4.0 has given birth to one of the most celebrated inventions, Artificial Intelligence (AI). AI has provided endless opportunities for businesses respective of industry. However, AI adoption frameworks have been limited as AI is a new phenomenon in South Africa. Previous studies in food retail marketing have identified low interest in AI adoption due to a lack of guidance. Therefore, the study aimed to develop an AI adoption framework for the food retail marketing industry in South Africa. In achieving the main objective, the study examined the influence of AI on marketing strategy outcomes, the influential determinants of AI adoption in the food retail marketing industry, and the major AI technologies adopted by retail marketers and assessed the moderating effect of competitive intensity. Guided by the Innovation Diffusion Theory, Technology-Organization-Environment framework, Institutional and Productivity Paradox theories, the study established the influential factors that determine AI adoption. Using literature, theoretical constructs were drawn on AI technologies adopted, the marketing mix components (4Ps), the competition intensity elements, and strategy outcome measures. The study adopted the quantitative research method. Data were collected through self-administered questionnaires distributed to 380 respondents from food retail firms and marketing agencies with backgrounds in marketing, management, computer science, analytics, and sales. Data was analysed through SPSS version 27, where several analysis procedures were performed, such as CFA, EFA, model fitness and predictive power assessment. Partial Least Squares-Structural Equation Modelling was performed to examine the significance and ascertain relationships. The study found that systems complexity, finance, firm size, perceived AI risk, vendor participation, and external pressure influenced AI adoption in retail marketing. The research also discovered that AI technologies adopted (robots, chatbots, data analytics systems, CRM, and communication tools) improve marketing mix components by influencing the price, placement of products, R&D procedures, and sales techniques. The study found that competition intensity significantly moderates the relationship between AI adoption and marketing strategy outcome. This study further emphasizes the importance of integrating AI technology in the retail food industry, given that it enhances their marketing mix capabilities with direct positive implications on their marketing outcomes. It is evident that decision-makers need to re-strategize and pivot towards innovation integration. Therefore, the study recommends that food retail marketers adopt AI technologies as they positively influence sales, ROI, profit, and market share. Equally, food retailers must understand the adoption determinants, followed by the AI technologies that can effectively improve marketing tasks, examine how the 4Ps can be strategically tailored to suit AI integration and assess the impact through marketing strategy outcomes. The findings of this study contributed to the development of the first AI adoption framework contextualized for the food retail industry. Theoretically, the findings provide extended and new knowledge about AI adoption in food retail marketing. The empirical findings also settle debates surrounding inconclusive determinants of AI adoption. The study provides potential technologies that food retail marketers can use and ranks them according to their use and cost. The findings prove that AI integration can improve the marketing practices of food retail marketers. It gives clear solutions on how AI can be used for descriptive, diagnostic, prescriptive and predictive purposes. Future studies could focus on developing frameworks for other non-marketing functions and how AI can be regulated to avoid unforeseen consequences should they be successfully integrated.

**Keywords:** *Artificial intelligence (AI), Competitive advantage, Food retail industry, Marketing mix and strategy, Technology adoption framework.*

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| | |
|---|---|
| AI | Artificial Intelligence |
| ML | Machine Learning |
| DL | Deep Learning |
| CFA | Confirmatory Factor Analysis |
| EFA | Exploratory Factory Analysis |
| SPSS | Statistical Package for Social Sciences |
| SEM | Structural Equation Modelling |
| LM | Linear Model |
| 4iR | Fourth Industrial Revolution |
| R&D | Research and Development |
| AVE | Average Variance Extracted |
| PLS | Partial Least Squares |
| CR | Composite Reliability |

# CHAPTER ONE: RESEARCH BACKGROUND AND SETTING

## 1.1 INTRODUCTION

*"Just as electricity transformed almost everything 100 years ago, today I actually have a hard time thinking of an industry that I don't think AI will not transform in the next several years" (Andrew Ng).*

The quote by Andrew Ng (2017) above has become more relevant as artificial intelligence (AI) has increasingly become a very popular subject across the world and has been perceived to be a digital transformer (Bughin et al., 2018). Chatterjee et al. (2021) believe AI is the present-time technology genre. Nevertheless, it is anticipated that AI will destabilise the existing business models (Brynjolfsson & McAfee, 2014), influence policymakers (Schwab, 2017) and change how humans live and interact with each other (Watson, 2016; Kaplan, 2022). Although quite paradoxically, AI has taken the world by storm (Brynjolfsson, Syverson & Rock, 2019). The efforts towards perfection in other fields of science and business management have been progressing slowly for over half a century, making it difficult to assess its potential and exact influence across industries (Brynjolfsson, Rock & Syverson, 2019). AI is not hype; it can transform the world's output through technological developments, scientific knowledge, and entrepreneurial work (Marr, 2019). The transformative nature and the overly anticipated potential of AI are accompanied by a lack of industry guidance on integrating AI technologies.

Food retail is critical in any economy and works parallel with other industries, such as agriculture, to ensure food availability and access. Therefore, the retail industry is deemed to be one of the biggest beneficiaries of technological advancements (Manyika et al., 2018), and there is a need to assess the synchronisation processes to evaluate the gains or losses. Because of limited literature surrounding AI in developing economies, undocumented guidelines, and uncertainties within the realms of the rapid rise of technology development and adoption, this study was aimed at providing adoption guidance by developing an AI adoption framework for the food retail marketing industry in South Africa after investing the attributes of AI and its other affiliate core elements. The chapter begins by setting out the research background. It is followed by the problem statement, objectives, purpose of the study and delimitations, among other aspects.

## 1.2 BACKGROUND TO THE STUDY

This section starts by providing background information in support of AI technology and its importance in the food retail industry. In recent years, AI has gained momentum and attention in different fields like science, technology, medicine, automobile, retail, manufacturing, and education (Chen, 2019). AI has also reached marketing (Jarek & Mazurek, 2019). AI is already part of our daily lives. Soni et al. (2019) agree that these emerging technologies, i.e., AI, big data, internet of things (IoT), data science, cloud computing and blockchain, impact how we live, work, and behave.

AI can be classified as systems that mimic humans and repetitively perform tasks with some human intelligence (Davenport et al., 2019). Chen (2019) argues that AI is not a new term because it has been used scientifically. Soni et al. 2019 assert that AI is 63 years old. Considering the age factor, one may wonder why AI is gaining so much attention after all these years of discovery. Jarek and Mazurek (2019) propose that AI originates from information technology (IT) and, in most cases, is often used interchangeably with words like automation or robotisation. However, there is confusion between AI technology terminology and machine learning (ML) algorithms which normally leads to ambiguity in AI definition.

Soon, it is highly likely that AI will influence the marketing strategies of firms, sales processes, and customer service options, as well as customer purchasing behaviours (Davenport et al., 2019). Previously, AI had been drawing the attention of IT experts and computer engineers (Paschen, Kietzmann & Kietzmann, 2019). However, it is now rapidly moving outside its traditional areas of occurrence, making an ever-increasing significant mark in marketing (Jarek & Mazurek, 2019). Such patterns prove that marketers in any industry are increasingly using AI. Extreme connectivity and high demand for hyper-digital solutions have led to a rapid increase in innovative technology development and accelerated adoption; thus, such has given birth to the fourth industrial revolution (4IR) (Schwab, 2017). With firms embracing the 4IR era, AI facilitates machine-to-human interaction (Manyika et al., 2017a) while disrupting the existing business models (Rust & Huang, 2021). AI has transformed lives for the better, improved living conditions and has become a catalyst for discovering automated advanced ways to solve business challenges (Schwab, 2017).

Bughin et al. (2018), in an AI impact survey, discovered that AI was poised to extricate a new wave of digital turbulence; hence companies should ready themselves for it. Although early evidence suggested that AI can remit real value to serious early adopters while being the catalyst for powerful disruption, the study also revealed that non-tech companies were taking few steps. Such was verified by the investments made by big tech institutions like Google, Microsoft, and Baidu. It was estimated that tech giants spent up to $30 billion on AI in 2016, with 90% splashed on R&D and adoption and 10% on AI acquisitions (PwC, 2018). Grants, Venture capitalists (VC), Private Equity (PE) financing, and seed investments also grew rapidly to a combined total of $9 billion (Bughin et al., 2018). Accenture (2018) also empirically proved that 85% of executives sampled had devised adoption plans and designed strategic frameworks to invest substantially in AI-related technologies over the next three years. However, the adoption of AI by firms outside the technology sector was still early and often said to be experimental.

Demandbase's (2016) results showed that 98% of marketing managers spoke positively about adopting AI's potential and benefits. However, only 28% felt confident using AI technologies, with only 10% of the sample population managers having already adopted AI in their operations. Such statistics are worrisome for companies in countries like South Africa because they are viewed as 'users' rather than pioneers in digitalisation (Phillips, Seedat & Westhuizen, 2018). Marr (2019) suggests countries like South Africa are unattractive to big tech companies; hence stakeholders should watch the country becoming consumers and never producing anything of substance which can be exported. The views expressed align with those of Oclarino (2021), who predicts that Americans and Europeans will realise 80% of AI benefits, and partially Asians, thus leaving 20% to the rest of the world with limited benefits.

Between 2012 and 2015, Eastern Asian countries, China, Korea, and Japan in particular, and the United States of America were accountable for discovering and maturing between close to 100% of the top 20 ground-breaking AI technologies in ICT, while Korea and Japan dominated the inventions of AI technologies across all spheres (Szczepański, 2019). In 2015, the patent rate of AI technologies had increased by 6% compared to the last three previous years, and measured by inventions patented, Japan, Korea, the United States and China contributed over 62% of those inventions considering that there were about 18 000 new inventions recorded in that year (OECD, 2017). Questions on the types of technologies South African firms invent or adopt remain partly answered or unanswered for some industries. Considering the food retail sector, whose inventions must be "business to consumer", national policies such as that 3rd party data processing consent and the poor information technology infrastructural it has made it difficult for players in that industry to be innovative, although they are pivoting towards digitalisation.

Assessing the state of readiness in AI adoption by South African corporates, 78% of the executives agreed that they needed to increase their organization's competitiveness by investing in AI technologies (Accenture, 2018), notably with immerse computer vision (Marr, 2019), predictive power (Rust, 2020), and machine learning capabilities (Fluss, 2017). However, the disappointing reality was that only a third of those companies plan to invest significantly in AI over the next three years. Such outcomes raise concerns about the adoption appetite of companies in the country and their belief in AI potential. In addition, it is argued that in the marketing spectrum, little has been said or investigated about AI on marketing activities and how corporates measure its success (Jarek & Mazurek, 2019**;** Manyika et al., 2018). Researchers are in the dark about which technologies marketers integrate into their marketing strategy formulation process (Chen, 2019).

Despite little investment by non-tech companies and information inadequacy on AI and marketing (Davenport et al., 2019), AI of late is heavily utilized, appreciated, and highly regarded as the outright major source of innovation in the marketing space (Rust & Huang, 2021). McKinsey & Co's (2017) study of different industries and their business functions exposed that AI's gigantic exponential merits are from clusters associated with marketing and sales. For example, currently, there is excitement around the use of AI ChatGPT-3, which is viewed as the next best technology innovation capable of processing data and giving output without human interaction or assistance. Therefore, within the marketing sphere, it can provide absolute conclusions on strategies, empower the marketing mix components, and give a sense of direction towards achieving marketing goals. Numerous emerging studies focus on Chat-GPT and explore strategies for users to harness this innovation. Thus, past scholars have confidence in AI integration for marketing purposes. Chat-GPT-3 is a strong communicative AI innovation. Just as Davenport et al. (2019) assert that the impact of AI on marketing activities will include the next-best offers to clients, programmed buying of digital advertisements (Marr, 2019), and the ability to predict lead scoring (Harding, 2017). The above scenarios align with justifications for marketers' high usage of AI technologies. However, it does not satisfy the arguments relating to its influence on marketing strategy design and how those technologies are integrated within the business structures. The lack of guidance on structural reforms is a crucial element that needs attention. The few major reasons for low adoption rates are the lack of knowledge, vendor participation, or external support structures to assist in advanced technological applications.

A study by Salesforce of America indicated that in marketing, AI-powered technologies would be the most adopted in a few years to come (Columbus, 2019). There is so much optimism about AI, its potential, and investments which have accelerated AI adoption over the past few years (Brynjolfsson, Rock & Syverson, 2019). It has been an on-and-off appearance trend for AI on the marketing scene. This has been influenced by its developmental improvements, potential applicability, and perceived benefits for commercial use (Janek & Mazurek, 2019). However, some scholars argue it is here to stay forever (Schwab, 2017; Marr, 2019). This lives to suffice beliefs that AI has great potential and disruptive power in any industry while yielding positive results if well implemented in any function across the business. It is also necessary for each country or company to align themselves with the best suitable innovations rather than adopting all as they may fail in the long run.

In marketing, the power of AI languishes in its ability to process large data in any format in numerals, text, images, and sound, providing adopters with some valid insights to act on (Kaplan & Haenlein, 2019). Data influence AI in marketing, i.e. AI is data-driven (Szczepanski, 2019). Another AI attribute lies within its predictive ability. Tjepkema (2017) believes that AI can assist companies in predicting future sales. Rust (2020) expects AI to play a vital role in predicting prices, purchases, and promotions' impact on sales. Rust (2020) postulates that accurate pricing and relevant promotional activities increase sales, thus, a critical area of scrutiny for any marketing stakeholders. However, Davenport et al. (2019) warn that we are in danger of pitching AI as the answer to everything, while Columbus (2019) echoes those sentiments by arguing that AI is not what most companies are geared for as it is far off due to the nature of their customer base. The above sentiments raise the need for in-depth analysis and adopters to examine the influential factors to be considered when deciding to take up an innovation.

Determinants of AI adoption are generated from the technological environment of the firm, knowledge creation and transfer, top management support, customer orientalism, external pressure and optimism surrounding the success of AI (Davenport et al., 2017; Baker, 2012). Even though debates still exist on which factor influences AI adoption the most, optimism surrounding AI, lags, and mismeasurement of its impact are the major contributors to the AI adoption paradox (Brynjolfsson et al., 2019). Identifying the determinants of technology innovations has long lied in the hands of scholarly theories, mainly Roger's Innovation of Diffusion Theory (IDT), the Technology-Organization-Environment (TOE) framework by Tornatzky and Fleischer and the Production Paradox Theory by Solow. The first three theorists believe there are three distinct categories of innovation determinants which are technological, organizational, and environmental. In contrast, the last theorist argues that technology-related output inconsistency has disputed technology adoption; hence there is a need to quantify every adopted innovation.

Agrawal et al. (2018) state that we live in the age of paradox where systems that use AI either match or exceed human-level performance in other domains while enhancing accelerated rapid strides in other innovative technologies and resulting in increasing stock prices yet providing negative productivity growth rates in USA of the last ten years. Rust (2020) indicates that some outspoken technology ambassadors like Elon Mask believe the accelerated rapid growth and development of AI technologies are scary and very dangerous, while others believe that the world is about to realize the full potential of AI on marketing activities due to its capabilities (Vlačić et al., 2021). Brynjolfsson and McAfee (2014) argue that, like any other technological innovations, their full effects will not be realized until some other new waves of complementary technologies surface and are well implemented. Some AI researchers and commentators believe that exceptional AI systems rooted in machine learning have not yet been distributed and used accordingly across industries (Brynjolfsson et al., 2019). Considering the global south stance, the countries may need those complementary technologies to ease their adoption processes, especially considering unpleasant socio-economic conditions.

However, despite not being at the same magnitude of qualified human display and capabilities, Facebook's AI Research division taskforce recently achieved the best machine language translation algorithms obtainable using convolutional neural net sequence prediction techniques (Gehring et al., 2017). Whereas Cowen (2011) long offered a series of multiple justifiable arguments why innovation may be lagging in accelerating the growth of economies for a while, (Webb et al., 2019) indicate that some studies of technological progress in productivity, research has failed dismally. Nordhaus (2015), on his hypothesis test on accelerated technology and growth, various tests failed. The mismatch between statistics and expectations vividly indicates research gaps and opportunities for exploitation within AI boundaries. Scholars are left with the need to identify if AI plays a role in industries of their choice or if it is only hype. Therefore, this study focused on quantifying AI adoption in food retail marketing in South Africa and preparing that much-needed guiding formula.

Like any other sector in the world, the retail sector is arguably in a considerable position of change and transformation (Seranmadevi & Kumar, 2019). The whole retail industry is trying to adjust and deal with the fast-changing customer purchasing trends and giving importance to moving towards or integrating online retailing with traditional retailing (Sicular et al., 2019). Retailers have invested more resources in their supply chains to become more digital and web-centric (Amrita, 2018), making use of different technologies, including AI and robotics, data analytics, logistics automation and self-service innovations (Infosys, 2017), to achieve competitive advantage, profitability, customer-orientation and be highly responsive to demand and industrial opportunities (Oosthuizen et al., 2020). Cheng (2019) hints at the need for a sound integration plan from marketing experts within the retail sector. Considering the impact of Covid-19 as well, a drastic shift toward online retail is recognised (Huang & Rust, 2022).

Amrita (2018) indicates that retail giants such as Amazon, Walmart and a few other companies are swiftly modernizing their retail functions, facilitated by technology advancements. Retailers are turning to virtual applications, data analytics, face recognition features, augmented reality, and staff-less trading to magnify their marketing strategy (Watson, 2014). Decision-making by retail marketers has improved due to the use of Artificial Intelligence User Interface (AIUI), which helps them decide on what to display, the order of display and the times when to display products (Oosthuizen et al., 2020), what products or services to promote at the front of the traditional retail store, or website (Sindhu, 2018), and this paves the way for cross-selling and upselling to end-users rooted on previous sales trends (Chung et al., 2018). Gartner (2019) asserts that the retail industry's continued digital transformation and development has escalated the adoption appetite. This has led to the need for evolution within the retail value chain to match the rapid technological transformation (Bolton et al., 2019). For retailers to stay afloat, remain competitive, and survive in this ever-changing 4IR and unpredictable customer environment, there is a need to innovate their functions by adopting new technologies (Lee et al., 2018), be more agile (Goworek, 2014) and much leaner (Wirth, 2018). However, most retailers still employ the traditional value chain models (Van Esch & Black, 2019b). The adoption expense, literature or information inadequacy on actual gains surrounding AI adoption and knowledge about digital technologies are the major sources limiting AI integration rates (Oosthuizen et al., 2020).

Bughin et al. (2018) consent that most retailers already use AI technologies in some parts of their value chain. As part of the value chain processes within retailers' functions, marketing has benefited from AI adoption. For example, through big data analytics, retailers are improving their price prediction accuracy (Kaplan & Haenlein, 2019). It is worth appreciating that AI can influences traditional and digital trading. Overall, AI revolutionizes both physical and digital food retailing experiences by improving operational efficiency (Davenport et al., 2019), personalizing interactions (Huang & Rust, 2021), enhancing convenience (Rust, 2022), and optimizing decision-making (Marr, 2019). AI enables retailers to better understand customer preferences, anticipate demand, and offer seamless shopping experiences across various channels, that is, either digital or physical (Nazir et al., 2023). This is mainly attributed to data analytics, which drives data-driven decision-making processes (Chen, 2018). Thus, the study targeted AI's influence on digital and physical stores. Physical stores have also been improved through smart manufacturing. Value chain stores have integrated smart manufacturing techniques to improve the process of product development. Kusiak (2017) indicates smart manufacturing makes retailers more efficient, profitable, and sustainable. This integration of marketing activities to core retail functions has been around for a while and is commonly known as retail marketing (Lee & Trim, 2006). Davenport et al. (2019) argue that although retail marketers are now utilizing AI, they are at the infancy stages of completely understanding the adoption and application of AI technologies into their functions and lack the guidance of overall AI integration. Considering the influence of AI on marketing and how it is utilized in retail activities, little has been said about its influence on marketing strategy design, application, determinants for adoption, the influence and assessment of the potential application by AI-enabled solutions across retailing (Brynjolfsson & McAfee, 2017; Davenport et al., 2019)

When analysing the food retail sector in South Africa, it is important to note that different studies present contrasting perspectives. On the one hand, Oosthuizen et al. (2020) argue that a few larger firms dominate the sector. On the other hand, Chisoro-Dube and Das Nair (2020) suggest that SMEs in the informal sector primarily dominate the sector. Hence, assessing how AI integration plays a pivotal part in the overall sector considering both large and small firms, is critical. The rapid growth and ever-increasing trends in online purchases have provided a new set of purchasing dynamics within the food retail industry. Thus, marketing as the link between customers and the products, and its interest in AI technology to achieve their strategic goals has never been more relevant. However, like any industry, AI innovation adoption and integration hasn't been easy. The food retail industry has faced problems in adopting AI (Chisoro-Dube & Das Nair, 2020). Equally, due to the lack of guidance from literature and the weak digital ecosystem prevailing in the industry, challenges encountered are still detrimental. It was in the interest of the study to try and close such existing gaps.

## 1.3 RESEARCH PROBLEM

Industry 4.0 has brought endless opportunities and has produced numerous problem-solving techniques which any industry can utilize (Schwab, 2017). Gabriel (2019) states that automation facilitates creativity, innovation, and gives the power to solve existing traditional problems. Calof, Richards and Santilli (2017) believe AI can enhance strategy formulation. Because of the large data volumes generated, data has become a crucial business asset that every business must incorporate in decision-making (Gartner, 2019). With AI-powered tools, ideally, it would be noble for marketers to adopt those tools as they present analytics capabilities for predictive, descriptive, diagnostic, and prescriptive purposes. Industries like food retailing and marketing have been tipped to be one of those at the forefront of utilizing AI, proving its potential to any industry, especially outside its areas of occurrence which is IT. Therefore, Marr (2019) expresses retailers' need for strategic shifts towards full automation. Russell and Norvig (2016) second that it is rational to dispatch AI agents to carry out strategic tasks.

However, the reality is that a few industries are positioning themselves to uptake AI solutions (McKinsey & Co, 2017). According to Accenture (2018), although 78% of firms' executives believed in AI being the catalyst for growth and company competitiveness, only a third were planning to invest in AI technologies in South Africa. Davenport et al. (2019) suggest that firms use AI technologies strategically. However, South Africa is believed to be unattractive for technology-related investment due to the socio-economic conditions prevailing in the country (Senyolo et al., 2018). Additionally, the global south firms are viewed as adopters rather than pioneers compared to the global north (Chui, 2017); hence there is a misalignment between the ideal situation and reality. Equally so, the lack of knowledge surrounding AI determinants and appropriate tools to utilize for retail marketing has been a challenge. Furthermore, the on-and-off appearance trend of AI on the marketing scene has escalated the debates, but some studies argue that it has given room for improvements to those systems (Janek & Mazurek, 2019). Digital transformation is regarded as business capital. Lastly, the existing literature mainly focuses on AI's transformative nature and benefits (Davenport, 2018), yet little has been said about the potential frameworks that retail marketers can adopt when integrating AI within their activities.

Consequently, the gap between the ideal situation and reality has brought so much uncertainty within the boundaries of AI and its adoption procedures. The lack of literature and actual documentation of experiences by food retail marketers in South Africa about procedures which may be followed to adopt AI technologies successfully continues to be a major stumbling block for potential adopters. Battersby and Marshak (2017) argue that the lack of technology uptake for strategic purposes has contributed to several food retail business failures in South Africa. Moreover, there is so much uncertainty about the systems which food retail marketers can use. They must understand the pros and cons of currently limited information in the sector to adopt certain systems.

Additionally, the ever-changing customer environment and the erosion of trading boundaries have made designing an effective marketing strategy more complex for retail marketers (Eriksson et al., 2020), mostly fuelled by the large data volumes generated. Davenport and Ronanki (2018) suggest that although cognitive technologies enhance marketing activities such as strategy formulation, many ambitious AI projects have failed. It can be due to several reasons, such as poor implementation or inaccurate systems adopted because of the lack of a proper adoption framework or the firm's inability to navigate the barriers of adoption. Lastly, because South Africa is viewed as unattractive as 'users' rather than 'pioneers', their focus should have been on 'incremental' AI technologies adoption instead of the 'transformative' approach, which focuses on completely replacing human judgement. Additionally, considering that AI technologies require huge financial investment without guaranteed success, this has led to poor performance of AI, resulting in the rise of the adoption paradox.

Therefore, the study, guided by the background and the existing gap between reality and the ideal situation, identifies the common and controversial determinants of AI adoption within the food retail marketing industry in South Africa. From there, the study considered the AI technologies used and how they were channelled to use within the retail marketing space. This enabled the researcher to bridge the gaps in AI technologies' influence on marketing strategy. The study utilized the marketing mix components to examine the influence of AI. Overall, identifying the determinants and the systems used and examining the influence of AI on marketing activities formed a basis for the primary research area, which focused on developing an AI adoption framework for food retail marketing in South Africa.

## 1.4 RESEARCH OBJECTIVES

The study's main objective was to develop an AI adoption framework for food retail marketing in South Africa. Aggregated efforts meant to solve the identified problems that were involved in this research were clustered around clear but different identifiable sub-objectives as follows:

1. To examine the AI technologies adopted for food retail marketing activities in South Africa.
2. To determine the factors that influence AI adoption in food retail marketing in South Africa.
3. To examine the influence of AI adoption in designing food retail marketing strategies in South Africa.
4. To examine the moderating effect of competitive intensity on the relationship between AI technologies adoption and marketing strategy outcome.

5. To propose an AI adoption framework for food retail marketers in South Africa.

## 1.5 RESEARCH QUESTIONS

Based on the study intent, the main research question was to develop an AI adoption framework for food retail marketing in South Africa. From the stated objectives, this research aimed to answer the following questions:

1. What are the AI technologies adopted for food retail marketing activities in South Africa?
2. What factors influence AI adoption in food retail marketing in South Africa?
3. What is the influence of AI in designing a food retail marketing strategy in South Africa?
4. What is the moderating effect of competitive intensity on the relationship between AI technologies adoption and marketing strategy outcome?
5. What AI adoption framework can the South African food retail marketing sector adopt?

## 1.6 SIGNIFICANCE OF THE STUDY

The inferences from the discussed literature and the objectives above provided a basis for the study's contribution. Firstly, the study significantly contributed to the theory. The study provides a theoretical framework that can be used for future research locally and internationally. Equally, the theoretical contributions can be adopted and contextualized for other industries. Furthermore, the study contributed immensely to the body of knowledge and had policy implications for retailers and policymakers. For the retail marketing sector, the study will empower retail marketers and other upcoming trailblazers who embrace the value of AI. The research will solve the AI adoption uncertainty on the side of retail marketing strategy formulation as it proves the exact influence of AI on marketing mix components and how it transforms those components to obtain an effective marketing outcome. There is an important attribute to South African retail and marketing firms that go against all odds and adopt AI. Hence, the study showcased the resilience of those early adopters who champion numerous initiatives and utilize available platforms to improve and enhance their activities while highlighting the resilience measures through typically adopted technologies, the determinants and deducing the adoption framework. Additionally, although numerous studies have been carried out globally, the study contributed to the body of knowledge through the contextualization of the study, considering the socio-economic attributes of South Africa. Due to sparing literature in the niche sphere of retail food marketing, the study developed an adoption framework indicating a possible path for stakeholders. Lastly, for policymakers and the government facing policy implications due to ballooning industry 4.0 pressures at a national level, the study significantly contributed to new policy designs, which factor in the challenges or determinants firms encounter when adopting. The systems used as they aim to come up with an accurate regulatory framework.

## 1.7 DELIMITATIONS

This research was limited to a maximum of four major theories of technological integration within business functions (Innovation Diffusion Theory (IDT), Technology–Organization–Environment Theory (TOE), Institutional and Paradox Theories). Although many factors influenced technological adoption, the researcher followed the IDO and TEO framework of considering only the technological, organizational, and environmental factors in this research. In addition, despite adopting many AI technologies within the retail sector, the research focused on the technologies used only for marketing purposes. As much as AI is a broad subject, this study mainly focused on narrow AI facilitated by machine learning innovations and has common features that retailers can relate to. The study was delimited to Gauteng and Western Cape food retail companies in South Africa.

## 1.8 STRUCTURE OF THE THESIS

*Chapter 1: Background of the Study*

In this section, the background and study context are introduced. The section details the problem statement, research objectives and questions guided by the background literature. The chapter indicates the significance of the study and the delimitations.

*Chapter 2: Literature Review*

The chapter defines the key terms and concepts and operationalises the study's definitions. A detailed literature review on all study variables follows this. From there, it gives a detailed review of the theories adopted for the study and the justification. This is then followed by the conceptual framework, which gives a basis for proposed hypotheses guided by the study.

*Chapter 3: Research Methodology*

The chapter gives a detailed account of the methodological approach adopted for the study. Different philosophies and paradigms adopted for the study are mentioned, and justifications for their usage are explained. The research instrument, the target population, the sample population, the sampling techniques, and the data collection procedures followed are described in the section, with ethical guidelines not being exempted. Furthermore, data cleaning and analysis issues and procedures are also addressed in the section, together with the analytics tools to be used. Lastly, validity and reliability concerns regarding the data collected are also addressed in the chapter.

*Chapter 4: Presentation of findings*

The chapter aimed to present the findings of the study. Based on the processes and procedures discussed in the methodology section, the chapter will present the data, show findings, and speak on the conceptual framework, hypotheses and analytics performed on the data. The study was quantitative; descriptive statistics, confirmatory analysis, exploratory analysis, and structural equation modelling outcomes will be presented.

*Chapter 5: Discussion of findings*

The chapter provides a detailed discussion of the findings presented in chapter 4. The findings discussed are mostly coined on the research questions, objectives and hypotheses proposed for the study. The chapter details the links between existing literature whilst exposing the study's shortcomings as per the findings, which may be subject to further studies.

*Chapter 6: Conclusions and recommendations*

The final chapter of the research explains the conclusions of the study based on the data findings. The conclusions give room for recommendations and future study basis as per the study findings and shortcomings.

## 1.9 CHAPTER SUMMARY

The chapter introduced the overall study and gave a detailed background on AI, marketing, and retailing industry. Definitions, scholarly and futurist views, and the position of AI in real business situations were covered. The background also incorporated literature on adoption theories, strategy creation and how AI can play a role in designing an effective food retail marketing strategy outcome in South Africa. Traditional problems associated with strategy creation and how AI applications can solve those problems took centre stage. The background facilitated the establishment of a sound research problem. Existing crucial gaps from background literature assisted in research problem identification. It is from the research problem; research objectives were identified together with the research questions. The above gaps and discoveries allowed the researcher to explain the study's significance and how it will contribute to knowledge.

Moreover, it allowed the researcher to devise the proposed adoption framework. Lastly, the chapter highlighted the possible challenges which may limit the researcher, hence the inclusion of the delimitations section to cap the introductory chapter fully. Lastly, the structure of the thesis is illustrated.

# CHAPTER TWO: LITERATURE REVIEW

## 2.1 INTRODUCTION

The section seeks to discuss the existing literature on the study area. The main objective is to review the relevant literature to establish the study's theoretical and conceptual framework. In reviewing the existing literature, key terms will be defined, significant theories explored, and hypotheses developed. The chapter starts with an introduction and then defines key terms that will lead to exploring the theories and identifying determinants and technologies used. From there, the section reviews the literature on the marketing mix components and reveals how AI influences each component when designing an effective retail-marketing strategy. The chapter will review the literature, which examines the influence of those identified technologies towards marketing strategy design and how they align with the set marketing strategy outcome, thus forming a basis for the study hypotheses, which will deliver the study's conceptual framework.

## 2.2 DEFINITION OF KEY TERMS

The key terms for the research are Artificial Intelligence (AI), Retail Marketing Strategy, Marketing Strategy Outcome, Marketing Mix Components, Traditional and Online (digital) Retailing.

### 2.2.1 Artificial Intelligence (AI)

Kaplan and Haenlein 2019 (p.17) define AI as "a system's ability to correctly interpret external data, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation". Poole and Mackworth (2010, p.9) define AI as "the field that studies the synthesis and analysis of computational agents that act intelligently". AI is a wing of computer science that attempts to simulate human capabilities in a machine so that these machines can then fulfil an assignment that normally requires human intelligence (Reddy et al., 2017). The AI field has evolved over the years, and some researchers may argue that it came from humble beginnings to being a global influencer (Bartneck & Lutge, 2021) and hence on its definition, what must be included or excluded has changed as well over the years (Kaplan & Haelein, 2019). Despite the evolution, AI's key attributes are still rooted in designing, developing, and integrating intelligent agents into our lives and businesses (Huang & Rust, 2021). AI is associated with machines which impersonate cognitive capabilities.

Davenport et al. (2019) suggests two types of AI, strong and weak. However, Escott (2017) came up with three types, narrow (weak) AI, general (strong) AI, and artificial super-intelligent. Weak AI symbolizes machines that replicate thinking and perform as if they were intelligent (Russell and Norvig, 2016). Weak AI can emulate human logic through machine learning (ML) (Jarrahi, 2018). ML is a digitalized model used to achieve AI (Marr, 2019). ML algorithms input prescribed data into AI technologies and use statistical models to facilitate AI systems learning platforms to give meaningful and accurate outcomes, thus enabling AI systems to get progressively superior to humans on assignments (Murdoch et al., 2019). In modern business, weak AI is coined on cognitive affairs associated with building an imitative agent with human intelligent attributes and focuses more on the epistemological side (Bishop, 2021). Weak AI technologies are common and highly utilized everywhere as we are believed to have only achieved it (Rust, 2020; Agarwal et al., 2020). The study adopted weak AI, mainly associated with ML learning algorithms, to learn and interpret data. More so, weak AI can't always fully operate without human interaction, as it sometimes requires human supervision.

Artificial Super-Intelligent (ASI) is the type of AI believed to be more capable than humans (Escott, 2017). ASI is believed to be a type of AI that will be achieved after strong AI surpasses human intelligence. Stiglitz (2014) argues that this will be achieved in 2040. With AI innovations like Chat-GPT emerging, the argument cannot be discharged. Strong AI is at a theoretical phase and will be achieved when it gets to a point where machines can now act, feel, respond, and think like humans (Marr, 2019). Although some technocrats argue that some industries are beginning to achieve strong AI due to a noticeable increase in the number of robots usage, most studies are still on the notion that strong AI is debatably possible but not anytime soon (Borana, 2016). Bishop (2021) believes strong AI is when the engineered technologies seek to understand the causal influence of a human mind and is centred on the ontological part.

#### 2.2.1.1 Operational definition of artificial intelligence.

From the above definitions and types of AI, it can be concluded that AI incorporates machines or systems which attempt to perform tasks previously performed by humans (human-centric) more effectively and efficiently. As the study operationalizes AI, it views AI as automated machines which emulate human capabilities and thinks like humans when performing prescribed tasks. Deduced from the background, AI's key constructs (elements) are machine learning algorithms, virtual agents, and automated robots. Therefore, the reason why the study adopted weak AI. The systems or machines within weak AI boundaries use machine learning algorithms to learn from past experiences (data) inputted to achieve set objectives such as predicting future sales and profit margins (Huang & Rust, 2022). ML learning algorithms learn and interpret data.

Additionally, ML algorithms are used to build models within robots and artificial agents which can detect keywords and respond accurately as if there were humans. These are chatbots in modern technology language (Ashfaq et al., 2020). ML algorithms can also learn from images and voices and respond accordingly. Thus, the study refers to AI as machines, applications or systems acting as humans and performing tasks that previously needed human intelligence through analysing data in any format powered by ML algorithms to achieve set goals. Therefore, the two intelligence elements of the operational study AI boundaries are mechanical intelligence (designed to achieve automated repetitive tasks) and thinking intelligence (designed to process, learn, and interpret data to new decisions, knowledge, or conclusions).

### 2.2.2 Retail Marketing Strategy

There are many scholarly and industrial definitions of marketing. However, the underlying context of those definitions is that marketing incorporates deciding what, to whom, when and how to offer goods and services so that customers accept at a residual profit (Deepak & Jeyakumar, 2019; Urbach et al., 2019). A marketing strategy refers to the organization's important decisions in relation to the formation, communication and delivery of valuable goods or services to consumers (Varadarajan, 2015). Retail marketing constitutes the highest point of the marketing process: the point of contact between users and producers (Quix, 2019). Retailers have always strived to forge tight customer relationships by applying marketing mix analysis techniques (Hogreve et al., 2017). "The marketing-mix consists of a set of harmonized strategic elements that reflect managerially controllable decision parameters aimed to establish and sustain retail patronage and influence the short and long-term performance of retail organizations in terms of sales, profits, and return on investment" (Blut, Teller & Floh, 2018, p.116). For management to design an effective marketing strategy, they need to understand the marketing mix attributes (Kumar & Srivastav, 2020).

### 2.2.3 Operational Definition of Marketing Strategy Outcome

From the above definitions and boundaries of retail marketing strategy, it can be concluded that marketing strategies have short-term and long-term goals set from the onset. The study, aligned to the objectives and past literature definitions, then defines marketing strategy outcome as the overall goals the food retail marketers attempt to achieve by successfully integrating AI technologies within their value chain processes. These objectives include sales increase, profitability, market share increase, problem resolution effectiveness, cost of goods/service delivery reduction and improved return on investment. These objectives are consistent with Chen (2019), who identifies sales, profit, cost reduction and a positive ROI as major company goals they attempt to achieve yearly. They can be used as proxies for performance, company success and growth. Therefore, in essence, the study's marketing strategy outcome definition is bounded by the intention of food retail marketing strategists to achieve sales increments, reduced production costs, lower customer complaints, increase in returns on investments (ROI), increase in market share, and profit margins.

### 2.2.4 Marketing Mix Components

The marketing mix comprises four elements: Price, Place, Product and Promotion (4Ps) (Thabit & Raewf, 2018). Some literature has expanded it to the 8Ps (Chen, 2018). However, the research focused on the 4Ps. Price is the exchange value, the product is the qualities and designs of what is to be sold, the place is the degree of selectivity to whom the product will be sold, and promotion is devices for exposure and product benefits (Quix, 2019).

Fast forward to the digital era, some scholars have made huge calls for the reconceptualization of the marketing mix, claiming that the past dynamics no longer comprehend the current demands (Rust, 2020). 'Revionist' and 'conservative', as referred to by (Dominici, Yolles & Caputo, 2017), have different views. The former asserts that the marketing mix must catch up to the digital world despite some scholars arguing that the primary marketing-mix is perfect and the digital world's discoveries can be incorporated into the existing components (Mintz et al., 2021). The latter accepts the need for improvements in the marketing mix considering the changes made through technology integration, but they argue that radical revolution may lead to misleading attributes introduced; therefore, they still believe that the current 4Ps are adapt and remain consistent concepts for marketing mix (Bluta et al., 2018).

Therefore, the study adopted the Huang and Rust (2020; 2022) framework to examine the influence of AI adoption on marketing strategy design. Haung and Rust's (2020) conceptual framework of marketing strategy design on retailing is rooted in AI's impact on selling, product development, pricing, and targeting. AI influence is measured through designing an effective strategy, whose outcome is measured through increased growth sales, profits, reduced production cost, and return on investment. The framework provided the study with valid strategy components which were utilized in the building up of the framework.

### 2.2.5 Retailing (Traditional and Digital)

Due to the rapid acceleration of AI application developments and virtual worlds, drastic changes have occurred in retailing (Mozeryte, 2019). Before 2016, as most scholars would argue that it is when AI accelerated at a rapid pace, it gained momentum and attention (Brynjolfsson, Rock & Syverson, 2019). Traditional retailing had been pre-dominant, although some glimpses and promises of online retailing were facilitated by the previous existing technologies (Miklosik et al., 2019). In 2016, e-commerce accounted for 2% of the total retail spending in South Africa (Makhitha & Khumalo, 2019). This little contribution of e-commerce is consistent with Hortacsu and Syverson (2015), who argue that straight after physical store dominance, it was not e-commerce which followed. Instead, it was the expansion of warehouses and shopping centres. Such arguments align with the current state in South Africa, where shopping malls are dominant, and e-commerce is not viable as externals may think. Traditional retailing is a situation whereby buyers and sellers meet under one roof and trade goods for money instantly (Rust, 2020). In-store retailing has been the most dominant (Thomas & Housden, 2017). The predominance of physical stationary retailing over the past few years has been structurally put to the test as there is a rapid rise in a shift from traditional retail trading formats (store based) to online-based formats (Pauwels & Neslin, 2015). Kietzmann, Paschen & Treen (2018) believe technological advancements have catalysed this shift. However, Thomas and Housden (2017) suggest that a significant portion of online (digital) trading has gone to new players, Amazon being the major player in USA and Alibaba in China. In South Africa, we have Takealot. This raises concerns about why existing retailers struggle to shift online. Cost of digital adoption, lack of skilled personnel, lack of digital transformational guidance, geographical position, digital uncertainty, and resistance to change have been cited as some of the major reasons for this trend, particularly in developing economies (Baker, 2012; Manyika et al., 2018; Davenport & Westerman, 2018; Brynjolfsson et al., 2019; Marr, 2020).

Online trading is when buyers and sellers meet over the internet or use applications to trade goods and or services without travelling to the physical premises of the seller (Kietzmann et al., 2018). Rocket Internet CEO Oliver Samwer once stated that physical stores existed because the Internet had not been discovered (Grewal et al., 2017). Most customers now opt to use digital shopping due to its convenience, supplementary benefits like price comparison (Huang & Rust 2020), recommendations features (Pulles & Hartman, 2017) and augmented visualization (Soni et al., 2019). The above scholarly arguments prove consumers no longer rely on traditional retailing methods. Still, there are embracing the digital systems food retailers offer them. Although those sentiments may be more appropriate in first-world countries where there can facilitate a properly guided digital transformation journey from both the public and private sector, such cannot be said with countries like South Africa, which don't have proper adoption structures, lack tested frameworks and feasible policies in place for an effective shift from traditional to digital retailing.

Although Davenport et al. (2019) suggest technology adoption has been incorporated into marketing strategy design by retail marketers to assist in developing an effective strategy. AI is deemed to be the catalyst for that strategic shift, and the strategic shift, in some cases, has been deemed to be the reason for the profitability paradox (Sides & Skelly, 2021). The authors indicate that since retailers have discovered the drastic shifts in the consumer landscape, particularly towards online retailing, they must be digitally oriented and find ways to serve their consumers in the best possible methods. However, with the already squeezed profit margins, retailers have invested heavily in technology innovations such as robots, chatbots and many others to improve convenience and digital experience. Therefore, as they embark on AI-powered heavy digital investments, retailers engage data-driven third parties, industry technology vendors, and other stakeholders to facilitate the transformation journey. As a result, retailers fail to capture value in that digital return, which is the *profitability paradox*. Deloitte (2021) explains the profitability paradox, as shown in Figure 2.1.

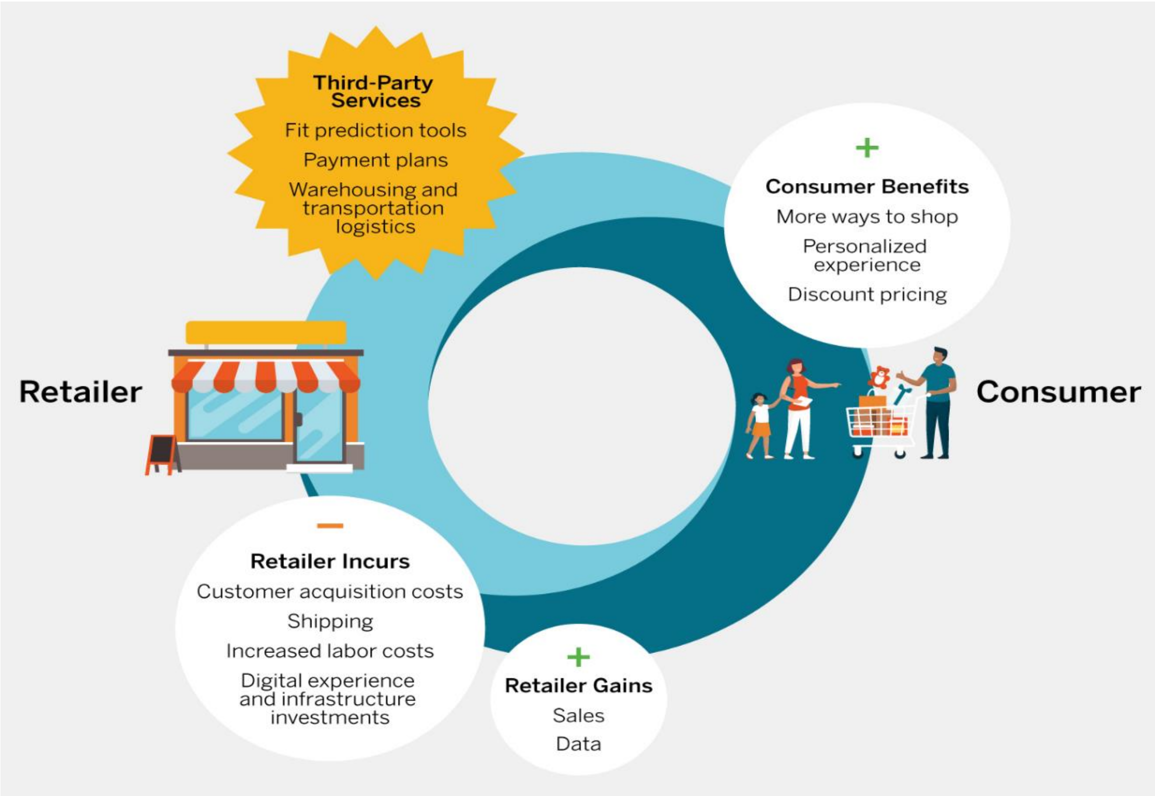


**Figure 2.1: The Profitability Paradox**

**Source: *Deloitte Development LLC (2021)***

As the diagram above illustrates, consumers are beneficiaries in this digital era within the food retail sector as they are given price discounts. They find more ways to shop through different platforms such as WhatsApp, Websites, Retail-Apps, and social media. The third party also benefits by getting business from retailers to fit AI predictive tools, offering auxiliary payment plans and logistic and warehousing services. Although retailers may gain in sales increase and data generation for data analytics which helps in decision making, they incur customer acquisition costs, shipping and warehouse costs, increased labour costs, digital expenditure, and infrastructure investment, which may be excessive for them. The losses incurred are expected as past literature emphasizes that technology adoption is expensive (Brynjolfsson et al., 2019).

Because of the profitability paradox, the uncertainty surrounding digital transformation and identified lack of proper adoption frameworks; the study adopted both online and traditional retailing elements to examine the influence of AI adoption in retail marketing strategy creation. More so, because the main study aimed at developing an adoption framework, the study proposed a sustainable framework in both retail worlds (online and traditional). Lack of guidance and limited literature on the mismatch between gains and expected returns of adoption (profitability paradox) has been the major contributory factor in designing such a sustainable framework.

### 2.2.6 Operational definition of Competitive Intensity

Porter (1979) defined competitive intensity as the measure of competition within a market. Competitive intensity reflects on the nature of the market, the aggressiveness against companies and the strength of companies. Competitive intensity is influenced by various factors, including market structure, industry dynamics, competitive strategies, and the overall competitive landscape (Davenport et al., 2019). For the study, competitive intensity refers to the extent of rivalry and competitiveness amongst food retailers in South Africa.

## 2.3 DETERMINANTS OF AI ADOPTION

This area seeks to address the factors which influence AI adoption within the food retail marketing industry in South Africa. The determinants are divided into three groups, Technological, Environmental and Organizational factors, as mainly supported by theorists (Solow, 1987; DiMaggio & Powell, 1983; Tornatzky & Fleischer, 1990; Rogers, 1985; 1995).

### 2.3.1 Technological factors

Technological factors include internal and external technology attributes important to the organization.

#### *2.3.1.1 Perceived benefits*

These are rooted in the potential benefits of AI technologies adopted by retailers (Chen, 2019). Sastararuji et al. (2021) postulate that firms adopt AI because it provides a wide variety of benefits, such as permanency, increased problem-solving speed, reliability, improved accuracy, and cost-effectiveness while reducing uncertainty. According to various authors, perceived benefits of innovation adoption lie within the realms of increased reach of potential clients, reduced overhead costs, the easy and more efficient way of conducting business, potential tap into new markets and the ability to withstand competition (Deloitte 2017; Davenport & Ronanki, 2018; Saruchera, 2014). The above-highlighted benefits prove that AI brings advantages that may enhance business performance. Firms welcome such benefits because, due to the increased complexity of customers' demands, IoT and smart technologies are highly recommended (Rust & Huang, 2020; Saruchera & Phiri, 2016). More so, because the market has become data-abundant (Marr, 2019), firms perceive that harnessing available data will be beneficial to shed off competition as there are exponential benefits of predictive and diagnostic power (Chui, 2017). Davenport et al. (2019) notes that the emergence of broadband, mobile internet, wireless connectivity, and the rapid increase of online shopping via intelligent mobile applications will improve retailers' competitive advantages. Therefore, they adopt AI technologies. However, Chowdhury and Sadek (2012); Chowdhury et al. (2022) bring a whole new set of dimensions regarding the perceived benefits of AI as the researchers emphasise that AI tools are utilised to stimulate human intelligence when solving a problem, or in decision-making hence there is some element of permanency and reliability benefits attached to it. The arguments are within the boundaries of postulating that, for example, due to AI's repetitive nature, accuracy, and data storage capabilities, if an employee within the company retires or is no longer accessible, data won't be lost. The life of knowledge within the decision-making and problem-solving processes remains unchanged because of AI programming capabilities. The magnitude of anticipated benefits will later possibly play a vital role in influencing firms to adopt AI tools.

#### *2.3.1.2 Compatibility feelings*

Compatibility originates from retailers' feelings about the technology they want to adopt. Retailers feel that the innovation must be compatible with their standards, previously utilized by other peers and the desire to adopt AI (Ullah et al., 2021). Branstad and Solem (2020) assert that if adopted technologies are consistent with the adopters' values, needs and experiences, the degree of perceived compatibility is deemed high. Chui (2017) indicates that for firms to integrate AI tools successfully, there is a need for a solid AI plan compatible with existing structures and must align with current strategies. This equates to the fact that should firms fail to have proper adoption guidelines or models incorporating their current structures. They are likely to abandon the digital transformation journey towards AI adoption. As Rogers (1995), in his theory of diffusion of innovation, referred to compatibility as the extent to which innovation and its potential can deliver value and enhanced experience for users while accounting for the desires of potential adopters, hence it is rightfully so that the AI tools under consideration must meet the requirements of retail marketers. More so, Chen and Tan (2004) have argued that old existing systems and traditional company structures are regarded as strong restrictors of new technology adoption, such as AI, because those are no longer compatible with modern innovations. This can also be linked to the company's inability to pivot towards digital transformation and or negative attitude towards innovation adoption. Such debates are a cause of concern as it shows a lack of agility and resistance to change, which has a negative outcome as it is likely to affect performance or even result in shutdown as many technocrats have lamented the need for adoption to remain in business. Therefore, one can strongly suggest that if the perceived compatibility level is high, retailers have a high probability of adopting AI technologies, while the vice-versa is true.

#### *2.3.1.3 Complexity*

This is the level of difficulty adopters face when deciding to use AI. Ferran (2021) believes this is the major factor influencing firms not to adopt AI. AI is perceived as complex, complicated, and difficult to either use or integrate (Rust, 2020). Hardgrave, Davis and Riemenschneider (2003) argue that technological complexity negatively affects adoption. Rogers (2003) conceptualizes complexity as the degree of difficulty in using innovation; hence advises adopters to examine their internal capabilities before adopting an innovation. Previous marketing studies have suggested that if marketers perceive AI systems as complex, they tend to have little desire to use them (Chang, 2016). Complexity is also attributed to a lack of knowledge (Marr, 2019). Viewed from a lack of tested digital transformation framework, retailers may face complex systems they cannot integrate within their operations. This could be due to recommendations or increased pressure to adopt AI because some industry peers are doing so. Such sentiments perfectly align with the scholarly work of Alam and Noor (2009), who indicates that the absence of ease to use and industrial pressures warrant the forced adoption of unwanted and complex systems. Therefore, it is expected that innovations that are easy to use and integrate tend to lead to a positive attitude towards adoption. Contextualizing the presented arguments and considering the nature of the labour force in South Africa, this may be viewed as a critical adoption factor to be assessed as skills shortages in the Information Technology sector are high (IT). In such instances, it proves the need for a healthy digital ecosystem to cover skills gaps, although outsourcing may prove costly.

### *2.3.1.4 Trialability*

Trialability is the extent to which adopters believe they must experience the technologies before adoption (Ullah et al., 2021). This is regarded as the experimental phase of innovation to assess the need for adoption on a limited basis. Banerjee, Wei, and Ma (2012) assert that since trialability is the belief that shapes attitude towards innovation adoption, adopters must always try to experience these innovations before embarking on full adoption. AI is expensive, complex, and not for everyone hence the need for trials before adoption (Brynjolfsson & McAfee, 2017). The rapid increase in optimism and potential of AI has led to firms taking up technologies they do not need, therefore, justifying the need to experience AI before fully committing to adoption (Baker, 2012). The arguments are consistent with Rogers (2003), who indicates that technology innovations are very costly with limited guaranteed success. Therefore, firms prefer to try them out before fully integrating them into their operations. However, Banerjee et al. (2012) argue that this can be an inconclusive influential factor when it comes to determining the adoption of innovation because, in cases of complex innovation (which is their nature), high risk and uncertainty, the belief-based approach and conceptualisation of experiments without evaluating the actual outcomes is dubious. Light and Papazafeiropoulou (2004) share the same sentiments and further explain that adopters' perceptions are often inaccurate and misguided; therefore, adopters must gather all the necessary information to eliminate pre-existing misconceptions, which will then lead to making a proper acceptance or rejection decision of an innovation. Therefore, it is under such conditions trialability experiments outcomes and evaluation can become imperative for innovation adoption.

### *2.3.1.5 Risks, Compliance and Acceptance*

Risks associated with the technology adoption, compliance status and how it can be accepted within the industry are crucial determinants. Data privacy issues may harm a firm’s AI adoption desire (Rao & Verweij, 2017). AI biases have been another subject which is an ongoing concern for adopters (Marr, 2019). An accepted system is adopted by many, therefore if intra-industry peers frequently ask about adopted technologies for feedback, which stimulates peer discussion of new ideas, tallying with compliance requirements (Lou & Li, 2017). Chatterjee et al. (2021) indicates that firms within an industry tend to adopt close or similar technological innovations because of the need for a sense of belonging. This is facilitated by the industry networks these players share, proximity, and the nature of competition as they will fight for similar customers. However, when understanding the sources of risk, retailers must examine the uncertainty surrounding AI adoption. Uncertainty exists when considering all the perceived benefits of AI; adoption yields no profits or business processes.

A study by Gartner (2017) reported that nearly 60% of companies were pivoting towards AI adoption. However, the interesting part is that in the same report, researchers are unclear on how AI adoption will improve business strategies. Additionally, Margherita and Braccini's (2020) second notions stipulate that there is much uncertain and unclear how AI technology could improve company practises. Such debates have unearthed potential risks that adopters must consider before adoption. Furthermore, researchers attempt to quantify expectations versus actual statistical gains of AI adoption to measure the risks. Brynjolfsson et al. (2019), in their attempt to solve this paradox, have acknowledged that there are many risks which may inhibit innovation adoption. This proves that business benefits are absent despite investment in money, time, and skills. Narrowing the literature discrepancies to the study context, retailers are bound to abort adoption because of high risks, industry acceptance and compliance concerns. It can then be strongly seconded that should risks be low, there are existing systems accepted unconditionally by industry peers, and there are not many compliance challenges, retailers are likely to adopt the AI-embedded technologies.

### 2.3.2 Organizational Factors

Consistent with the theories of innovation diffusion as well, organizational determinants refer to the resources or internal assets that a firm has, and those resources can facilitate or play a major role in the decision-making process of a firm to adopt an innovation or otherwise (Baker, 2012; Yoon, 2009). These resources or attributes include management’s support, firm size, finance, and skilled labour force. Many of these factors have been previously investigated. Still, their inclusion in the study was justified by the inconclusive nature and the attempt to contextualize them, as some of these factors are subject to geographic considerations. Despite the above reasoning, they have long been the primary critical organizational factors influencing innovation adoption.

*2.3.2.1 Management support*

Davenport and Ronanki (2018) indicated that it is very important for management to support any firm's structural changes because their positive attitudes towards change are essential, especially for resource allocation and technology maintenance. According to Müller and Jugdev (2012), it is important to have management backing when adopting IT solutions. Elbanna (2013) emphasizes the need for sustained and consistent management involvement from the beginning till the end of the adoption process; otherwise, the exercise might fail. Managers can allocate human, financial, and other resources to the adoption process and ensure successful implementation (Lui et al., 2010). Davenport et al. (2019) agree that this complex digital paradigm shift requires pure commitment from everyone within organizations, but managers are at the focal point as they detect proceedings. A positive attitude and the manager's technical knowledge are also required (Marr, 2019). This also aligns with Taherdoost's (2019) sentiments, who believe management support does not solely lie on managers availing resources. Still, it's also about their skills in heading the firm's adaptations to advanced technological developments such as AI.

Additionally, Garrison et al. (2015) view management abilities as intangible assets that are a prerequisite in adopting AI-powered technologies due to their rapid evolvement and complexity. However, this can be a subjective factor considering that managers may not have the skills and can be reluctant to upskill, given past literature suggesting that the technology-related educational route is very challenging. Nevertheless, it can be strongly interpreted that a manager's involvement, ability to adapt and positive attitude towards digital transformation is positively linked to innovation adoption.

*2.3.2.2 Technical capabilities (skilled personnel)*

Rosero et al. (2020) refer to technical capabilities as physical attributes that a firm possesses and are necessary for AI adoption. They represent firms' overall resources for AI integration foundation (Wang et al., 2016). Garrison et al. (2015) expand the technical capability scope by including intangible assets such as employee technical knowledge, IT infrastructure development, integration strategies, and communication processes that can effectively facilitate the easy integration of new technologies. As a key factor influencing AI adoption, these may be subject to compatibility concerns as firms have to examine their existing infrastructure and determine possible opportunities for integration (Garrison et al., 2015). Those arguments are consistent with

Taherdoost's (2018) sentiments, who indicated that past technology infrastructure or systems play a critical role in accommodating the new age of technology and are not easily disposable. Thus, companies with strong technical capabilities can infuse new technology with ease or limited challenges. "Strong technical capability reduces the complexities of integration and allows IT department to deliver AI technologies rapidly and efficiently" (Chen et al., 2021, p.42). Technical capabilities are positively related to adoption (Yoon, 2009). Considering that IT-related skills are scarce in South Africa, many companies may suffer in this regard. More so, such conditions have affected the adoption confidence level as most of these challenges are costly to overcome individually, whereas little government assistance has not made it any easier (Dubey et al., 2020).

#### *2.3.2.3 Firm Size*

Organisations can be measured in different formats (Bachmann et al., 2021), and size is one of the ways to measure firm size. Karlsson (2020) stipulates that size can be informed by several assets (physical and intangible), employees or in financial terms. The researcher quantified this construct through the number of employees for the study. This means firms with over 100 employees are considered big, whereas those with less than 100 are small. Thus, size has been investigated in many past studies on technology innovation boundaries and is regarded as one of the top indicators of organizational complexities when adopting AI. Furthermore, past literature overly suggests that the bigger the firm size, the likelihood of AI adoption (Sayginer & Ercan, 2020). This has been taken from views that larger firms, compared to SMEs, possess the skilled workforce essential for integration (Rosero et al., 2020), have the financial backing since AI is costly and can create accommodative structures for AI applications within their infrastructure (Rao & Verweij, 2017).

Therefore, large organizations are positively linked with adoption. Baker (2012) argues that despite extensive research on the size, inconclusive relationship arguments exist between technology adoption and size. Size is deemed a crude proxy because some systems or applications adopted are not correlated to size (Marr, 2019). Furthermore, a series of discoveries indicate a negative relationship between size and AI adoption, especially considering systems like cloud computing (Alhammadi et al., 2015). Small companies can also acquire AI-powered innovations tailored for small-scale operations.

Furthermore, there are now open-source tools which firms can adopt at little or no cost, such as data analysis, marketing, and web creation applications. This means boundaries surrounding size as an important measure for innovation adoption have been destabilized by the emergence of AI. The new wave of technological patterns is non-discriminatory, and developers are coming up with tailor-suited innovations to accommodate smaller firms. However, Salah et al. (2021) argue that this is subject to industry affiliation as some industries require huge, automated machinery for production as they serve a bigger clientele. Rust and Huang (2020) lament that regardless of industry and size, the artificial intelligence tools used are closely related, if not similar.

#### *2.3.2.4 Financial stability*

AI technologies integration processes and infrastructure are costly (Rao & Verweij, 2017). Heavy financial investments are needed for firms to adopt AI successfully (Kruse et al., 2019). This is regarded as the first element management deliberates on because every project needs a budget (Salah et al., 2021). Most firms fail to adopt AI because of the cost associated with the adoption process (Baker, 2012). However, Marr (2019) argues that some AI applications have become free to use, although they have limited features. Financial stability is closely linked with size and is negatively related to adoption. As controversial as this factor is, the reality is that most firms have failed to adopt AI innovations due to the high cost of purchase, integration and or maintenance.

Additionally, in the global south, where a healthy digital ecosystem is missing, which could have facilitated partnerships and cost-sharing propositions of AI technologies, has contributed to low AI adoption rates. In the Middle East, suppliers have engaged through their professional boards to create a customer-centric industry strategy which progressively combines operations, production, and auxiliary services, that is, marketing, sales, and customer care to achieve value addition and increased customer retention for retailers through digital resource sharing (Salah et al., 2021). This move has been celebrated by many in the region as, most importantly, it reduces acquisition costs and improves the chance of innovation (Kinkel et al., 2022). This indicates that AI technologies require hefty financial investment, and that’s why it will influence AI adoption always.

#### *2.3.2.5 Amount of slack resources*

The number of slack resources available also influences innovation adoption within firms. Slack resources are those complementary assets which firms have, such as physical space and support structures (Baker, 2012). Rogers (1995) earlier indicated that the availability of slack resources encourages adoption. However, recent extended work suggests otherwise. Instead, researchers believe that technology adoption can happen in absentia of slack resources because of the nature and rapid developments of the latest technologies (McAfee, 2014). Although some firms may deem their existence helpful and desire them, their absence means nothing (Tornatzky & Fleischer, 1990).

### 2.3.3 Environmental Factors

Environmental factors include industry norms, government intervention, regulation, and competitors (Oliveira & Martins, 2011). External environmental factors can encourage or create barriers to adoption (Gibbs & Kraemer, 2004). Baker (2012) expresses that the factors which fall under the environmental sphere, the organisation itself has no control over and, in most cases, is forced to behave in a certain way under the “norm banner”.

#### *2.3.3.1 Government Involvement*

Government policies are vital in invigorating IT innovation development and adoption (Tariq et al., 2017). Nam et al. (2019) state that most researchers have classified government intervention as a catalyst for AI integration. The designed regulations can remove or implement barriers to introducing new IT systems. The rapid development and disruptive nature of AI technologies, issues surrounding security, privacy, biases, and social ethics have been a concern when firms think of adopting (Marr, 2019). AI needs a well-aligned regulatory environment. However, governments are uncertain as AI is a new phenomenon in many countries (Dora et al., 2022). Agrawal et al. (2019) assert that state support provides a conducive territory for AI structures and will facilitate integration while guarding against potential AI hazards. Equally so, the government is the regulator, initiator, and supporter of digital transformation as their policies may determine adoption, their support through incentives or financial rewards and their role in creating the digital infrastructure for easy integration influences the adoption of innovation (Nozari et al., 2022; Chen et al., 2022; Ali-Abbasi et al., 2022). The government must regulate whilst creating conducive digital environments.

### *2.3.3.2 Market Uncertainty*

Market uncertainty factors arise from the lens of stiff competition, complex demand for products by customers, and customer loyalty levels, irrespective of the fact that all those factors are external, and the firm has no control over them, but they can impact their activities and performance (Rust, 2020; Huang & Rust, 2022). Brynjolfsson and McAfee (2017) believe AI is still in its infancy stage. Hence, firms have shortages of experienced IT professionals and technical personnel (Davenport, 2018). AI potential cannot be ignored; its footprint already shows a strong vitality while giving companies more competitive opportunities (Kaplan & Haenlein, 2019). For example, despite immaturity, chatbots and voice assistants increase efficiency and reduce labour costs for firms (Hildebrand & Bergner, 2019). Data privacy and AI ethics are now major concerns that create uncertainty as companies are obliged to protect customer data and use innovations that are ethical to society and humans (Kaplan, 2022).

### *2.3.3.3 Competitive Pressure*

Many scholars suggest that competitive pressure is one of the major driving forces of AI technology adoption within industries (Rust & Huang, 2020; 2022). Adopting new technology is commonly viewed as a strategic competitive tool in the marketplace (Martin & Golsby-Smith, 2017). According to Porter and Millar (1985), innovation can change industry structure, manipulate rules, give an advantage to players for new means to outclass rivals and change the nature of the competitive environment. Pressure is visible when other industry peers adopt certain technologies, making the company adopt them instantly to remain relevant in their competitive space (Oliveira & Martins, 2008). The benefits and potentials of AI, such as product improvement and competitive advantage, drives AI adoption desire for other firms (Chen et al., 2021). However, some recent scholarly discoveries have created a digital divide (Youssef et al., 2022). Large corporates who enjoy the economies of scale and have the finances, skills, and infrastructure to integrate and utilise AI technologies fully are the ones enjoying the benefits and thus suppressing the SMEs to suffer as they don’t have equal resources to compete at that highest level (Schoeman, & Seymour, 2022). This is the digital inequality which many regulators are failing to solve (Saruchera & Mpunzi, 2023). In South Africa, where most companies are SMEs, and the food retail industry is dominated by fewer large firms (oligopoly), this could be another cause of the digital divide emanating from competitive pressure.

*2.3.3.4 Vendor participation*

The generic stand is that most firms do not have all the internal technical and digital transformational expertise to promote and manage AI integration, hence the need for collaborative partners and IT vendors to assist (Kroll et al., 2018). Kleibrink et al. (2018) discovered that vendor involvement plays a significant role in adopting AI. Danquah and Amankwah-Amoah (2017) assert that vendor partnership has been statistically justified as one of the critical elements for innovation adoption. Suppliers play a unique and significant role in AI; they bridge internal gaps in organizations. They also offer other important AI-related services in the digital ecosystem (Columbus, 2019). A healthy digital ecosystem means information, skill, and knowledge transfer, enabling smooth digital transformation. However, there are debates surrounding the support of vendor participation as an important determinant because most AI tools, particularly for marketing purposes, are once-off bought and are tailor-made; hence, there is no need for continued support (Nozari et al., 2022). Furthermore, (Dora et al., 2022) argue that systematic digital ecosystems lead to a lack of creativity within industries as companies are likely to adopt similar technologies, thus causing stagnation in technological advancement as they are likely to source from the same supplier. Therefore, such contrasting views need careful attention when deciding on innovation adoption.

## 2.4 THE MODERATING MECHANISM

Little et al. (2007, p.207) defined moderation as “the changer for a relationship in a system”. Bhandari (2020) postulates that the moderation mechanism not only does it change or shapes the relationship direction but also influences the intensity of the two variables. Deduced from the above definitions, the moderating variable (moderator) acts upon the relationship between two variables (AI technology adoption and marketing strategy outcome) and changes the direction or strength. Bhandari (2021) asserts that moderators provide the researcher with a judgemental basis for external validity by identifying the limitations of when the relationship between variables holds. The study identified competitive intensity as the moderating variable. The research aimed at analysing the role of competition in the food retail sector and how it can influence firms to adopt artificial intelligence tools.

### 2.4.1 Competitive Intensity

Competitive intensity is the pressure exerted by industry peers on one another. Porter (1979), the father of the 'five forces framework,' stated that competition is healthy within industries as it acts as an impetus for innovation and creativity. Therefore, competition drives efficiency and effectiveness for individuals and firms while encouraging them to improve. According to Porter (1979), several factors (elements) may lead to competitive pressure among firms.

One of those influential factors is cost. There are so many costs which firms may face, such as high fixed costs or storage costs which may fuel the rivalry. For example, the high fixed cost may increase product prices, but competition intensifies once prices drop. Another factor is product differentiation. Competing goods like food give little room for differentiation as firms compete for the same consumers; hence competition is stiff. As a result, this may strengthen the relationship between AI technologies adoption and marketing strategy outcomes as firms will look for innovative ways to increase sales and become profitable in such a highly competitive market. Lastly, another factor is the concentration level. Highly concentrated industries are likely to be highly competitive, whereas oligopolies or monopolies are likely to be less competitive.

It can be argued that Porter’s competitive forces are valid but must factor in current developments and include the technological aspect. The rapid and continued increase of AI in retail has disrupted modern competitive levels and is now viewed as a catalyst for the increased competitive dynamics. By adopting the appropriate AI-powered technologies, a retailer can improve their performances by realising an increase in profit margins; they reach greater heights of effectiveness and efficiency while ensuring they retain their competitive advantage (Moghavvemi, 2012). Considering the rapid way data is generated nowadays, therefore, to fend off competition from rivals in this dynamic competitive landscape, firms must obtain valuable data. That data is gathered through engaging AI tools as they make it a prerequisite for decision-making (Davenport et al., 2019). Hence, industry concentration levels may determine the relationship strength between AI adoption and strategy outcome. However, Zuhroh (2019) argues that concentration is an inconclusive measurement parameter as competition levels tend to be high where fewer larger firms are involved considering the nature of the financial stability, size, and customers they serve.

As Porter and Millar (1985) long indicated, competitive advantage is realised when the value addition exceeds the cost of production. Therefore, because AI has the potential to minimize costs whilst increasing the value of a product through product quality and reduced purchase price, this intensifies competition and forces retailers to adopt AI for their marketing purposes. Stiff competition makes retailers look for innovative ways to fight competition, and the current best solution comes from AI. Chatterjee et al. (2021) establish that rare resources characterized by irreplaceability, expensive, valuable, and difficult to copy perfectly and organisational capabilities to be flexible, adaptative to change and agile lead to sustained competitive advantage. To achieve sustained competitive advantage in the intensely competitive industry, retailers must be able to implement which can be supported by the internal strength of the organisation and improve on their internal flaws too, which allows them to neutralize threats (Moghavvemi, 2012). In that regard, AI is advocated as the necessary and critical input retailers adopt to realise competitive advantage. Therefore, AI can be deemed a reliable source to deal with the intense competition prevailing in the retail sector. Thus, pushing the supported narrative that competitive intensity strengthens the relationship between AI adoption and strategy outcomes and positively improves outcomes.

## 2.5 TYPES OF AI RETAIL TECHNOLOGIES

There is more excitement surrounding the potential of AI than the level of implementation itself in marketing (Cannella, 2018). Davenport et al. (2019) argue that such discrepancies diminish as most marketers integrate AI into their operations. Several tools and applications have been widely used by marketers regardless of industry. Al-Naimat et al. (2020) state that marketing is the 6$^{th}$ biggest industry adopting AI and the fourth biggest in cases relating to resources spent on AI innovations. Although, due to the lack of literature in South Africa, just like in many African countries, AI in marketing remains vague (Accenture, 2017). The disconnect in implementation and promise serves as an indicator for possible adoption. Many industries are grabbing the opportunities, and so should retail marketers (Cao & Li, 2018).

With AI being more easily integrated, companies are taking different technologies to solve their challenges. Despite a few companies robustly integrating AI systems, some have taken the opportunity to pilot rather than be spectators, while others are adopting at a smaller scale (Grewal et al., 2020). To visualize this, the researcher created a low, medium, and high scale based on adoption level (intensity) to determine which AI technologies retail marketers can utilize. Adoption intensity is the degree to which AI technologies are integrated to play a critical role in influencing retail marketing strategy outcomes. The scale is consistent with the theories of diffusion, backed by the views of other scholars that low-level adopters are likely to experience limited benefit, although associated with fewer barriers.

In contrast, high-level adopters are likely to realize full potential benefits despite encountering huge barriers to adoption (Guha, 2021). On a more critical approach, adoption intensity levels provide evidence that not all firms can adopt available AI tools. Zolas et al. (2021) indicate that in their research on AI applications, a hierarchical pattern is observed when adopting sophisticated technologies and basic applications core-exist within firms. For instance, they claim that communication technologies with low-level basic integration will be present where cloud computing technologies with high levels of digitalization are applied. Contradictory to the above observations, Brynjolfsson et al. (2019) state that despite the findings of key technologies being closely interlinked with certain adoption characteristics such as cost, finance, and firm size, amongst others, in their study of AI and adoption influence on critical industries, some substantial heterogeneity pattern present cannot be justified. Therefore, such different views present scholarly gaps to be exploited, as there is a need to understand the gaps. However, Marr (2020) believes user demands and readiness determine adoption patterns.

With the myriad AI technologies marketers can adopt, firms can apply many innovations to improve their marketing strategy process. Determining which AI innovation to be applied requires an internal in-depth organizational analysis (Mozeryte, 2019); however, for this study, the adoption intensity levels provided an overview of the characteristics and typical AI systems adopted by retail marketers.

### 2.5.1 Low-Level (Intensity) Adoption

Low-level adoption is characterized by third-party AI solutions that do not need huge resources to implement and manage. The resources mainly include time, money, and expertise (Baker, 2012). However, McAfee (2014) argues that AI technologies are a new phenomenon which requires a new set of skills, possibly non-existent with current personnel. Socioeconomic conditions of the global south may attribute to the lack of knowledge. These technologies usually have fewer adoption barriers, have limited benefits, and are deemed less powerful. Ma and Sun (2020) indicate that these technologies do not form the company's core value proposition. Soni et al. (2019) state that most of these technologies have a small monthly subscription fee, are freely installed and possess other readily available solutions. These include:

#### *2.5.1.1 Google search engine optimization (SEO)*

SEO is the process of driving traffic and improving the volume of visits to a company's website through search results (Li et al., 2017). Marketing personnel use Google SEO for information and visit competitors' online presence for environmental scanning reasons. Online data search is a ubiquitous and equally important practice for digital retailing (Wang et al., 2011). Optimising the search engine is a crucial link between users and content owners. SEO occupies an important position in the online world, mainly in marketing activities, as it plays a significant role in advertising (Das, 2021). As much as SEO has been around for a while, the recent developments of artificial algorithms attached to it have made it unique and gained momentum in the adoption of late (Lewandowski et al., 2021). Companies fight to be on the first page of the search engine as that increases chances of notice and client retention. It alludes that for SEO to be more profitable, companies need to invest in words which are attractive to users, and the brand must be trusted by the consumer landscape as Yao and Mela (2011) indicate that marketers must produce a vigorous systematic model of keywords marketing which covers customer behaviour trends. The cost of this exercise is usually low, where in some cases, companies have hired an SEO specialist to provide that dynamic marketing keyword model. Retailers have embarked on SEO exercises, which givse them a fighting tool in the online competitive world. However, Das (2021) states that SEO is for digital trading and physical shopping, as customers will go to the physical store guided by the adverts seen online.

#### *2.5.1.2 WhatsApp*

One of the most sought-after consumer communications domains across academics and industry is the AI-based customer communication domain (AIBCC) (Ganesha & Aithal, 2020). Overly, it is asserted that access to customer data via effective communication channels gives one some competitive advantage (Aithal, 2015). With the growth of automatization in the world, increased uptake of AI technologies and the competitive nature, companies are resorting to AIBCC applications to gather data which is then used to drive data decision-making processes. AIBCC applications commonly used are WhatsApp, Facebook, Instagram, and Twitter (usually referred to as social media).

WhatsApp is used for text, imagines, voice calls and video calls. According to Statista (2021), WhatsApp has 2 billion monthly active users making it the number one used communication platform. Sharma and Srivastava (2017) assert that retailers are the beneficiaries of WhatsApp because it will allow businesses to trade, track and automate responses to enhance clients' value. Fast forward to 2021, we have business WhatsApp, where businesses can advertise, gather client databases, and respond or advertise to existing firms' contacts. In India, the application introduced payment features in 2021. Credit goes to AI through ML, which tracks and filters clients' behaviours and recommends products for marketing purposes. Canhoto and Clear (2020) indicate that AI has made WhatsApp a viable application for marketing and data generation, which management can utilize to improve their sales. Moreover, the application has automated responses for business functions, providing businesses with an extra marketing tool as customers will think they are communicating with an actual human.

#### *2.5.1.3 Facebook*

A parent company to WhatsApp, founded in 2004 by Mark Zuckerberg, Facebook has become one of the most accepted social network platforms for internet audiences globally, with over 2, 85 billion users as of July 2021 (Statista, 2021). AI has contributed to the growth of Facebook numbers because it has a digital marketplace where retailers trade; therefore, many retailers utilize the forum. More so, due to machine learning on posts (pictures and written), Facebook algorithms learn user patterns, identify friends, and recommend products according to those patterns, thus, increasing reach. Retailers have adopted this platform and paid certain subscriptions in some circumstances for filtering and recommendations to enhance their marketing strategy outcome. Ramsaran-Fowdar and Fowdar (2013) assert that Facebook communities, such as the marketplace, are critical for marketers because they understand user tastes. Thus, creating an opportunity for segmentation and product targeting marketing strategy formulation, which translates to effective marketing. The Facebook marketplace can filter using age, types of products, location, and gender, to name a few. To prove its commitment to the continued application and use of AI, the company changed its name to Meta in 2021, becoming an all-AI-backed firm with different subsidiaries.

#### *2.5.1.4 Google: My Business Account*

Google my business is an online tool which allows businesses to optimize profiles and manage their account digitally (Das, 2021). This is free to use the platform, but firms must pay a certain fee if they need more features. This technological breakthrough allows firms to be competitive in the digital environment. Food retailers, not excluded, can utilize this platform to increase reach and access to as many customers as possible. Integrated with SEO, it considers the location, analyses customer background, and recommends products for searchers. Crediting AI through machine learning, filtering and recommendation features have been the most successful features of the google my business platform. The platform has enabled food retail SMEs with digital fighting tools whilst levelling the field caused by this digital era (Chui, 2017). However, the digital divide continues to be a major concern as some firms pay for all features which enriches their competitive edge.

#### *2.5.1.5 Adobe Creative Cloud (Photoshop)*

This is a creative design software used to enhance image types, quality, and colour. Duncen (2021) emphasises the software's creative, editing and content creation prowess while indicating how AI has integrated the software and given marketers a marketing tool. Often used to edit picture content with its comprehensive functions of drawing, retouching, and repainting tool (Sharma & Tiwari, 2021). For marketing purposes, Photoshop has evolved thanks to AI advancement (Fajoye, 2021); it has enabled video editing, 3-D content and image analysis functions that may appeal to clients while improving reach. With the continuous improvements of the software, marketers have the leverage to produce attractive content which may influence purchasing behaviour (Duncen, 2021). Thus, creative content creation is critical in marketing as appealing content lures consumers. The software usually has a once of purchase fee, which is of industry standard and thus regarded as a low-level adoption tool despite its commendable features and contribution.

### **2.5.2 Medium Level (Intensity) Adoption**

Medium level adoption phase is characterized by AI applications designed to handle medium-oriented tasks. Cannella (2018) suggests that some medium-level use cases involved AI reducing human involvement in labour and time-intensive practices but still require human input and supervision. Davenport et al. (2019) believe medium-intensity AI systems use moderately robust technological power in certain business functions; for example, in marketing strategy, it is for price prediction through data analytics. These systems are frequently used in marketing because of their interactive nature to connect with customers rather than playing an important role in overall company strategy formulation (Jarrahi, 2018). Gabriel (2019) argues that these systems play an integral part in overall company strategy design for SMEs who are not resourceful. Medium-level adopted AI technologies require some medium-level financial resources, infrastructure, and expertise due to their complexity attribute (Eriksson et al., 2020). These include the tools explained below.

#### *2.5.2.1 Customized Chatbots*

Since early 2016, Chatbots have been portrayed as an important technological development and trend (Baier et al., 2019). Chatbots are "computer software programs that interact with users using natural language processing" (Shawar & Atwell, 2007, p.29). The language processed is either in text or speech (Rese et al., 2020). Therefore, in simpler terms, these chatbots are deployed to identify phrases and words with the objective that they reply with content useful or relevant to consumers on common questions. Retailers have been tipped to be one of the biggest beneficiaries of chatbots as they improve customer service, sales/marketing output and order processing thus, enhancing customer experience (Mindbrowser, 2017). Chatbots are often accurate, and it can seem like one is chatting with a living human online (Nadikattu, 2016). According to Ashfaq et al. (2020), chatbots have a 46% success rate and are 78% effective in responding to frequently asked questions. More so, in the USA, Mindbrowser's (2017) research on retailers' application of chatbots discovered that it is likely to increase customer service by 95%, sales/marketing by 55% and order processing by 48%. Such statistics indicate the impact and probably continued use of chatbots by retailers. Equally, in a 2016 chatbot efficiency study, 61% of consumers believed chatbots will be part of their lives for the longest time (Aspect Software, 2018) and are often internally designed.

However, Mindbrowser (2017) argues that chatbots are not all glamourous as they can be costly for adopters, particularly large retailers with different customer dynamics, because their programming for different products requires huge investments. More so, some customers may reject chatbots as they cite inhuman and immature and thus prefer physical shopping to interacting with natural humans (Chatbots Magazine, 2019). It is, therefore, important to understand the customer's nature. This is crucial in countries like South Africa, with many online fraudsters and a reluctant society regarding technology integration (Oosthuizen et al., 2020). Notwithstanding the abovementioned challenges, the benefits of chatbots prove that this technological innovation can help food retailers with their marketing efforts. Due to the online shopping increase in South Africa, many retailers have begun utilizing chatbots as marketing and communication tools.

#### *2.5.2.2 Virtual Assistant (Agents)*

Virtual assistants or agents, as referred to in some cases, are human-like embodiments who solely respond to information through verbal or non-verbal instructions (Kinsella & Mutchler, 2018). Virtual agents are prescribed to sense the digital room and respond to customers' demands. That sensing capability uses AI through algorithms to differentiate demands and act accordingly. For example, voice agents can help a user perform multifarious tasks like checking their schedule and web searches are made to be customized along with the sending of commands to a different application (Rao & Verweij 2017). Typical voice agents commonly used worldwide are Apple’s Siri, Google Assistant and Amazon’s Echo (Savago et al., 2019). Because of the increase in digital interaction and online retailing (Marr, 2020; Keitzamann et al., 2018), retailers have adopted virtual agents who assist shoppers online. Virtual agents help shoppers with the best alternative recommendations and decision-making and can facilitate transactions/purchases (Mindbrowers, 2017). AI is essential in the working and performance of these agents since they can learn from a single user and their interactions (Köhl & Gremmels, 2015). Chatfuel is the most adopted application in terms of user traffic, widely used to create over 360,000 voice agents serving more than 17 million users (Root Info Solutions, 2018). Chatfuel targets marketing campaigns, promotions, and simplicity (Rao & Verweij, 2017). Sayago et al. (2019) brings interesting views on how virtual assistants have played a pivotal role for older adults who might find it difficult to operate smartphones; hence voice recognition is a highly appreciated feature.

As previous studies have shown embedded communication abilities for virtual agents, somehow, they have been criticised for lack of emotional intelligence. Poushneh (2021) postulates that virtual agents struggle to express autonomous emotions such as sadness, disappointment, or joy. However, Kim et al. (2018) indicate that most computer programmers and scientists work on such social features through their machine learning algorithms improvements and design. All the above benefits present an opportunity for adoption by retailers as they are likely to increase their customer engagements and improve user experience on online retailing platforms.

#### *2.5.2.3 Automated Email and Newsletter Marketing*

With digital marketing having gained momentum over the years (Nam et al., 2018), fuelled by the Covid-19 pandemic over the last couple of months (Guha et al., 2021), email and newsletter marketing has rapidly increased as sellers try to stay in business (Paschen et al., 2019). However, this is not a new trend, as email marketing has been available for a long time and is widely used by companies. The benefits of email marketing are well documented. For example, in the USA, a study by Direct Marketing Association recorded a return on investment (ROI) from email marketing of $28.50 for every $1 spent, four times more than direct mail/post-marketing ways (Schiff, 2012). Email and newsletter marketing combined was expected to grow by 10% in 2016. AI was cited as the catalyst for this growth as it can produce automation features, and its machine learning algorithms will forecast potential users (Van-Boskirk, 2014). This was clear from long ago that companies will not abandon email and newsletter campaigns.

Therefore, currently, AI systems have the power to email company products regularly and randomly. Considering the increase in digital usage and customer interactions, email marketing has succeeded as the target audience receives those adverts instantly. Aufreiter et al. (2014) argue that this marketing model acquires more customers than Twitter and Facebook. Hartemo (2016) cited the need to understand when email marketing can be viable. However, during this digital consumption time, email marketing facilitated by AI can be more useful since online trading has increased, and customers, to their convenience, always check products online. Retailers can utilise automated AI email marketing campaigns, meaning continued advertising exercises. The messages are more filtered as the content closely aligns with customer attributes and demands (Hartemo, 2016). The data management and personal identity through machine learning algorithms make email marketing more suitable during this digital era as there is so much data to analyse, which plays a pivotal role in decision-making for email distribution and content filtering on newsletters.

### 2.5.3 High-Level (Intensity) Adoption

This level of adoption is characterized by companies that have adopted AI technologies or adopt AI intending to make them an integral part of their business functions. Marketers adopt AI to automate and apply it in their marketing activities fully. AI becomes the core value proposition in this phase, directly affecting the overall strategic design and other marketing activities (Eriksson, Bigi & Bonera, 2020). Cannella (2018) indicates that these AI-powered systems are usually highly customized and in-house built. Huang and Rust (2018) postulate that these are robust systems with some cutting-edge technology capabilities coiled to company operations and are very costly.

Moreover, these require some heavy structural changes. Acemoglu and Restrepo (2017) emphasise that these changes take time. However, decision-makers in an organisation will then initiate ways that economize those highly expensive resources. Moreso, with these systems, firms don't only evaluate and reconfigure their internal processes and operations but, in most cases, include the distribution and supply chain as the disruptive magnitude is high. These may include data analytics, and CRM systems, amongst others.

#### *2.5.3.1 Big Data Analytics*

The success of AI lies in the availability of big data (Manyika et al., 2017a). Big data analytics refers to gathering analytics models and technologies specifically programmed to analyse large data sets and assist decision-making (Ridge et al., 2015). Retailers apply big data analytics to improve their target marketing exercises, gain insights, and understand purchasing behaviours (Kaplan & Haenlein, 2019). In the early 2000s, when data was generated, many stakeholders didn't see its use. However, some companies in the retail sector, like Amazon and Walmart, used it to understand their customers (Haenlein et al., 2019). Nowadays, data is no longer used to understand customers only; it has become a critical input component for decision-making utilised at all stages of the retail value chain (Lee et al., 2018). This has brought numerous benefits, such as improved productivity, competitive advantage, and increased sales (Davenport et al., 2019).

Despite the perceived benefits of big data analytics, a few have adopted it, while many have been slow to adopt it (Lekhwar et al., 2019). The main challenges for the slow adoption have been attributed to the cost of the AI systems, insufficient data, and skilled personnel to effectively utilised data analytics (Huang & Rust, 2021). The major focus on big data analytics has been on algorithms and systems development used to understand customers in-depth for insights and decision-making (Yadav & Kumar, 2015; Chen & Zhang, 2014); however, on retailing in South Africa, less information is available about big data application (Ridge et al., 2015). Many systems have been developed and utilized in the marketing space for data analytics and storage purposes, and these include Java, Python, R, SQL, Power BI, Qliksense, and Tableau (Marr, 2019; Grus, 2019). Big data equips marketers with the predictive power essential for sales planning and success. Patterns on the preferences of consumers are unearthed through data analysis.

Furthermore, narrowing down big data analytics applications to the food retail industry in South Africa, there has been a visible increase in demand and application of big data analytics. This trend is visible as there has been so much demand for data analysts in the labour market since they possess the necessary technical skill to harness data. Data analytics does not solely lie in the company's abilities to purchase the above systems but also in obtaining the rightful personnel with the necessary expertise, which in this case are data analysts. Figure 2.2 illustrates how retailers can use big data for different purposes.

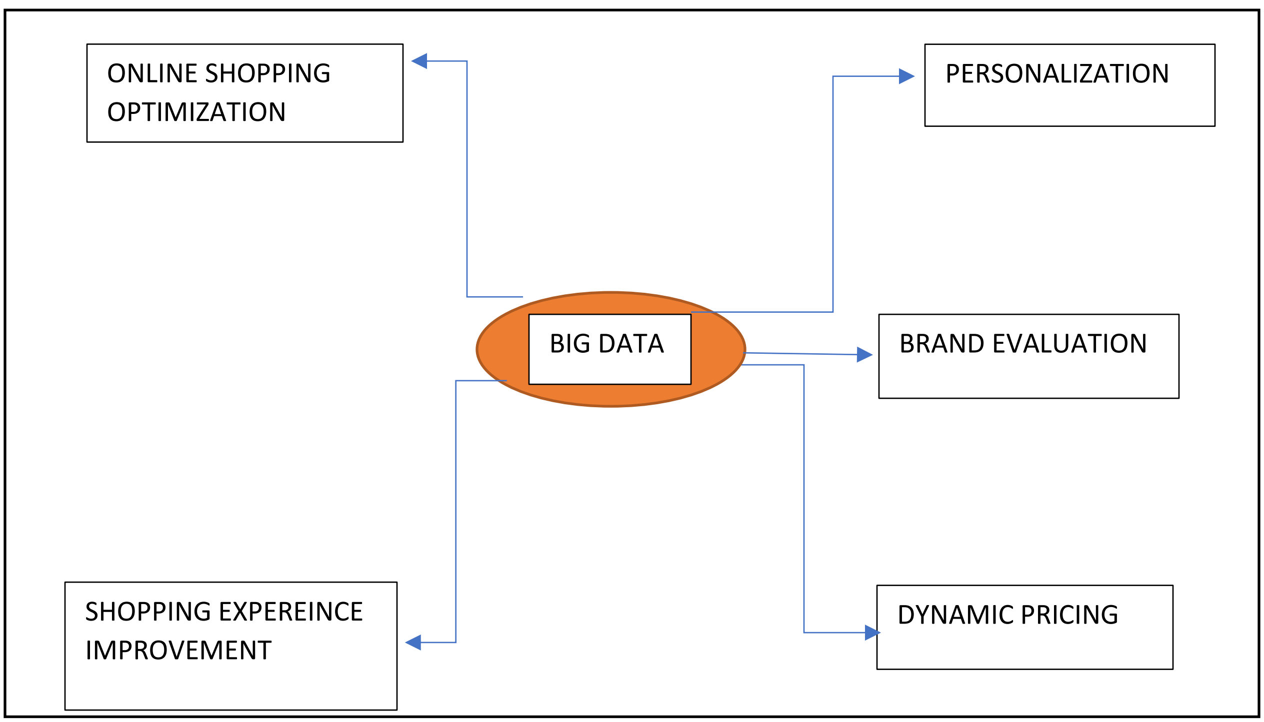


**Figure 2.2: Big data application in the food retail sector**
**Source: QBurst (2015)**

Figure 2.2 indicates that big data normally facilitates clients' personalisation. It helps firms connect with their clients in a more intimate and unique format, which builds a feeling of belonging and familiarity that often leads to sales. On dynamic pricing, big data analytics often offers retailers predictive prowess to deduce the appropriate prices for their products. Furthermore, as indicated in Figure 2.2, big data enables online shopping optimizations as firms can create and customize online stores to meet customers' demands more user-friendly and engagingly. Therefore, should that be achieved, retailers will likely maximise sales. Dubey et al. (2019) emphasise that when it comes to performance evaluation by retailers, they use big data. Normally comparative studies will be performed between physical and online stores. Equally so, when it comes to brand evaluation, big data analytics is applied through the lens of frequent purchases from similar customers; thus, decisions are taken to retain those specific customers continuously. Dzyabura and Hauser (2019) appreciate that many firms aim to satisfy their customers, which is evaluated through acknowledgement by customers of their continued purchases. Lastly, big data analytics is applied to improve the in-store shopping experience. QBurst (2015) elaborates that retailers' efforts to prioritise e-commerce must be transferred to in-store to retain those physical shoppers. The experience must be unique and appealing for shoppers; thus, big data analytics are applied to analyse their behaviour and purchase patterns.

#### *2.5.3.2 Customer Relations Management (CRM) Systems*

CRM technologies have been in existence for a long time. Still, the rapid burst of AI has given them a whole new dimension, giving retailers the strength to automate tracking, task digitalization, sentimental analysis, intelligent recommendations, predictive analysis, and image recognition (Cannella, 2018). Gray and Byun (2001) argue that CRM is not a technological system. Instead, it is a business process modelled strategically to manage customer relationships. Shang and Fen (2006) then argue that CRM is a technology assimilator integrated within business functions to build a lasting relationship with clients. For such reasons, CRM systems have become the core of customer management. Hence, they are expensive. Salesforce Einstein is the common CRM software used by marketers. Others include On-Contact, CRM 7, Oracle E-Business Suite CRM, Zoho Support, SAP CRM, RightNow, Microsoft D365, AWS, and CX.

#### *2.5.3.3 Programmatic Marketing*

Programmatic advertising is the automation of online buying through machines. Previously, online buying was a daunting task involving price coordination, redistribution channels, and much other information in advertising agreements, resulting in inefficiencies for marketers (Davenport et al., 2019). However, currently and thanks to AI, programmatic marketing has far changed the dimensions of digital buying by automating processes with the help of customer data to give meaningful insights, and marketers can deliver highly targeted and personalized advertisements (Chen, 2019). Retail marketers have taken similar routes and can now better their performance, efficiently deliver products, and segment according to individual demands (Rahimi, 2017). This is one of the most sophisticated programmes as it is usually in-house built and tailored for specific customers. Albert AI, Sales-fusion, Salesforce Marketing Cloud, Microsoft Dynamics, IBM Watson, and SAP are the common systems used for programmatic advertising.

#### *2.5.3.4 Personalized User Interface (IU) And Experience (IX)*

One of the most celebrated AI capabilities is personalising customer experiences and interacting with customers more personally (Kim & Duhachek, 2018). AI designs applications which can be utilized to personalize UI and UX, which are then adjudged to possess tremendous potential in enhancing client value (Sindhu, 2018). Cannella (2108) postulates that through AI integration within marketing activities, clients can interact with brands digitally, allowing businesses to optimize their websites and deliver according to individual consumer purchasing behaviours. AI-powered UI and UX have strong recommendation functions that most big retailers like Alibaba and Amazon utilize through past searches or purchases (Lee, 2018).

#### *2.5.3.5 Cloud Computing Technologies*

Cloud computing is an innovation which came into existence to ease reliance on local servers or personal storage and other computing resources (Armbrust et al., 2010). Cloud computing refers to delivering computing services such as storage, processing power, databases and applications, amongst others, over the internet. This innovation allows users to access and utilize these resources remotely through a network of servers hosted on the internet. Considering the food retail sector, where a lot of data is generated, cloud computing services have proven pivotal in data storage, processing, and database management. Aligned with the demands of retail marketers, cloud services come in various models, that is, Infrastructure as a Service (IaaS), which provides virtualized computing resources for users (Amazon Web Services, 2017), Software as a Service (SaaS); which delivers software applications over the internet, accessible through a web browser or client application, eliminating the need for installation and maintenance for users. SaaS is the commonly adopted service for clients with large databases who do not have the infrastructure to handle their data (Makhlouf, 2020). Lastly, Platform as a Service (PaaS) is a complete revolution on the development and deployment of online platforms that firms can easily access (Amazon Web Services, 2017). Retail marketers can greatly benefit from integrating cloud computing services, as it offers a wide range of advantages, including flexibility, cost efficiency, and reliability.

## 2.6 THEORETICAL FRAMEWORK

Past studies have theoretically examined and come up with different complementary and competing ways to understand the factors that influence adoption (Al-Rahmi et al., 2019). The common theories scholars and practitioners utilise include the Innovation Diffusion Theory (IDT), Technology-Organization-Environment framework (TOE), Institutional Theory and Paradox Theory. Baker (2012) believes these theories have the most influential theoretical background on innovation diffusion. Researchers have expressed satisfaction with developing an adoption framework with one or more adoption theories (Puklavec et al., 2014). Due to the extant literature around innovation/technology adoption theories, past studies suggest using one or more theories because of the similarities in characteristics. Most theories are an extension of the IDT theory, which seamlessly includes all innovation diffusion factors. Therefore, based on this background, the study employed the above-highlighted theories to identify the determinants of AI adoption. Based on the nature of the determinants identified, the theories adopted provided a basis for arguments and enhanced the study capabilities to explain contradictory and outdated factors which determined AI adoption.

### 2.6.1 The Innovation Diffusion Theory (IDT)

The IDT by Rogers (1983;1995) is viewed by many researchers as an important theoretical foundation mechanism for innovation adoption across industries (Baker, 2012). The theory was first designed in 1983 and later refined in 1995. Jeyaraj et al. (2006) indicate that the theory has existed for several years and formed the basis for technology adoption. Rogers (1995, p.2) defined innovation as “an idea, practice, or object perceived as new by an individual or unit of adoption”. IDT's primary focus is on innovation diffusion within organizations, which is “the process by which an innovation is communicated through certain channels over time among the members of social systems” (Rogers, 1995, p.10). Rogers (1995) refers to adoption as the decision institutions or individuals take to integrate innovation within their operations. The IDT is mainly applied to investigate innovation adoption-related issues which individuals, companies, or other stakeholders encounter, meaning it considers the individual, internal and external organizational environment (Puklavec et al., 2014).

Adopters possess different degrees of willingness to adopt innovations (Mannan et al., 2017). Innovations are characterized by certain attributes, viewed through the lens of adopters, often determining whether to adopt or not the prescribed innovation (Venkatesh et al., 2012). Rogers (1983; 1995) suggested that these innovation attributes are or at least must offer relative advantages, perceived compatibility, have low complexity, possess potential trialability and some observability which enhances widespread across industries and increases the rate of diffusion within structures. These characteristics are aligned with the technological factors which influence technology adoption. Each attribute aims to reduce uncertainty about innovation in relation to the expected gains of adoption for potential adopters (Ax & Greve, 2017). The generic view of IDT is that adopters would assess technological innovations on the anticipation of their identified attributes and postulate that innovations with favourable qualities will be adopted or increase the willingness to adopt (Chiu et al., 2017).

Additionally, the theory suggests that adopting an innovation (AI) successfully requires a manager's overall acceptance of change, a positive attitude towards the proposed technology, and a willingness to channel resources towards adoption-related activities (Carreiro & Oliveria, 2019). The organizational structure must be flexible and interconnected to allow idea-sharing within the firm (Yeh & Hsieh, 2017). In that case, the chances of successful adoption and implementation of AI are high. Taherdoost (2018) states that managers' positive attitudes and a flexible organizational structure favour innovation adoption. The above elements are attributed to the organisational factors which influence technology adoption.

Lastly, Rogers (1995) strongly believed that firms with greater knowledge about the external environment in which they operate are more likely to adopt an innovation. Commonly known as the PESTEL factors (Porter, 2008), however, scholarly advancement has changed the boundaries and dynamics of external environments, which adopters should consider now (Sun & Medaglia, 2019). With the current technological developments, external environment scanning has become more essential (Chui, 2017). The increase in data generation, robotics advancements and loss of jobs has created many obstacles which policymakers attempt to protect against (Dwivedi et al., 2019). Additionally, the industrial gaps AI creates where big IT and other retail giants only harness the benefits have become a huge concern (Sun & Medaglia, 2019). Data privacy and ethics-related issues are also visible (Desouza, 2018). Due to AI being a new phenomenon, industries are unfamiliar with its pros and cons; hence, it is necessary for external environment analysis (Wirtz, Weyerer & Geyer, 2017). The current external environment must be well examined as the failure or success of innovation adoption is mapped by it (Dwivedi et al., 2019). The above factors are consistent with the environmental factors which affect innovation adoption.

### 2.6.2 The Technology-Organization-Environment Framework (TOE)

IDT is the mother of all innovation adoption theories (Alharbi & Drew, 2014). Esteve et al. (2020) postulate that theories that have emerged after Roger's IDT are purely extensions or improvements of the IDT. Baker (2012) widely argues that one of the theories that emerged in the past, widely reviewed, and utilized as a basis for innovation adoption is the TEO framework by Tornatzky and Fleischer in 1990. The TOE framework acts as an organizational-level theory explaining that three distinct categorical elements influence innovation adoption decisions, and those are technological, organizational, and environmental (Tornatzky & Fleischer, 1990).

Technological influential factors describe internal and external technologies relevant to the organization (Baker, 2012). It involves all existing technologies the firm can utilise and is deemed relevant regardless of whether they are already in use (Ifeduba & Christopher, 2018). Those unused technologies are considered complementary and alternative technological solutions (Brynjolfsson et al., 2019). The availability of supporting or alternative technologies in the market is closely linked with adoption as they prove demand (Ming et al., 2018). Like in IDT, the technologies must have favourable features to encourage adoption. Technologies must be easy to use, benefit the company and be compatible with existing structures (Herath et al., 2020). TOE framework postulate that positive technological factor analysis outcomes increase adoption.

Baker (2012; Ganguly, 2022) explain that organizational context involves the analysis of features and resources of a firm that determine technological adoption. These characteristics include leader support, firm size, slack, number of skilled personnel, finance, communication processes and structure (Fan et al., 2020). The TOE framework suggests that the existence of linking agents across different functions is positively related to the adoption of innovation (Varian, 2019). Ansong and Boateng (2018) assert that attributes like top management support, proper communication structures, skilled personnel availability, and disposable funds may facilitate adoption, just like with IDT. However, factors like size and finance have come under scrutiny as the former is viewed as a crude proxy with no conclusive arguments linking it to adoption. In contrast, to the latter, researchers believe there are now less costly innovations which require little subscription fees for maintenance (Varian, 2019). Therefore, accounting for organizational attributes is crucial for innovation adoption.

Lastly, the environmental context contains the industry-related factors or issues influencing adoption. The existence or non-existence of technology service providers, regulators, competitors, and governments are examples of environmental factors which organizations must consider (Ali-Abbasi et al., 2022). The government's role in creating a healthy digital ecosystem is deemed a necessity. Technological changes have fuelled drastic changes in the legal systems, policy developments and employment protection acts (Sun & Medaglia, 2019). Automation has created industry gaps which result in unfair competition and practices (Brynjolfsson & Mitchell, 2017). However, on the flip side, innovation improves creativity, increasing competition and product quality (Rust, 2020). All these factors can act as barriers or motivators for adoption. Chui (2017) asserts that external environment attributes increase uncertainty. Therefore, firms need to consider all those externalities before adoption as they play a huge part in the overall automation adoption process (Marr, 2019). Recently, this technological turbulence has left governments overwhelmed and unable to devise proper regulations (Manyika et al., 2018). However, some authors agree that government intervention can be detrimental or beneficial for innovation (Ming et al., 2018).

### 2.6.3 The Institutional Theory

The institutional theory was propounded by DiMaggio and Powell (1983) to provide an external pressure-based framework for innovation adoption. The theory assumes companies adopt AI due to external pressures. The theory states that there are three types of external pressures to which companies succumb. These external institutional pressures are mimetic, coercive, and normative. All these pressures can constrain or facilitate technological innovation adoption (Dubey et al., 2019). Firms adopt technology for survival, legitimacy, and industry acceptance (Baker, 2012; Phuoc, 2022), and these factors constitute the source of identified pressures (Sun et al., 2018).

Mimetic pressure refers to the pressure that makes a company copy other companies' behaviours within their environment. When other companies adopt technology, it exerts pressure on the company, resulting in adoption (Ukpabi et al., 2019). Useful and successful innovations are prone to influence adoption positively (Soares et al., 2020). Coercive pressure is formal or informal pressure which may come in the form of invitation, threats or force and becomes evident when one company depends on another or from industry-culture expectations (Dubey et al., 2019). Stakeholders (suppliers, regulators, customers, and governments) can exert coercive pressures to find comfort for their needs (Srinivasan, 2002). Many organizations succumb to coercive pressures and adopt innovations for legitimacy and acceptance (Meyer & Rowan, 1977). Lastly, there is normative pressure, which the theory suggests that this pressure originates from the new norms and values learnt within its industrial environment across various sources. These sources may include the Internet, trade workshops and professional body seminars (Lou & Li, 2017). Because organizations learn new norms, they adapt to normative pressures by adopting innovations even if they do not necessarily need them (Dubey et al., 2019).

### 2.6.4 The Productivity Paradox Theory (PPT)

Solow (1987) founded Productivity Paradox Theory (PPT). PPT emerged due to the debates caused by inconsistent outputs of statistical benefits of applying ICT within business activities (Brynjolfsson et al., 2019). Country productivity is a significant subject for economies, mainly used to measure country growth (Polak, 2017), a foundation for firm decision-making and quantifying technology progress (Acemoglu & Restrepo, 2017). In attempting to quantify ICT's contribution to productivity, contradictory outcomes have been noted (Cirera & Maloney, 2017). Kohli and Devaraj (2003) summarized their empirical results from a meta-analysis of ICT contribution at the firm level and declared no productivity paradox. Dedrick et al. (2003) refuted the productivity paradox after their narrative review of research evidence from several sources.

However, Acemoglu et al. (2018) argue that the development and usage of ICT have increased by 70% since 1970 in the USA. Still, productivity has stagnated since the 1990s, given the potential attached to ICT. Cowen (2011), in his tests, concludes that accelerated technological growth is not realized. McAfee and Brynjolfsson (2014) suggest that a modern productivity paradox exists and could be due to a lack of information, mismeasurement, false hope, concentrated distribution and restructuring lags which is of the notion that it is perfect to be optimistic about technologies. Still, they also take time to mature and firms to realize the gains (Brynjolfsson et al., 2019). AI adoption paradox has provided the need to examine AI influence in any business function. The lack of conclusive arguments about the influence or benefits of AI adoption has created more debates about its potential (Baker et al., 2021). This theory is linked to technology adoption uncertainty, as most adopters would refer to, due to contradictory outcomes from the technocrats or ICT players. The adoption paradox can also be matched with the findings of Gartner (2017), who established that hype and expectations in real experiences hardly match over time.

Table 2.1 summarises all the theories and their contribution towards the study. The four discussed theories form a basis for the theoretical contribution of the study. These theories have been widely used in AI or innovation studies; however, based on other scholars' extensive use and conclusions, the researcher took an interrogative approach to select factors with inconclusive arguments when determining adoption. This approach enhanced the study's theoretical contributions as it aimed to contribute meaningfully to settling debates around subjective innovation determinants. Therefore, despite the theories providing a basis for AI determinants, a few subjective factors were selected for the study.

**Table 2.1: Summary of theoretical contributions to the study**

| Theory | Technological elements | Organisational elements | Environmental elements |
|---|---|---|---|
| IDT by Rogers (1995) | Complexity,<br>Relative advantages,<br>Compatibility,<br>Trialability,<br>Observability. | Positive attitude,<br>Management skill,<br>Organisation interconnectedness,<br>Flexibility. | Economic conditions,<br>Uncertainty,<br>Vendor participation,<br>Legal considerations,<br>social impact. |
| TEO Framework by Tornatzky and Fleischer (1990) | Easy to use,<br>Availability of substitutes,<br>Provides advantages,<br>Relevant technologies. | Internal infrastructure,<br>Skilled personnel,<br>Management support,<br>Financial stability,<br>Size,<br>Slack resources. | Regulation and Policies,<br>Competition levels,<br>Government role,<br>Data privacy,<br>Technology ecosystem. |
| Institutional Theory by DiMaggio and Powell (1983) | | | External Pressure:<br>Mimic,<br>Coercive,<br>Normative. |
| Productivity Paradox Theory by Solow (1987) | Effectiveness on the actual outcome. | | |

**Source: Author's Compilation (2022)**

## 2.7 INTEGRATION OF THE THEORIES FOR THE STUDY

In line with study requests, IDT, TOE framework, Institutional Theory and PPT were introduced to AI adoption literature to identify the influential determinants of adoption by firms and how questions surrounding the influence of AI can be answered. Fortunately, the innovation diffusion theories can simultaneously identify the crucial determinants because of their similarities. IDT, the primary source of those theories, focuses on major attributes that firms must possess to adopt AI (Sun & Medaglia, 2019). The TOE framework, which has been applied by many and viewed as an outright extension of IDT, distinguishes the factors by sub-uniting them into the Technological, Organizational and Environmental contexts (Dwivedi et al., 2019). The institutional theory brings a different dimension to the environmental factors, which asserts that companies do not normally adopt AI to achieve efficiency and effectiveness. However, they adopt due to exerted external pressures in the form of mimetic, coercive and normative pressures (DiMaggio & Powell, 1983) to achieve legitimacy and survival (Scott et al., 2003).

PPT, which brings a different element to adoption and the actual influence, is aimed at examining the influence of adopting AI technologies by retail marketers in strategy outcomes. Firms continue to adopt AI in a paradoxical environment caused by inconsistent outcomes (Brynjolfsson & Mitchell, 2017). Despite AI's optimism and promise (McAfee & Brynjolfsson, 2017), the sad reality is that AI has both success and failure stories (Marr, 2019). Therefore, the study seeks to answer the modern paradox in the retail marketing sector by empirically examining the influence of AI adoption on retail marketing strategy. The PPT is consistent with different literature, which indicates inconsistencies in outcomes, the uncertainty surrounding the different systems that are useful for retailers, and the actual influence of AI on strategy outcomes since some studies have retained negative results. The discussed theories are crucial in determining the conceptual framework as they provide a basis for its development. They provide a background for the critical determinants of adoption, an overview of the common technologies adopted, the influence AI has on retail marketing practices and a possible strategic adoption framework for a firm. Therefore, the study allowed the integration of all the explained theories to form a basis for the theoretical research framework.

## 2.8 HYPOTHESES DEVELOPMENT

### 2.8.1 AI Determinants and Adoption Relationships

As many scholars highlight, AI adoption is influenced by many factors. Some factors hinder while some encourage adoption (Taherdoost, 2018). There are some factors whose relationship is straightforward, for example, management support. If a manager has a positive attitude towards AI adoption, the company will most likely adopt ceteris-paribus (Rust, 2020). However, there are some controversial factors whose relationship is inconclusive as gaps in the literature continue to exist. Baker (2012) argues that firm size is a crude proxy as scholars struggle to identify a relationship between size and adoption. Marr (2019) asserts that some firms cannot afford AI technologies as they are costly, whereas (Raisch & Krakowski, 2021) states that with current rapid technology expansions, firms can afford to adopt certain technologies which require little financial investment but serve the purpose of adoption. With new laws coming into effect to regulate within the AI boundaries (e.g., POPIA in South Africa), past researchers argue that regulation can be detrimental to AI capabilities hence discouraging adoption (Manyika et al., 2017), whereas (Brynjolfsson & Mitchell, 2017) argue that early adopters have the power to twist regulation in their favour, therefore, encourage adoption. Furthermore, Prior studies indicate that companies adopt for survival, to enhance functions and increase sales (Baker, 2012). However, Bag et al. (2021) argue that firms adopt due to exerted pressures by industry peers. Such arguments influenced the researcher to identify the inconclusive but crucial determinants and examine how they influence AI adoption within food retailers in South Africa; thus, the following hypotheses were proposed:

*H1a: Complexity (ease to use) positively influences AI adoption at a firm level.*

*H1b: Risk, Compliance and Regulation positively influence AI adoption at a firm level.*

*H1c: Firm's financial stability positively influences AI adoption at a firm level.*

*H1d: Firm size positively influences AI adoption at a firm level.*

*H1e: Competitive pressure influences AI adoption at the firm level.*

*H1f: Vendor participation influences AI adoption at a firm level.*

### 2.8.2 Relationship Between Retail Marketing Mix Components and AI Adoption

Chen (2019) asserts that AI benefits for marketers fall within their capabilities to hyper-personalize products, deep analytics for actionable insights and efficient spending. Huang & Rust (2018) argue that all these benefits can be realized if marketers can strategically get it right from the onset, that is, through adopting AI in their strategy formulation process to come up with accurate prices, exact products on demand, effective promotional tools, and efficient placement channels. Therefore, for effective marketing strategy creation, AI powers the 4Ps with a whole new set of capabilities previously unattainable. AI integration in strategy creation amplifies retail marketers' capabilities in different forms, such as pricing, product development, selling and promotion capabilities.

#### *2.8.2.1 Pricing Capabilities*

Pricing capability is a significant benefit provided by AI technologies. Pricing capability refers to a firm's ability to identify rivalry prices, develop a pricing strategy, and implement that price accordingly (Liozu & Hinterhuber, 2013). Past literature extensively narrates how AI can help companies determine prices through data analytics from past purchasing data (Rust, 2020). Data is used to build quantitative models enabled by machine learning algorithms to identify patterns, enable pricing options individually and examine if the company's profit optimization objectives are met (Liu, 2020). Dekimpe (2020) states that retailers can apply big data analytics to optimize dynamic best-response pricing algorithms, which consist of consumer preferences, opposition responses, and supply boundaries. Exploiting this capability can influence the strategy design; hence the following hypothesis was proposed:

*H2a: AI adoption positively influences the retail marketer's pricing capabilities.*

#### *2.8.2.2 Place (Selling) Capabilities*

The selling capability is a combinative operation of using collective knowledge, information, unique skills, and resources to carry out certain tasks in a prescribed time frame, such as selling (Vesal, Siahtiri & O'Cass, 2021). Previously humans have been able to perform those tasks (Gries & Naude, 2018). However, AI tools enhance a firm's selling capabilities to obtain clients and sell faster and more efficiently (Brynjolfsson & Mitchell, 2017). Brynjolfsson et al. (2019) assert that AI in practice is meant to make repetitive tasks more efficient. "AI tools could be regarded as a competitive equivalence in providing firms and salespeople with more precise, efficient, faster, and reliable information about the customers, competitors, markets, and the firm" (Chen, 2019, p.66). AI allows strategic adaptive selling to salespeople at a faster rate. Prior, salespeople spent 80% of their time qualifying a lead and 20% in closing (Porter & Heppelmann, 2017). In contrast, AI generates leads with less human effort and has better outcomes than humans (Chen, 2018). Based on the above, the following hypothesis was proposed for testing:

*H2b: AI adoption positively influences the retail marketer's selling capabilities.*

#### *2.8.2.3 Product Development Capability*

Product development capability is the timely way a firm develops, manages, and offers the product to end users. Creating new products is a daunting and complex task. However, humans still play a pivotal role (Carolan, 2018). The research and development phase is challenging as firms chop and change prototypes. Avery (2018) argues that with the birth of AI technologies, some processes in the development stage have become automated and positively influenced outcomes. Market research is integral to new product development (Wen, Choi & Chung, 2019). The company's marketing teams have recently taken up AI technologies to conduct research resulting in useful insights for product development (Dekimpe, 2020). Antons and Breidbach (2018) postulate that data analytics can help predict market change, influencing new products developed and precisely capturing all customer's demands. Additionally, topic modelling advances innovation and creativity (Dzyabura & Hauser, 2019), while adaptive systems enhance hyper-personalization (Wilson & Daugherty, 2018), of which both play a significant role in product development. Hence the following hypothesis was proposed:

*H2c: AI adoption positively influences the retail marketer's product development capabilities.*

#### *2.8.2.4 Promotional Capabilities*

Promotional capabilities are regarded as an exposure weapon (Hartmann et al., 2019). The firm can effectively convey information about the products to guarantee selling success (Srivastava et al., 1998). Haung and Rust (2018) view this as a means of communication between the firm and customers. AI has amplified a firm's promotional capabilities by automating repetitive and data-intensive tasks (Davenport & Ronanki, 2018). Most promotional automated tasks included social media targeting and retargeting, media planning and word searches. AI-powered programmatic advertising is one of the major applications applied nowadays (Kaplan & Haenlein, 2019). From the above evidence, the following hypothesis was proposed:

*H2d: AI adoption positively influences the retail marketer's promotional capabilities.*

### 2.8.3 Marketing Components Capabilities on Effective Marketing Strategy Outcome

Huang and Rust (2017) assert that technology drives the design of an effective strategy by powering marketing mix components. Marr (2019) echoes those sentiments as he postulates that AI applications have recently become key contributors to strategy design processes in any industry. Artificial intelligence provides exceptional power to facilitate pricing, advertising, distribution, and product development (Dekimpe, 2020; Davenport et al., 2019). Janek and Mazurek (2019) believe such capabilities play a significant role in developing an overall effective marketing strategy whose outcome is positive on measurable elements. These powered AI marketing mix components enable the firm to reach intended strategic outcomes. Therefore, from the above contributions, the researcher proposed to test the following hypothesis,

*H3: Marketing mix components with AI-powered capabilities positively relate to a positive marketing strategy outcome.*

### 2.8.4 The Moderating Role of Competitive Intensity Retail Marketing

Literature between AI technology adoption and food retail marketing remains insufficient (Davenport et al., 2019; Oosthuizen et al., 2020), with South Africa included (Ridge et al., 2015). The previous elite scholars and the current researchers have often agreed that AI adoption is mainly influenced by technological, organizational, and environmental factors; regardless of recent extensions, these have always formed a basis for adoption (Lou & Li, 2017). Despite all the existing adoption barriers, retail marketers globally are either adopting AI technologies or are gearing themselves for this disruptive phenomenon (Seranmadevia & Kumara, 2019) and using these factors to navigate the digital world (Baker, 2012). Past studies suggest that companies that examine the influential adoption factors tend to understand the barriers and benefits of AI adoption (Gartner, 2017). The above discussion is centred on prior adoption determinants. However, the role of competitive intensity as a moderator points out that, in some instances, competition strengthens the relationship between AI technologies adoption and marketing strategy outcome.

This can translate that customer dynamics which have increased competition for retailers, can force food retailers to adopt certain AI tools to cater for those dynamics whilst withstanding competition. Because of the costs associated with caring out specified marketing tasks, such as higher fixed and storage costs, the limitations of differentiation and industry concentration versus the need to become profitable, increase sales and reduce customer complaints, firms are faced with the need to adopt AI technologies which will make their strategic marketing activities more fruitful and resulting in a positive outcome, thus strengthening the relationship.

Therefore, firms will conduct an in-depth analysis of competitive intensity elements in line with the ‘five forces framework’, which suggests that firms will attempt to limit the intensity consequences by adopting innovation and, by so doing, become profitable and reduce associated costs. More so, the food retail industry is highly competitive because of the continuous promotional wars, calculated daily marketing moves and existing price competition. Such dynamics forces companies to become innovative (Rust, 2020). Therefore, being innovative means incorporating digital transformation into their strategy. Subsequently, intensive competition levels will lead to firms being more customer-centric to gain market share. Considering that sustained competitive advantage is achieved through the application of rare technologies which make value addition exceed production costs and thus typical AI technologies. Retailers will aim to adopt those AI tools to influence their targeted outcomes which in this case is to improve sales and profit, reduce production costs and limit customer complaints. However, all this will be motivated by the competitive nature of the industry, where in the retail sector, it is very intense. Thus, guided by the above arguments, the study proposed the following hypothesis:

*H4: Competitive intensity will strengthen the positive relationship between AI technologies adoption and marketing strategy outcome.*

### 2.8.5 AI Adoption on Retail Marketing Strategy Outcome

This automation transformation unearths the ability for calculated utilization of digital innovations to solve the previous existing traditional problems (Gabriel, 2019). Digital transformation has also unleashed innovation and creativity mentalities within firms. Due to the rapid increase in AI technology developments (Acemoglu & Restrepo, 2017), most retailers have adopted certain technologies while others are positioning themselves for adoption (Marr, 2019). The use of AI in marketing activities has been welcomed by many, asserting that it plays a pivotal role in strategy design (Eriksson et al., 2020). However, some literature argues that despite AI's capabilities to improve the efficiency and effectiveness of marketing strategy creation, its integration is still an ongoing concern for many (Ma & Sun, 2020). New data is being generated rapidly, making it a vital input component for strategy design (Bharadwaj, 2018). Big data is a prerequisite in strategy formulation as management needs to refine data into reasonable alternatives, forming a basis for decision-making (Bharadwaj, 2018). Currently, firms are embarking on data-driven-decision making processes. Hambrick and Mason (1984) believe the strategic decision-making process is a cognitively daunting task that needs applicable alternatives to be selected. AI brings forth a systematic model which can process and interpret large datasets, learns to reach set targets, and enables accurate adaptation from the available options (Kaplan & Haenlein, 2019). Dekimpe (2020) assert that companies adopting AI can now translate big data into helpful information and insights, which is now a core input to effective sales and marketing strategy creation. AI is already taking up previously managerial-orientated tasks efficiently (Rust & Huang, 2020), making it a fundamental component for business growth (Markiewicz & Zheng, 2018) and providing promises of effective and efficient strategic marketing formulation. With all the potential benefits and the recorded excellence of AI, it means the strategy outcomes are positive once adopted. Hence, the study proposed the following hypothesis based on the presented arguments above:

*H5: AI adoption has a direct positive influence on retail marketing strategy outcomes*.

## 2.9 CONCEPTUAL MODEL

Figure 2.3 below summarizes the study hypothesis in a conceptual model rooted in integrated theories. There is a positive relationship between all hypothesized constructs.

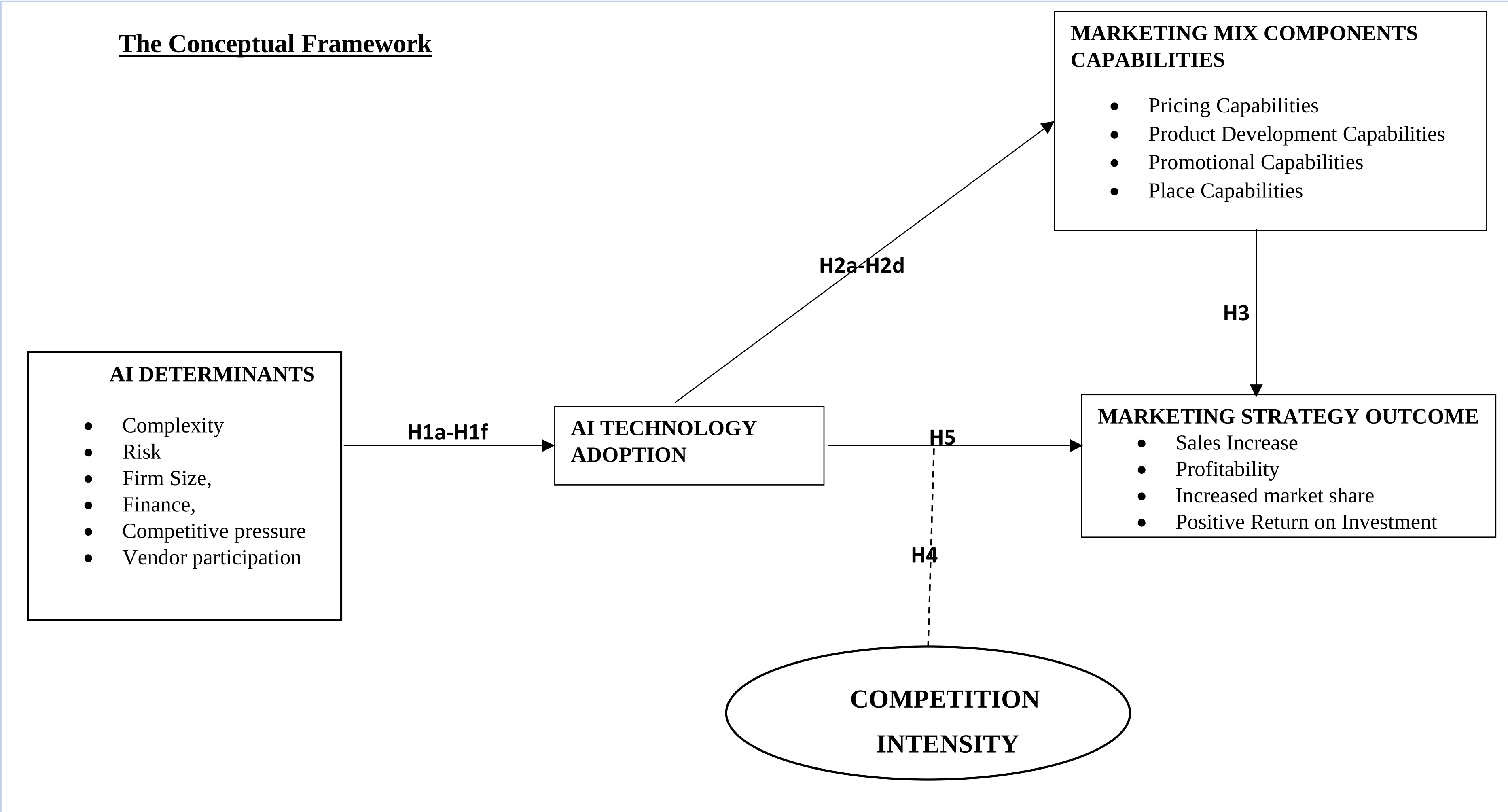


**Figure 2.3: Conceptual framework of the study**

**Source: Author's Constructs (2022)**

The above framework shows the proposed conceptual model. The framework initially shows the relationship between the controversial determinants of AI and adoption, denoted as H1a-H1f. From there, the study tested the relationship between adoption and marketing components (H2a-2d). Furthermore, the study tested the relationship between capabilities and strategy outcome to examine how these AI-powered marketing mix influence strategy formulation and result in the assessment of overall contribution via sales, profitability, increased market share and a positive return on investment analysis, denoted as H3. Equally, the relationship between AI adoption and marketing strategy outcome was also to be tested, denoted as (H5). Lastly, the study examined how competitive intensity affects or strengthens the relationship between AI adoption and marketing strategy outcome, thus denoted as H4. In that case, the conceptual framework would form a basis for the adoption framework, which was the major study objective. The following table summarises the hypothesis.

**Table 2.2: A summary of hypotheses**

| Hypothesis | Description |
|---|---|
| H1a | Complexity (ease to use) positively influences AI adoption at a firm level. |
| H1b | Risk, Compliance and Regulation positively influence AI adoption at a firm level |
| H1c | Finance positively influences AI adoption at a firm level. |
| H1d | Size positively influences AI adoption at a firm level |
| H1e | Competitive pressure influences AI adoption at the firm level. |
| H1f | Vendor participation influences AI adoption at a firm level. |
| H2a | AI adoption positively influences the retail marketer's pricing capabilities |
| H2b | AI adoption positively influences the retail marketer's selling capabilities. |
| H2c | AI adoption positively influences the retail marketer's product development capabilities |
| H2d | AI adoption positively influences the retail marketer's promotional capabilities |
| H3 | Marketing mix components with AI-powered capabilities positively relate to a positive marketing strategy outcome. |
| H4 | Competitive intensity will strengthen the positive relationship between AI technologies adoption and marketing strategy outcomes. |
| H5 | AI adoption has a direct positive influence on retail marketing strategy outcomes. |

**Source: Author's Compilation (2022)**

## 2.10 CHAPTER SUMMARY

The chapter began with an introductory section highlighting the literature's scope to be reviewed. It went on to define the key constructs of the study, namely AI, Retailing and marketing mix components. Furthermore, the chapter identified the common factors often determining AI technology adoption and the types of technologies normally adopted.

Moreover, the chapter addressed the issue of competitive intensity as the moderating variable which strengthens the relationship between AI adoption and marketing strategy outcome. Additionally, the chapter addressed theories adopted within the innovation diffusion process to explain adoption challenges and benefits. Integrating the IDT, TOE, Institutional theory, and paradox theory paved the way for the hypothesis creation, which the chapter explained. The hypothesis development section formed the conceptual model of the study. The hypotheses described the relationships between variables which overall answers the study questions as the concepts discussed above are a build-up for the main objective, which is to develop an AI adoption framework for food retail marketing. The chapter continuously combined literature with theories to map a framework basis. Therefore, the following section demonstrates the methodologies used to answer the research questions.

# CHAPTER THREE: RESEARCH METHODOLOGY

## 3.1 INTRODUCTION

This chapter discusses the various methodological approaches the researcher used for the study. This chapter covers the important methodological concepts, i.e., the research paradigm, philosophies, research design, population size, sampling technique used, research instrument for data collection, procedures followed when collecting data, data analytics techniques and instruments for results interpretation.

## 3.2 RESEARCH DEFINITION

Saunders et al. (2009) define research as the act researchers undergo to discover new things and increase their knowledge systematically. “Research is a standardized set of techniques for building scientific knowledge, such as how to make valid observations, how to interpret results, and how to generalize those results” (Bhattacherjee, 2012, p.15). From the above definitions, we can assert that research is a purely strategically planned activity that aims to develop new facts, information, and knowledge about a certain phenomenon. The research process constitutes problem identification or research interest. The identified problem translates into a research area where data is collected, analysed, and findings reported. Therefore, researchers must understand the essential research principles as they determine the choices and steps to be followed during the research period (Khaldi, 2017).

Saunders et al. (2009; 2019) designed a ‘research onion’ widely adopted by researchers as a model for designing an effective research method. The study also adopted the ‘research onion’ to help design the overall research methodology pathway.

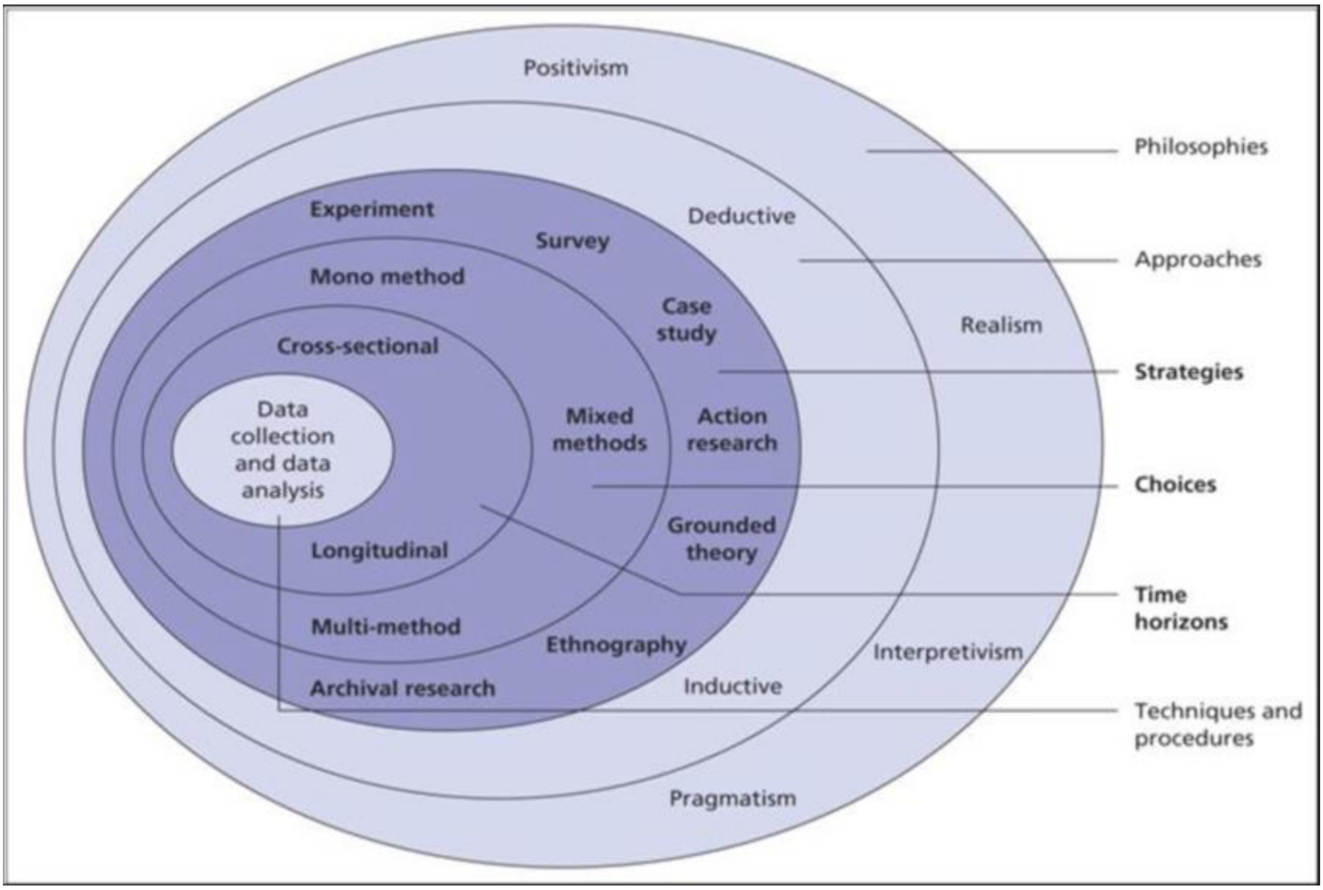


**Figure 3.1: Research Onion**
*Source: Saunders, Lewis, and Thornhill (2009)*

### 3.3 RESEARCH PHILOSOPHY

Research philosophy determines the research methodology the researcher chooses to adhere to. Research philosophy determines the research objectives and instruments to be used and designs models in the quest for solutions to identified problems (Willis, 2007). It is influenced by practical assumptions (Hiller, 2016). These assumptions are either ontological or epistemological, where the latter includes realities, the researcher comes across during the research, and the former is from human knowledge (Khaldi, 2017). Hiller (2016) declares that researchers may accurately design effective research based on ontological and epistemological knowledge. Johnson and Clark (2006) argue that deducing if the research is philosophically-informed is unnecessary. Still, it is rather important to critically reflect, defend and justify our philosophical choices as researchers against the alternatives available. The study adopted positivism and objectivism paradigms from the ontological and epistemological philosophies. The paradigms are aligned with the nature of the study, which was purely quantitative research.

## 3.4 RESEARCH PARADIGM

Research paradigm refers to the beliefs guiding the researcher's inquiry (Lincoln et al., 2011). From the definition above, paradigm suggests that most investigators approach research with one or more similar or interlinked and sometimes mismatched philosophical assumptions, views, and opinions. These philosophical assumptions form a basis for the research design process (Creswell, 2014). Saunders et al. (2019) postulate that the philosophy adopted by the researcher will have an important meaning on how the researcher views the world in relation to the study variables. Researchers primarily bring their world perspective, indicate their sets of paradigms to the research project, and these will strategically direct the manner of carrying out the study. Mason and Ritchie (2020) indicate that when explaining their paradigmatic view as a researcher, the interaction between ontological and epistemological assumptions, meta-theoretical base, research questions, and research methodology takes precedence.

Ontology is the study of being (Crotty, 1989), concerned with the nature of reality (Creswell et al., 2003). Saunders et al. (2009, p. 110) state that "ontology philosophy raises questions of the assumptions researchers have about the way the world operates and the commitment to particular views". Researchers need to take a stand regarding their assumptions of how things are and how things work. Therefore, ontological factors deal with the nature of views, what exists, how it is, what it includes and how various components interact (Smith, 2012). There are two ontological perspective orientations: objectivism and subjectivism (Bryman, 2016). Remenyi et al. (1998) defined objectivism as a paradigm that the world is real, systematic and can be altered by the researcher and subjectivism as a paradigm which exists in the researcher's mind and is hence solely responsible for the construction and interpretation of the views. The study adopted the objectivism perspective orientation because it allowed the researcher to explore and understand the subjective meanings motivating firms' actions to adopt AI and how its application has influenced the marketing strategy design. Objectivism follows social constructionism views which assert that reality is socially constructed (Saunders et al., 2019). Due to variations in studies, interpretations, and understanding, AI adopters hold diverse perspectives on the determinants of AI adoption, reasons for implementing specific technologies in their operations, and the impact of AI adoption on their marketing strategy development. Therefore, the researcher adopted the objectivism perspective orientation to understand the subjective different socially (retail-industry) constructed actions, motives, and intentions to answer the primary research questions.

Epistemological assumptions are concerned with knowledge creation. It focuses on how a phenomenon can be known and how reliable and dependable knowledge is developed (Hiller, 2016). Epistemological assumptions are coined on what is deemed acceptable knowledge. Epistemological assumptions have two perspective orientations: positivism and interpretivism (Saunders et al., 2019). Positivism assumptions are law-like generalizations from an observable social reality (Remenyi et al., 1998). Alharahsheh and Pius (2020) suggest that interpretivism orientation is vested in the notion that researchers must understand differences between humans in their role as social actors. It stresses the gap between conducting research among people rather than objects. Based on the nature of the research, the study adopted the positivist approach because the study anticipated dealing with AI, which is observed from a social reality. Moreso, the positivist approach aims to uncover objective truths and causal relationships between variables by emphasizing empirical evidence and the use of quantitative data. Since the study had proposed thirteen hypotheses, the positivist approach helped confirm/disregard those with empirical evidence found in the study.

The study was centred on dealing with facts rather than impressions, and those facts are consistent with the belief of 'observable social reality' (Remenyi et al., 1998). Secondly, the positivist approach allowed the researcher to create a research strategy to generate credible data by using existing theory to develop hypotheses (Saunders et al., 2019); of which in this study, the researcher intended to follow that approach because the onset, the theory has formed a basis for a conceptual framework. Additionally, the positivism approach is best suited for these types of studies because it assumes that the researcher takes an external position meaning they cannot alter or interfere with the data collected; the researcher is independent of the process as they are not affected or doesn't affect the subject of the research (AI adoption on retail marketing and strategy creation), and the researcher's feelings are not attached (Remenyi et al., 1998; Saunders et al., 2019). Therefore, in this case, the researcher was independent (not from the retail marketing space, instead, the research came from the academic spheres) and hence couldn't influence the respondents as the research instrument was sent directly to the participant without the researcher helping to answer the questions. Moreover, the researcher had no feelings attached as the study was concerned with facts rather than impressions. More so, because the researcher targeted testing different hypotheses, this required numerical values. The positivism approach advocates for quantitative observable variables involvement as the emphasis is on statistical analysis, thus justifying the adoption of the positivism approach. The justifications were consistent with the views of (Remenyi et al., 1998; Creswell and Creswell;

2013), who established that the positivism approach allows researchers to develop a research strategy which enables them to collect numeric data guided by theories and further develop hypotheses which will be later confirmed or refuted thus can be a basis for future studies as well. The statistical analysis came in regression analysis, exploratory and confirmatory factor analysis, which required input of numeric values. Table 3.1 illustrates the differences between the two philosophies.

**Table 3.1: Comparison of the two study research philosophies.**

| | Positivism | Subjectivism |
|---|---|---|
| Ontology:<br>*The researcher's view of the nature of reality or being* | External, objective, and independent of social actors. | Socially constructed, subjective, may change multiple times. |
| Epistemology:<br>*The researcher's view regarding what constitutes acceptable knowledge.* | Only observable phenomena can provide credible data and facts. Focus on causality and law-like generalisations, Reducing phenomena to simplest elements. | Subjective meanings and social phenomena. Focus upon the details of the situation, a the reality behind these details, subjective meanings motivating actions. |

***Source:*** *Saunders, Lewis, and Thornhill (2009)*

From Table 3.1 above, the two adopted approaches (positivism and subjectivism) from the two philosophies (ontology and epistemology) are closely related in their attributes. All of them are coined on the nature of reality; the research is external and independent from the social realities. Equally so, their subject to meanings motivating actions, interest in credible facts (numeric form) and reduces the study phenomena, which is AI to its simplest understanding.

## 3.5 RESEARCH APPROACH

Based on the adopted philosophies and paradigms, the researcher used two common research approaches: inductive and deductive (Alharahsheh & Pius, 2020). Adopted from the positivist paradigms, the deductive approach empirically examines how existing theoretical knowledge is applied together with discovered inconsistencies, information is validated, and reliably measured (Cohen et al., 2007). The inductive approach adopts the interpretivism paradigms, which lie within realism, constructivism and phenological assumptions (Saunders et al., 2019). Consistent with the positivist epistemological paradigm, the study intended to adopt the deductive approach because the approach allowed the researcher to test for the proposed relationship between two or more variables from theory (Robson, 2002) and in the study, the researcher wanted to establish the relationships between AI adoption and retail marketing strategy design so that it can be confirmed if AI influence had a positive effect on the outcomes. More so, Robson (2002) states that the deductive approach indicates how variables (AI influence, marketing mix capabilities and effective marketing strategy) are measured and tested, and the relationship outcome is quantified. It is centred on identifying the causal relationships of variables. Therefore, the deductive approach was justified since the researcher wanted to establish, examine, measure, and test the relationships between identified variables from theories and existing literature.

The deductive approach was best suited for this research as it aligned well with the research objectives, which required empirical evidence. The deductive approach is closely associated with surveys which are more coined on quantitative research (Saunders et al., 2009; 2019). Therefore, guided by the research objectives, the study intended to use surveys. It is because of the survey's ability to facilitate large data collection from a wide pool (population) in a more economical way (cheap) allowed the researcher to obtain numeric data which can be analysed using descriptive and inferential statistics and the ability to give control over the research (Robson, 2002; Remenyi et al., 1998), is what justified the researcher's choice. The research philosophies, paradigms and approaches proposed above formed the basis for the research design, which was important for the researcher to develop.

### 3.6 RESEARCH DESIGN

Research designs are propositions of conduct that guide the orchestration of set conditions for data collection and analysis (Cohen, Manion & Morrison, 2007). These designs provide the researcher with explicit action plans. Cavana et al. (2001) propose that the scope of research designs exceeds data collection and analysis methods. Furthermore, it covers information about the choice of the population for the study, the sample size and measurement tools. Saunders et al. (2019) indicate that the time horizon is critical for research. The time horizon is the expected span of the research or scope of knowledge to be exhausted, which often comes in either cross-sectional or longitudinal studies (Melnikovas, 2018). Based on the nature of the expected data (not time series data), the study adopted a cross-sectional study approach.

The cross-sectional design has observational attributes which provide a snapshot of the study and simultaneously produce results at a particular measured interval hence suitable for this research. According to Olsen and St George (2004), cross-sectional designs are less costly and a fast way to conduct research. Considering the nature of academic research, which can be very expensive and have a limited timeframe, it was noble to use cross-sectional studies.

Furthermore, longitudinal studies are best suited for time series data (Bryman, 2016; Cohen, 2007), which demands observing variables over a long period, which is not the nature of this study data. After considering the time horizon, the researcher had to consider the approach of research which would be used. However, guided by the paradigms and philosophies, and as indicated earlier that the researcher would use surveys, it became apparent that a quantitative approach was ideal for the study.

Additionally, aligned with cross-sectional studies, the study took the descriptive research design approach. According to Saunders et al. (2019), descriptive cross-sectional research is a scientific method used to systematically collect, analyse, and interpret data to describe and explain a phenomenon in context. The aim was to produce a comprehensive and accurate narrative of the data patterns, behaviours, and relationships. Therefore, consistent with the study objectives, descriptive research was appropriate as it enhanced the understanding of the relationships (hypotheses) proposed. There are three descriptive research design types: casual, exploratory, and descriptive. Exploratory is more aligned with qualitative approaches as it aims to explore new relationships; hence inappropriate for the study. Casual research design is a scientific investigation that aims to determine cause-and-effect relationships between variables (Creswell, 2014). It seeks to establish whether changes in one variable directly cause changes in another. This causal effect was not examined as it is mostly appropriate for comparative and longitudinal studies. Thus, this study followed a descriptive research design and a cross-sectional approach. The descriptive research design is aligned with quantitative data, thus providing a segway to quantitative research boundaries.

## 3. 7 QUANTITATIVE RESEARCH

Apuke (2017) describes quantitative research methodologies as approaches aimed at hypothetically testing theories, discovering facts, exhibiting relationships between investigated variables, and predicting possible outcomes. Hair et al. (2017) elucidate that quantitative research methods adopt the natural sciences models, which achieve objectivity, generalizability, and reliability. Every research instrument must live to suffice its adoption through its potential to enable hypotheses testing, deduce relationships amongst variables and draw conclusions that add to knowledge (Jackson, 2018). Because the research is focused on testing hypotheses, discovering casual relationships, and predicting outcomes, this guided the researcher to adopt a quantitative approach. The quantitative approach will allow the researcher to use the questionnaire for data collection.

## 3.8 RESEARCH POPULATION AND SAMPLING

### 3.8.1 Research Population

A research population is a group of individuals, institutions or objects with similar characteristics used for a scientific probe (Black, 2019). Polit and Beck (2004) claim that the population must meet certain research demands. The population for this study consisted of food retailers, marketing practitioners and IT experts. However, the researcher aimed at distributing the questionnaire via professional platforms such as LinkedIn and emails, which was highly effective as most responded through those channels. Using profile scanning on LinkedIn resulted in a higher response rate for the study. This approach ensured that the selected participants were suitable for the research and had a genuine interest in the subject matter. As a result, their active participation was facilitated. GAIN (2018) reported that there were 1800 retail and food production companies, where food retail contributed close to $44.9 billion in 2017 and claimed that a few large firms dominate the industry. Statista (2020) projected that over 2000 marketing or advertising agencies in South Africa were estimated to be worth R30.4 billion, and over 60% of those firms were concentrated in Gauteng and Western Cape Provinces (Hurter, 2020). Self-administered questionnaires were digitally distributed to participants within the identified population. Table 3.2 shows a detailed overview of the proposed sample population.

**Table 3.2: Research Population**

| **Industry** | **Number of Establishments** |
|---|---|
| Food/Grocery Retailers | 1 800 |
| Marketing/Advertising Agencies | 2 000 |
| **TOTAL** | **3 800** |

**Source: Author's Compilation (2022)**

### 3.8.2 Sample Size

The sample size represents a portion of the aggregate research population (Creswell, 2014). It is important to attain a suitable sample population for survey research (Bryman, 2016). The study adopted the Gill, Johnson, and Clark (2010) percentage desirability table to determine the sample size. The percentage desirability table indicates the need to consider a large percentage of the sample size with characteristics that collectively answer the research questions. In each industry, the researcher identifies key contributors whose responses significantly aligned with the set questions of the study.

Although the desirability table allows any percentage level choice deemed fit by the researcher, it recommends 50% of the sample size (Gill et al., 2010) and however, the researcher desired sample size of 10% of the research population due to the geographical limitations and the nature of the sample population which only involves participants who are knowledgeable about AI (purposive sampling) since AI is regarded as a new phenomenon (Brynjolfsson & Mitchell, 2017) hence the chances of extensive knowledge about AI amongst the research population is limited, thus limiting the sample size too.  Table 3.3 shows the proposed sample size.

**Table 3.3: Proposed Sample Size**

| **Industry** | **Roles/Positions held** | **Number of people within the Establishments** |
|---|---|---|
| Food/Grocery Retailers | Marketing Managers, Salesperson, IT Technicians, Digital Analysts | 180 |
| Marketing/Advertising Agencies | Marketing Managers, Marketing Experts, Research Executives, Digital Analyst | 200 |
| **TOTAL** | | **380** |

**Source: Author's Compilation (2022)**

### 3.8.3 Sampling Technique

Sampling translates to the selection process of a sample size (Polit & Beck, 2004). Taherdoost (2016) believes sampling helps researchers make inferences about the target population and or generalize in relation to existing theories. There are two types of sampling techniques, probability (random) sampling and non-probability (non-random) sampling (Creswell, 2013). The study adopted non-probability sampling because not everyone within the retailing industry has adopted AI; hence, in this research, the selected participants were individuals who knew about the study subject. Consistent with non-random sampling, the study adopted purposive sampling, supported by Brink et al. (2006), who indicate that participants must justify the inclusion, therefore in this research, participants' inclusion was justified by their knowledge of the study subject, which is AI and is already utilizing it within their business functions. Thus, the chances of participants sharing significant information, reflecting on past experiences, and understanding the problems are high.

Furthermore, the participants had experience with AI tools or interacted with some elements of AI within their operations. These were why data scientists, analysts, marketing analysts, researchers, IT technicians, computer engineers, sales and marketers were chosen. Although cluster sampling would have been ideal for studies that are fragmented over large geographical space as it saves time and money (Davis, 2005), purposive sampling was appropriate as AI is regarded as a new phenomenon in South Africa; thus, the study required knowledgeable participants who are likely to share appropriate experiences.

## 3.9 RESEARCH INSTRUMENT

The researcher intended to use a questionnaire as the core research instrument. Questionnaires are used because they provide numerical values which provide empirical evidence on relationships, behaviours, and knowledge about the study subject. Some advantages of using questionnaires are that they can be digitally distributed, which increases reach and is a fast and efficient way to collect data. Questionnaires promote honest answering as they are confidential (Creswell, 2014). The questionnaire was constructed with three sections; section 1 aimed at obtaining information about the respondents, such as demographics, background, and qualifications. Section 2 focused on the firms' background, for example, the number of employees, how long it has existed and the location. Section 3 aimed to gather information on the perception, past experiences, and their current position about determinants of AI adoption, how retail marketers use AI, the common AI systems applied, and the influence AI has on retail marketing strategy design and effectiveness. When constructing the questionnaire, the primary sources of indicators (constructs/themes) were adopted from the pre-validated indicators chosen from different literature sources, which cover the whole research objectives. These indicators include AI, adoption determinants, strategy influencers, types of AI applications, marketing-mix components, and strategy outcomes. Using prior validated and publicly issued questions saves time and resources, facilitates comparison opportunities, reduces measurement errors, and reduces validity and reliability uncertainties (Mourougan & Sethuraman, 2017).

For the above reasons, AI measurement items were pinpointed and utilized (Rust, 2020; Huang & Rust, 2020; Brynjolfsson et al., 2019; Marr, 2019; Manyika et al., 2018), where participants were expected to express their knowledge of AI, AI technologies used, pros and cons of adoption and how it has impacted their operations. Determinants questions were adopted from (Oliveira & Martins, 2011; Sayginer & Ercan, 2020; Baker, 2012; Roger 1995). Respondents were expected to acknowledge the critical factors to consider when deciding on their digital transformation journey and the levels at which they must integrate their innovations. Marketing-mix components and their involvement in strategy design questions were taken from (Davenport et al., 2019, Paschen et al., 2019; Porter & Heppelmann, 2017; Rust & Huang, 2021). Respondents were subjected to a report on the perceived influence of AI in marketing activities, how AI influence marketing strategy and the actual benefits realized through AI adoption in marketing boundaries. Competitive intensity construct questions were adopted from the scholarly works of (Porter, 1980), where participants were expected to acknowledge price competition, promotional wars, differentiation challenges and daily movements in marketing initiatives as factors existent in the market. Lastly, as for the strategy outcomes, the constructs and elements were obtained from the scholarly works of (Solcansky & Simberova, 2010; Sanaei & Sobhani, 2018), and it aimed to request participants to confirm or disregard at different levels of AI adoption increases sales, profit, ROI and or reduces complaints and costs. The questionnaire captured all important aspects of the study constructs (themes), covering the overall research questions to achieve the objectives. A good questionnaire must produce reliable and valid answers to something we want to describe (Fowler, 2002). Therefore, the questionnaire aimed to give valid and reliable outcomes that would immensely contribute to knowledge creation and answer the research questions. Table 3.4 depicts a snapshot of the questionnaire used. Please refer to Appendix A for the detailed questionnaire.

**Table 3.4: Research themes and measurement scales**

| **Themes** | **Items** | **Sample questions** | **References** |
|---|---|---|---|
| Artificial Intelligence Determinants | AID01<br><br>AID05 | -I find AI technologies complex to use.<br><br>- I find AI technologies risky and uncertain about their integration | Baker (2012); Sayginer and Ercan (2020); Rust (2022); Roger (1995); Oliveria and Martins (2011); Accenture (2018) |
| Marketing mix components | MCC01<br><br>MCC02 | - AI technology adoption increases pricing accuracy.<br>- AI technology adoption increases product offering accuracy. | Davenport et al. (2019); Paschen et al. (2019); Porter and Heppelmann (2017); Rust & Huang (2021); |

| | | | |
|---|---|---|---|
| | | | Vlačić et al. (2021); Syam & Sharma (2018) |
| Artificial Intelligence Systems Adopted | AIT02<br><br>AIT03<br><br>AIT04 | - My company uses AI technologies for customer targeting/ new market search purposes.<br>- My company uses AI technologies for predicting future sales.<br>- My company uses AI technologies for effective resource allocation tasks. | Rust (2020); Huang and Rust (2020); Brynjolfsson et al. (2019); Marr (2019); Manyika et al. (2018); Bloom et al. (2021); AWS (2017); Puklavec (2014) |
| Competitive Intensity | CIRM01<br><br>CIRM02 | - Competition in our industry is very intensive.<br><br>- There are many promotional wars in the industry. | Porter (1980); Corporate finance institute (2015); Davidsson and Wiklund (2006) |
| Artificial Intelligence adoption on marketing outcome | MSD01<br><br>MSD02 | - AI technologies adoption increases sales growth rate.<br><br>- AI technologies adoption increases profit margins. | Eriksson, Bigi and Bonera (2020); Bharadwaj (2018); Jarrahi (2018); Brynjolfsson and McAfee (2014); Paschen et al. (2019); Oosthuizen et al. (2020) |
| AI-powered marketing mix components and strategy outcome | MXMS02<br><br>MXMS03 | - Integrating data analytics technologies enhances the overall company marketing activities.<br>- Utilizing customer targeting/ segmenting systems significantly increases the distribution efficiency of the company. | Martinez-Lopez and Casillas (2013); Kaplan and Haelein (2019); Taherdoost (2018); Rust et al. (2021) |

**Source: Author's Compilation (2022)**

### 3.9.1: Questionnaire Administration

Questionnaire administration is a critical part of research as it details how the researcher intends to distribute the survey (Creswell, 2014) and the participant's background and justifies the distribution channel. Since the study was purely quantitative, the researcher used a survey distributed via emails and a professional platform, LinkedIn. The study adopted purposive sampling, meaning the research population was expected to know the subject matter. Therefore, using LinkedIn enabled the researcher to scan profiles, identify participants with knowledge and expertise around AI. From there, the survey was sent to participants' inboxes through a link. Qualtrics platform was used to design the digital questionnaire, which was later electronically distributed.

### 3.9.2 Response Format

Response format is the process in which questions are answered or responses are gathered from the questionnaire (Taherdoost, 2019). Geuens and Pelsmacker (2017) state that response formats can be in different dimensions like open-ended, Likert-scale or multiple-choice questions. Likert-scale questions were used in the study. The reasons are that they reduce misinterpretations, are relatively easy to understand and are not time-consuming, hence avoiding fatigue consequences for the respondents (Wulandari, 2019). They also increase the respondence ratio. The questionnaire had a 7-Likert scale ranging from strongly disagree to strongly agree; in the middle, there were slightly disagree, disagree, neutral, slightly agree and agree.

### 3.9.3 Pilot Testing

Brink (1996, p.60) states, "a pilot study is a small-scale version, or trial run, of the major study". The reasons for running trial runs are to look for potential gaps for improvements, discover loopholes and conduct a feasibility assessment (Hair et al., 2017). The researcher ran a pilot test on ten academics, industry experts and salespeople before the official distribution of the questionnaires to examine the effectiveness of the research instruments and identify potential gaps for improvement. The feedback was used to improve the questionnaire. Refining, improving, and minimising errors during pre-testing helped the researcher address the validity concerns.

## 3.10 DATA ANALYSIS

Data analysis is the process of analysing data which has been collected to gain insights and help draw research conclusions. The study used Structural Equation Modelling (SEM) as the main statistical model to analyse the conceptual research model. SEM is a statistical method to test the relationships between observed and latent variables (Hair et al., 2017). The former measures variables in the data collection process, while the latter measures variables by connecting to the observed variables because they cannot be directly measured (Civelek, 2018). SEM facilitates measuring the direct and indirect relationship in one model (Collier, 2020). SEM was utilized in the study because while testing for the hypotheses, it confirmed the correspondence of the data and the relationships identified in both conceptual and theoretical frameworks. So basically, SEM is a confirmatory statistical approach (Karagoz, 2016). Civelek (2018) asserts that SEM is not only rooted in descriptive analytics, which enabled the researcher to provide descriptive statistics on the types of AI technologies commonly adopted and the levels at which food retailers utilize these AI technologies, but also extends to exploratory and confirmatory factor analysis, hence guided by such literature, it was noble to use SEM for exploring and confirming variables.

Confirmatory factor analysis (CFA) allowed the researcher to account for errors and ways to rectify them. Moreso, CFA assisted the author in analysing and examining the strength of observed variables. The ability of SEM to combine and analyse relationships between observed variables (adoption determinants) and latent variables (AI) simultaneously (Hair et al., 2017) justified its use. The researcher ran multiple regression analyses to assess the strength of the relationships of observed variable outcomes. Furthermore, the study proposed a correlation analysis to measure the strength of the relationship between observed variables. The study used the variance-based SEM approach (Partial Least Squared-SEM) because of its rigorous dealing with complex structural models (Mueller & Hancock, 2019), possesses predictive capabilities (Sarstedt et al., 2017), and takes care of abnormal distributions (Mooi et al., 2017).

Furthermore, Hair et al. (2017) express the importance of dealing with outliers in a dataset. Consequently, it compensates for outliers because the study used PLS-SEM, which is suitable for more complex and exploratory models with no prerequisite of normally distributed data (Hair et al., 2017). Furthermore, the study addressed collinearity issues to redress high correlations or interdependence between variables. The study adopted the Principal Component Analysis (PCA) to reduce data dimensionality hence countering collinearity issues.

## 3.11 VALIDITY AND RELIABILITY

Because the study used questionnaires with a multi-scale system to measure the constructs, it was crucial to minimize errors by testing the research instrument's reliability and validating the responses. Validity and reliability are not only for error minimization but also for testing whether the constructs are consistent and measure what it purports to measure (Field, 2013).

### 3.11.1 Reliability Testing

When the research instrument can measure the repetition of findings and produce similar results, it is deemed reliable (Field, 2013). There are different reliability threats which researchers need to address to achieve reliability. The researcher identified two types of reliability threats which could affect the results. The threats were subject and observer reliability. The former surfaces due to factors influenced by research respondents, which in this case were the marketing, sales, and IT personnel. The latter arises from the interviewer's inability to interpret outcomes (Drost, 2011). In the study, observer reliability threat was non-existent as the survey was self-administered. To cater for subject reliability, the study initially proposed that respondents have enough time to complete the questionnaire, thus avoiding fatigue consequences and ensuring reliable responses. Furthermore, the study used previously tested scales that have proven to produce reliable outcomes and concentrated more on asking direct, clear questions that were properly worded to avoid compromising the instrument's reliability and outcomes.

Besides the above measures, Cronbach alpha is the commonly known and applied way to measure the instrument's consistency as it quantifies consistency. The study used Cronbach alpha, calculated through SPSS version 27 software, to assess the internal consistency of the responses. The Cronbach alpha is computed by correlating the score scales of each construct with the total scale score and then by comparing the results with variance for all individual scores (Field, 2013). The Cronbach alpha coefficient ranges from 0 to 1, and it is suggested that any coefficient above 0.7 is recommended (Hair et al.,2021). However, some scholars argue that any coefficient above 0.6 is acceptable (Drost, 2011). Table 3.5 illustrates the summative results of the reliability test.

### Table 3.5: Reliability Test Results (Cronbach's Alpha Coefficient)

| **Constructs** | **Cronbach's alpha (CA)** |
|---|---|
| AI Competitive Pressure | 0.866 |
| AI Complexity | 0.812 |
| AI Finance | 0.909 |
| AI Firm Size | 0.774 |
| AI Risk | 0.907 |
| AI Technology Adoption | 0.933 |
| AI Vendor Participation | 0.860 |
| Competitive Intensity | 0.926 |
| Marketing Strategy Outcome | 0.933 |
| Marketing Mix - Product Development | 0.878 |
| Marketing Mix – Place | 0.846 |
| Marketing Mix – Price | 0.812 |
| Marketing Mix – Promotion | 0.809 |
| **Final Cronbach's Alpha Coefficient** | **0.86** |

***Source: Author's Compilation (2022)***

With an overall Cronbach alpha coefficient of 0.86, internal consistency was achieved, thus indicating the reliability of the results.

### 3.11.2 Validity Testing

The study had to consider validity issues to ensure the validity of the constructs and that the research instrument purports its measurements, guided by the consistency of constructs from theories and pre-validated indicators. The researcher identified many types of validity that can be detrimental to the outcome if not well taken care of. However, guided by literature, theories, nature of the study (quantitative) and research themes, the study proposed to examine three types of validity: internal, discriminant, and construct validity.

Due to the study's use of theories and past literature to formulate the conceptual framework, construct validity was concerned with the questionnaire's level of concepts, theoretical constructs, and ideas intended to measure. Construct validity comes in two forms, divergent and convergent validity (Hair et al., 2021). To ensure that the theoretical constructs are consistent and related (convergent validity), the research performed factor analysis and the results are illustrated and interpreted in the following chapter. Additionally, to ensure that the constructs that are not theoretically related are asserted to be unrelated (divergent validity), the researchers ran a correlation test (PSL-SEM). Field (2013) postulates that the correlation test is done to ensure that we have no similar items measuring similar constructs and that it must conclusively demonstrate the uniqueness of variables.

Discriminant validity ensures that the observed variables used in the questionnaire help measure the latent variable (Civelek, 2018). Therefore, in the study, to determine discriminant validity, the researcher calculated the Maximum Squared Variance (MSV) and the Average Shared Squared Variance (ASV). The square of the highest correlation coefficient between factors is MSV, and the ASV is the value obtained from diving the sum of squares of the variance shared by other factors by the number of shared variances (Surucu & Maslakci, 2020, p. 2704). Discriminant validity showed that factors have different characteristics according to their nature, and it helped the researcher avoid using closely related constructs.

Internal validity is concerned with the ability of the questionnaire to give the same results repeatedly. Civelek (2018) laments that internal validity is concerned with the accuracy of the research instrument and consistency. Therefore, to ensure internal validity was addressed, the questionnaire was distributed to the correct population. More so, because this is not a new construct altogether, adopted themes and questions ensured validity while seeking honesty from respondents. Table 3.6 illustrates the validity results.

**Table 3.6: Validity Test Results**

| **Constructs** | **Average variance extracted (AVE)** |
|---|---|
| AI Competitive Pressure | 0.764 |
| AI Complexity | 0.638 |
| AI Finance | 0.782 |
| AI Firm Size | 0.686 |
| AI Risk | 0.784 |
| AI Technology Adoption | 0.718 |
| AI Vendor Participation | 0.703 |
| Competitive Intensity | 0.816 |
| Marketing Mix - Product Development | 0.735 |
| Marketing Mix – Place | 0.688 |
| Marketing Mix – Price | 0.728 |
| Marketing Mix – Promotion | 0.638 |
| Marketing Outcomes | 0.789 |

***Source: Author's Compilation (2022)***

Table 3.6 shows that convergent validity was achieved as all AVE coefficients are above the 0.5 threshold, as advised by past scholars (Hair et al., 2021).

## 3.12 ETHICAL CONSIDERATIONS

Creswell (2014) refers to research ethics as codes of conduct, laws, and standards to be met before conducting a research exercise. Saunders et al. (2019) indicate that respondents' participation in the research must be voluntary. Guided by the above definition and literature boundaries, respondents' participation in this study was voluntary, i.e., no one was forced to participate. More so, the participants held the right to withdraw anytime willingly while completing the questionnaire. Additionally, data were collected after obtaining approval from the school's ethics committee, Protocol number H12/11/39 (see Appendix B).

Moreover, introductory letters were sent by the researcher to participants in line with ethical standards to seek consent before data collection. The letter was attached to the research instrument as the survey was electronically distributed. Seeking consent was also following the newly approved Protection of Personal Information Act (POPIA) of South Africa (2013), Section (27) (a), which prohibits data processing from a third party without their consent. The researcher maintained confidentiality, privacy, and non-disclosure of participants' data while treating answers anonymously. No names, identity numbers or email addresses were requested from the respondents, which could jeopardize their anonymity or identify their organization. Data was securely stored in a locked cloud facility and scheduled for deletion after a 5-year retention period. The researcher is the only individual with access to the locked cloud facility. The researcher understood the importance of adhering to research ethics.

### 3.13 CHAPTER SUMMARY

This chapter described the research methodology steps which the researcher embarked on. The chapter gave an introductory overview of the methodology chapter before it went into detail. The researcher explained what research was and explained the research philosophies and paradigms that guided the study to contribute to knowledge. The schools of thought brought about the need to elaborate on the research design and the approach followed. A survey conducted quantitative research through questionnaires.

Furthermore, the chapter described the research population, the sample and the sampling criteria. The steps of how the questionnaire was constructed, distributed, and administered were also covered. From there, the chapter highlighted measures taken to ensure the validity and reliability of the research instrument. Lastly, ethics, which are codes of conduct on how to carry out this research, was extensively discussed.

# CHAPTER FOUR: PRESENTATION OF RESULTS

## 4.1 INTRODUCTION

This chapter deals with the presentation of the results of the study. Specifically, the chapter covers the following areas: empirical scale refinement of the determinants of AI technology adoption using principal component analysis (PCA), Structural Equation Analysis (SEM) involving both measurement and structural models and the confirmation of various hypotheses based on the results.

## 4.2 RESPONSE RATE ANALYSIS

From the sample size of 380, where questionnaires were distributed both physically and electronically, only 377 responded to the questionnaire. From the 377 responses received, 350 were considered useable. It was ideal for discharging the 27 unusable than to investigate, identify the problem and potentially complete the missing data as this would mean the data set would be manipulated, which is strictly against the research ethics. Considering that the study achieved an effective response rate of 92%, it translated that we could analyse the data as it was still a large data set. The missing responses were very much unlikely to pose a threat to the outcome. According to Gill, Johnson, and Clark (2010), any responses beyond 50% can be considered adequate for the study as it identifies as a proper representation of the population. Some scholars recommend at least 30% and argue that its adequate for results generalization (Bargozzi, 2004). Therefore, the high response rate can be attributed to the study interest and the effective means of questionnaire distribution which increased reach. Equally, using the LinkedIn platform, which allowed profile scanning and participant targeting helped achieve a higher response rate.

## 4.3 MISSING VALUES ANALYSIS AND REMEDY

Missing values are a big problem in statistical research, as Hair et al. (2014). Kline (2011) indicates the need to deal with missing values before running any statistical tests, particularly the exploratory and confirmatory factor analysis and structural equation modelling (SEM) carried out in the study. As a result, before analysing the data, it was important to recognize and treat all missing values. The research statistically tested the magnitude of missing values in the data set using the missing value analysis method in SPSS. The findings showed that the percentage of missing values was less than 10%. Several statistically approved methods can be used to handle missing valuables and vary according to the set of objectives and the nature of the data handled (Hair et al., 2017). As denoted in past studies, the expectation-maximization (EM) algorithm is one of the most adopted methods for handling missing or incomplete data (Hair et al., 2014; Cox et al., 2014; Schafer and Graham, 2002; Schafer and Olsen, 1998). As a result, this study relied on the EM algorithm to deal with missing values in the data set.

## 4.4 DEMOGRAPHIC PROFILE OF THE RESPONDENTS

There were two distinct categories in the demographics discussion section based on the questionnaire. There is a section for the respondent's and firm backgrounds, which were discussed respectively. The respondents' background comprises of academic background, employment history, current occupation, and qualification. Table 4.1 gives a detailed summary of the respondent's background.

### Table 4.1 Respondent's Background

| Variable | Category | Frequency | Percentage |
|---|---|---|---|
| Corporate/ Industrial Experience? | 0-3 years | 60 | 17% |
| | 4-6 years | 131 | 37% |
| | 7-10 years | 51 | 15% |
| | 11 + years | 108 | 31% |
| | **Total** | **350** | **100%** |
| Owner or Employee? | Owner | 19 | 5% |
| | Employee | 331 | 95% |
| | **Total** | **350** | **100%** |
| Highest level of Education obtained. | Matric | 12 | 3% |
| | Diploma | 46 | 13% |
| | Degree | 132 | 38% |
| | Honours | 90 | 26% |
| | Masters | 67 | 19% |
| | PhD | 3 | 1% |
| | **Total** | **350** | **100%** |
| Qualification | Computer Science/ IT | 34 | 10% |
| | Marketing | 125 | 36% |
| | Management | 110 | 31% |
| | Statistics | 49 | 14% |
| | Supply Chain | 23 | 7% |
| | Operations Research | 4 | 1% |
| | Other | 5 | 1% |
| | **Total** | **350** | **100%** |
| Current Job Title | Director | 24 | 7% |
| | Data Analyst (scientists) | 100 | 29% |
| | Sales Executive | 68 | 19% |
| | Supply Chain Manager | 20 | 6% |
| | IT Technician | 8 | 2% |
| | Marketing Analyst | 62 | 18% |
| | Software Developer | 7 | 2% |
| | Marketing Manager | 35 | 10% |
| | Market Researcher | 25 | 7% |
| | Other | 1 | 0% |
| | **Total** | **350** | **100%** |
| Department | Marketing or Sales | 188 | 54% |
| | IT | 62 | 18% |
| | Operations | 62 | 18% |
| | Supply Chain | 18 | 5% |

| | | | |
|---|---|---|---|
| | Other<br>**Total** | 20<br>**350** | 6%<br>**100%** |

***Source: Author's Compilation (2022)***

The common research demographics of participants, which are often captured, namely sex and age, were excluded from the study as there would not enhance the study outcome. Therefore, the research focused on the demographic elements, which proved participants' knowledge about the subject matter; this was mainly guided by the purposive sampling technique adopted by the study. As observed from Table 4.1, midcareer respondents (4-6 years corporate or industrial experience) dominated the response ratio with 37%, followed by highly experienced individuals who had more than 11 years at 31%, career beginners (0-3 years) ratio stood at 17% while the least where participants with experience between 7-10 years at 15%. The dominant ratio of mid-career and highly experienced individuals indicated that the study quality would be enhanced due to extensive industry knowledge from the participants. Almost all respondents (95%) were employees, while 5% were owners. Amongst the participants, 3% had formal education (Matric), 13% held at least a diploma, 38% had degrees, 26% had an honours degree, while 19% and 1% had masters and PhDs, respectively. The dominance of respondents with at least a degree and postgraduate education indicated a highly technical, skilled, and knowledgeable workforce. Furthermore, 10% of the respondents qualified as computer scientists (Information technology personnel), 36% as marketers, 31% within the management field, 14% as statisticians, and 7% were within the supply chain. In comparison, the remaining 2% was shared evenly by operations researchers and others.

As this is a retail marketing technology study, obtaining responses from IT, marketing, supply chain, and management meant that high comprehension levels of the questionnaire were achieved. Understanding the respondent's current positions (job titles) was vital as it would mean that the study could generalize their involvement to digital transformation engagement. Therefore, 7% were directors, 29% were data analysts/scientists, 19% were sales executives, 6% were supply chain managers, 10% were marketing managers, 2% were IT technicians, 18% were marketing analysts, 2% were software developers, 7% market researchers and 1% others. Their job titles demonstrated a link to technology, marketing, sales, and retailing, meaning they had extensive knowledge about the subject matter. Since the study focused on certain departments purposively, it was ideal for getting a background of the overall departments under which the study respondents operated. Slightly half of the respondents, 54%, were in the marketing and/or sales department, 18% in IT, 18% in operations, 5% in supply chain and 6%

in other unnamed departments. This clearly indicated the study's attempt to link marketing, IT, supply chain and operations to understand the broad role of artificial intelligence.

**Table 4.2: Firm's background**

| Variable | Category | Frequency | Percentage |
|---|---|---|---|
| Company affiliation or major activities. | Marketing | 50 | 14% |
| | Food Retail | 268 | 77% |
| | IT | 28 | 8% |
| | Other | 4 | 1% |
| | **Total** | **350** | **100%** |
| Company Age | 0-3 Years | 20 | 6% |
| | 4-8 Years | 37 | 11% |
| | 9-12 Years | 57 | 16% |
| | 13 + Years | 236 | 67% |
| | **Total** | **350** | **100%** |
| Number of employees | 1-100 | 52 | 15% |
| | 101-250 | 16 | 5% |
| | 251-500 | 40 | 11% |
| | 501 + | 242 | 69% |
| | **Total** | **350** | **100%** |
| Location | Gauteng Province (G.P) | 153 | 44% |
| | Western Cape (W.C) | 60 | 17% |
| | Both G.P and W.C | 137 | 39% |
| | **Total** | **350** | **100%** |

***Source: Author's Compilation (2022)***

Table 4.2 illustrates the participant's firm background. The table captures the firm's major activities, age, number of employees and location. 77% of the respondents came from the food retail industry, 14% from the marketing side, 8% from information technology (IT) and 1% from the other unassigned sides. The results indicated that since the majority is from food retail and marketing, the study responses will fully capture the expected results, and some reliability would be guaranteed. Furthermore, most of the respondents' companies were 13 years old (67%), while less than three years was the least with 6%, 4-8 years was the second least with 11% and 9-12 years was captured at 16%. It is evident enough that most companies had existed for over a decade by the time of this study.

Most of these companies had 500 plus employees, thus according to 69% of the respondents, 15% of the respondents came from companies with less than 100 employees, 11% from firms with employees between 251-500 and lastly, 5% from firms with employee between 101-250. More so, most of the respondents (44%) companies were based in Gauteng province only, 17% in the Western Cape only and 39% in both provinces meaning these could be national companies. Most companies participating in the study were relatively big, employing more than 500 employees, and were in Gauteng but with some national spread within the food retail sector. The appropriateness of the participants could be justified as most of these companies are big (measured through the number of employees and age) and hence have the potential to adopt AI technologies and share sound knowledge surrounding the whole digital transformation journey.

### 4.5 SCALE REFINEMENT ON AI DETERMINANTS

Hair et al. (2017) referred to PCA as a method used in statistical analysis for reducing the dimensionality of a large data set by transforming a large set of variables into a smaller one that retains most of the information. Therefore, the study used PCA to reduce the dataset dimensionality on the determinants of AI technology adoption, i.e., experimental scale refinement. However, for scale refinement to commence, there is a need to assess the reliability of the scale, commonly examined through Cronbach's alpha coefficient (expected to be above 0.7, Abonazel et al., 2020) and analysing the correlation coefficients of the 35 items (constructs), expected to be greater than 0.5 to confirm association (Chan et al., 2022). Both the correlation coefficients on the item against the item (35 items) and Cronbach's alpha coefficient of scale analysis were greater than 0.5 and 0.7, respectively.

The principal component analysis (PCA) was secondary to the scale refinement. The PCA was done through the varimax rotation, a statistical measure conducted through the rotation of factor variables solutions to identify the less correlated or uncorrelated variables within each variable construct (Shmueli et al., 2019). Hair et al. (2022) state that the major reason for varimax rotation is to discover the underlying component structure within research variables and then present them in smaller quantified variables. Therefore, considering the 35 items (variables), varimax assisted the researcher in revealing potential underlying components structure for the 35 variables.

To identify redundancy between variables (observed correlation matrix) after the varimax rotation solutions (identified matrix), the study used Bartlett's test of sphericity. Bartlett's test for sphericity is a comparative measure used to eliminate redundancy amongst variables by analysing observed correlations against the observed (Hair & Alamer, 2022). Checking for redundancy helps researchers summarize variables in a few meaningful variables (Chin et al., 2020). It is for the above-stated reason that Bartlett's test was performed. The result for Bartlett's test of sphericity was significant *($p < 0.001$, test sphericity = 8372.765)*. Furthermore, the sampling adequacy (MSA) measure was greater than 0.50 for the overall test and individual variable. The researcher performed five iterations, and the findings were that the seven (7) factors and thirty (30) items had an eigenvalue >1 and accounted for 73% of the total variance. Equally so, communality values were equal to or greater than 0.6. Factor loading coefficients were all above the recommended 0.5, while Cronbach's alpha coefficient was above the 0.7 threshold. Model fitness was also achieved at 67%, with non-redundant residuals being 9%, thus more than the 0.05 benchmark. Table 4.3 illustrates the findings.

**Table 4.3: Reliability analysis and PCA results**

| Parameters | Constructs (KMO value = 0.807, Bartlett"s test of sphericity= 8372.765 ($p < 0.001$), 9% nonredundant residual ($p > 0.05$)) | | | | | |
|---|---|---|---|---|---|---|
| | Complexity | Risk | Firm Size | Finance | Competitive Pressure | Vendor Participation |
| Eigen Values | 4.88 | 4.8 | 4.06 | 3.5 | 3.12 | 2.88 |
| Total Variance Explained | 13% | 13% | 11% | 9% | 8% | 8% |
| No. of Indicators | 5 | 4 | 4 | 6 | 6 | 6 |
| Factor Loading (Range) | 0.8-0.91 | 0.7-0.91 | 0.802-0.832 | 0.72-0.82 | 0.75-0.89 | 0.85-0.86 |
| Communality (Range) | 0.7-0.88 | 0.6-0.88 | 0.7-0.80 | 0.61-0.80 | 0.60-0.80 | 0.75-0.79 |
| Reliability | 0.94 | 0.922 | 0.902 | 0.888 | 0.873 | 0.896 |
| Item to total Correlation | 0.713-0.90 | 0.638-0.861 | 0.723-0.832 | 0.676-0.782 | 0.679-0.816 | 0.772-0.781 |

## 4.6 STRUCTURAL EQUATION ANALYSIS

Structural equation modelling (SEM) was the main statistical technique used to analyse the results. Specifically, this study used the partial least square structural equation PLS-SEM approach. PLS-SEM involves two stages: the measurement model quality analysis and the structural model expression (path relationships). These stages are later presented in the chapter.

### 4.6.1 Measurement Model Analysis – Lower Order Construct (LOC)

In the first stage, confirmatory factor analysis (CFA) using partial least square estimation was applied to the Smart-PLS version 4. Specifically, this study used the measurement model to confirm the factor structure of the data (Hair et al., 2022). In this regard, the indicator loadings, convergent validity, discriminant validity and reliability were assessed. Table 4.4 depicts the indicator factor loadings.

**Table 4.4: Indicator Loadings**

| Indicators | AI Competitive Pressure | AI Complexity | AI Finance | AI Firm Size | AI Risk | AI Technology Adoption | AI Vendor Participation | Competitive Intensity | Marketing Mix Product Development | Marketing Mix Place | Marketing Mix Price | Marketing Mix Promo | Marketing Outcomes |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| AIDeCPR5 | 0.954 | | | | | | | | | | | | |
| AIDeCPR7 | 0.829 | | | | | | | | | | | | |
| AIDeCPR9 | 0.833 | | | | | | | | | | | | |
| AIDeCpl1 | | 0.780 | | | | | | | | | | | |
| AIDeCpl2 | | 0.770 | | | | | | | | | | | |
| AIDeCpl3 | | 0.801 | | | | | | | | | | | |
| AIDeCpl4 | | 0.842 | | | | | | | | | | | |
| AIDeFS1 | | | | 0.832 | | | | | | | | | |
| AIDeFS2 | | | | 0.870 | | | | | | | | | |
| AIDeFS3 | | | | 0.780 | | | | | | | | | |
| AIDeFi1 | | | 0.804 | | | | | | | | | | |
| AIDeFi2 | | | 0.902 | | | | | | | | | | |
| AIDeFi3 | | | 0.895 | | | | | | | | | | |
| AIDeFi4 | | | 0.931 | | | | | | | | | | |
| AIDeRi1 | | | | | 0.889 | | | | | | | | |
| AIDeRi2 | | | | | 0.922 | | | | | | | | |
| AIDeRi3 | | | | | 0.924 | | | | | | | | |
| AIDeRi4 | | | | | 0.801 | | | | | | | | |
| AIDeVP1 | | | | | | | 0.789 | | | | | | |
| AIDeVP2 | | | | | | | 0.890 | | | | | | |
| AIDeVP3 | | | | | | | 0.821 | | | | | | |
| AIDeVP4 | | | | | | | 0.850 | | | | | | |
| AITech1 | | | | | | 0.723 | | | | | | | |
| AITech2 | | | | | | 0.884 | | | | | | | |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| AITech3 | 0.891 | | | | | | |
| AITech4 | 0.905 | | | | | | |
| AITech5 | 0.900 | | | | | | |
| AITech6 | 0.884 | | | | | | |
| AITech7 | 0.721 | | | | | | |
| Comints1 | | 0.920 | | | | | |
| Comints2 | | 0.932 | | | | | |
| Comints3 | | 0.902 | | | | | |
| Comints4 | | 0.859 | | | | | |
| MMPD1 | | | 0.801 | | | | |
| MMPD2 | | | 0.906 | | | | |
| MMPD3 | | | 0.918 | | | | |
| MMPD4 | | | 0.796 | | | | |
| MMPL1 | | | | 0.679 | | | |
| MMPL2 | | | | 0.883 | | | |
| MMPL3 | | | | 0.890 | | | |
| MMPL4 | | | | 0.848 | | | |
| MMPRO1 | | | | | | 0.832 | |
| MMPRO2 | | | | | | 0.825 | |
| MMPRO3 | | | | | | 0.841 | |
| MMPRO4 | | | | | | 0.687 | |
| MMPr1 | | | | | 0.880 | | |
| MMPr2 | | | | | 0.843 | | |
| MMPr3 | | | | | 0.836 | | |
| MOutC1 | | | | | | | 0.858 |
| MOutC2 | | | | | | | 0.879 |
| MOutC3 | | | | | | | 0.916 |
| MOutC4 | | | | | | | 0.891 |
| MOutC5 | | | | | | | 0.895 |

The study examined the underlying constructs' factor loadings or indicator loadings. It shows the representation of the item in the construct. The loading value should be greater than 0.7 (Hair et al., 2022). As can be seen from Table 4.4, all the factor loadings met this threshold.

**Table 4.5: Reliability and Convergent Validity– Lower Order Construct (LOC)**

| Constructs | Cronbach's alpha (CA) | Composite reliability (rho_a) | Composite reliability (rho_c) | Average variance extracted (AVE) |
|---|---|---|---|---|
| AI Competitive Pressure | 0.866 | 0.754 | 0.906 | 0.764 |
| AI Complexity | 0.812 | 0.825 | 0.876 | 0.638 |
| AI Finance | 0.909 | 0.987 | 0.935 | 0.782 |
| AI Firm Size | 0.774 | 0.796 | 0.868 | 0.686 |
| AI Risk | 0.907 | 0.920 | 0.935 | 0.784 |
| AI Technology Adoption | 0.933 | 0.944 | 0.947 | 0.718 |
| AI Vendor Participation | 0.860 | 0.880 | 0.904 | 0.703 |
| Competitive Intensity | 0.926 | 0.960 | 0.947 | 0.816 |
| Marketing Mix - Product Development | 0.878 | 0.887 | 0.917 | 0.735 |
| Marketing Mix – Place | 0.846 | 0.871 | 0.897 | 0.688 |
| Marketing Mix – Price | 0.812 | 0.813 | 0.889 | 0.728 |
| Marketing Mix – Promotion | 0.809 | 0.818 | 0.875 | 0.638 |
| Marketing Outcomes | 0.933 | 0.935 | 0.949 | 0.789 |

**Source: Author's Compilation (2022)**

Table 4.5 depicts the study findings on Cronbach's alpha (CA), Composite reliability (rho_a), Composite reliability (rho_c) and Average variance extracted (AVE). Hair et al. (2022) state that the Cronbach Alpha and Composite Reliability threshold is 0.7. As seen in Table 4.5, this threshold was met for both CA and CR. Further, the AVE values should preferably exceed 0.5 (Hair et al., 2022). From Table 4.5, it is evident that this threshold was achieved.

**Table 4.6: Discriminant Validity – Heterotraint Monotraint Ratio (HTMT)**

| Constructs | AI Competitive Pressure | AI Complexity | AI Finance | AI Firm Size | AI Risk | AI Technology Adoption | AI Vendor Participation | Competitive Intensity | Marketing Mix Product Developemnt | Marketing Mix Place | Marketing Mix Price | Marketing Mix Promotion | Marketing Outcomes |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| AI Competitive Pressure | | | | | | | | | | | | | |
| AI Complexity | 0.159 | | | | | | | | | | | | |
| AI Finance | 0.108 | 0.348 | | | | | | | | | | | |
| AI Firm Size | 0.066 | 0.613 | 0.435 | | | | | | | | | | |
| AI Risk | 0.119 | 0.458 | 0.231 | 0.453 | | | | | | | | | |
| AI Technology Adoption | 0.051 | 0.453 | 0.191 | 0.340 | 0.412 | | | | | | | | |
| AI Vendor Participation | 0.254 | 0.446 | 0.531 | 0.412 | 0.367 | 0.262 | | | | | | | |
| Competitive Intensity | 0.120 | 0.371 | 0.099 | 0.210 | 0.340 | 0.593 | 0.342 | | | | | | |
| Marketing Mix Pdevelopemnt | 0.073 | 0.198 | 0.412 | 0.172 | 0.068 | 0.102 | 0.260 | 0.198 | | | | | |
| Marketing Mix Place | 0.422 | 0.161 | 0.099 | 0.090 | 0.110 | 0.063 | 0.288 | 0.153 | 0.098 | | | | |
| Marketing Mix Price | 0.060 | 0.233 | 0.523 | 0.281 | 0.137 | 0.146 | 0.429 | 0.140 | 0.663 | 0.077 | | | |
| Marketing Mix Promo | 0.088 | 0.187 | 0.523 | 0.146 | 0.078 | 0.098 | 0.366 | 0.205 | 0.421 | 0.076 | 0.704 | | |
| Marketing Outcomes | 0.492 | 0.377 | 0.239 | 0.260 | 0.278 | 0.100 | 0.422 | 0.195 | 0.228 | 0.606 | 0.226 | 0.204 | |

**Source: Author's Compilation (2022)**

Discriminant validity assesses whether theoretically, unrelated constructs are unrelated. Discriminant validity is crucial because it demonstrates whether the test accurately targets the construct of interest or whether it assesses distinct, unintentionally related constructs (Hair et al., 2022). The literature has recommended a conservative threshold of 0.85 and a more liberal threshold of 0.90 to achieve discriminant validity based on the HTMT criterion. As can be seen from Table 4.6, this threshold was met for all constructs, thus confirming discriminant validity. Additionally, the study used the Fornell-Larcker and the Cross Loadings Criteria to confirm discriminant validity further, as shown in Tables 4.7 and 4.8. Both the Fornell-Larcker and Cross-Loadings criteria provided further evidence for the achievement of discriminant validity. Thus, the measurement model at the LOC is adequate for any further analysis.

**Table 4.7: Fornell Larcker Criterion**

| Constructs | AI Competitive Pressure | AI Complexity | AI Finance | AI Firm Size | AI Risk | AI Technology Adoption | AI Vendor Participation | Competitive Intensity | Marketing Mix Product Developement | Marketing Mix Place | Marketing Mix Price | Marketing Mix Promotion | Marketing Outcomes |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| AI Competitive Pressure | **0.874** | | | | | | | | | | | | |
| AI Complexity | 0.144 | **0.799** | | | | | | | | | | | |
| AI Finance | 0.100 | 0.307 | **0.884** | | | | | | | | | | |
| AI Firm Size | 0.020 | 0.483 | 0.371 | **0.828** | | | | | | | | | |
| AI Risk | 0.114 | 0.826 | 0.223 | 0.385 | **0.885** | | | | | | | | |
| AI Technology Adoption | -0.049 | -0.404 | -0.189 | -0.299 | -0.385 | **0.847** | | | | | | | |
| AI Vendor Participation | 0.224 | 0.370 | 0.471 | 0.343 | 0.332 | -0.246 | **0.838** | | | | | | |
| Competitive Intensity | 0.118 | 0.325 | 0.092 | 0.184 | 0.311 | -0.549 | 0.307 | **0.904** | | | | | |
| Marketing Mix Pdevelopemr | 0.071 | 0.156 | 0.364 | 0.143 | 0.047 | -0.092 | 0.224 | 0.182 | **0.857** | | | | |
| Marketing Mix Place | 0.791 | 0.135 | 0.091 | 0.012 | 0.095 | -0.019 | 0.248 | 0.148 | 0.070 | **0.829** | | | |
| Marketing Mix Price | 0.043 | 0.184 | 0.444 | 0.224 | 0.119 | -0.127 | 0.365 | 0.124 | 0.558 | 0.051 | **0.853** | | |
| Marketing Mix Promo | 0.075 | 0.141 | 0.449 | 0.119 | 0.035 | -0.083 | 0.301 | 0.179 | 0.778 | 0.056 | 0.573 | **0.799** | |
| Marketing Outcomes | 0.437 | 0.320 | 0.221 | 0.227 | 0.251 | -0.096 | 0.376 | 0.189 | 0.206 | 0.548 | 0.198 | 0.177 | **0.888** |

## Table 4.8: Cross-Factor Loadings

| Indicators | AI Competitive Pressure | AI Complexity | AI Finance | AI Firm Size | AI Risk | AI Technology Adoption | AI Vendor Participation | Competitive Intensity | Marketing Mix Product Development | Marketing Mix Place | Marketing Mix Price | Marketing Mix Promotion | Marketing Outcomes |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| AIDeCPR5 | **0.9540** | 0.1450 | 0.0960 | 0.0080 | 0.1120 | -0.0590 | 0.2110 | 0.1110 | 0.0780 | 0.7040 | 0.0360 | 0.0990 | 0.3670 |
| AIDeCPR7 | **0.8290** | 0.0930 | 0.1050 | -0.0200 | 0.0610 | -0.0130 | 0.1950 | 0.0770 | 0.0370 | 0.6820 | 0.0630 | 0.0460 | 0.3390 |
| AIDeCPR9 | **0.8330** | 0.1140 | 0.0720 | 0.0550 | 0.1030 | -0.0290 | 0.1880 | 0.1120 | 0.0490 | 0.7480 | 0.0340 | 0.0140 | 0.4750 |
| AIDeCpl1 | 0.1260 | **0.7800** | 0.3580 | 0.5030 | 0.6450 | -0.2880 | 0.4010 | 0.2390 | 0.2600 | 0.1140 | 0.2670 | 0.2130 | 0.2910 |
| AIDeCpl2 | 0.1120 | **0.7700** | 0.2040 | 0.3640 | 0.6160 | -0.2620 | 0.3090 | 0.2470 | 0.1180 | 0.1330 | 0.1170 | 0.1340 | 0.3050 |
| AIDeCpl3 | 0.0900 | **0.8010** | 0.2540 | 0.3640 | 0.6150 | -0.3550 | 0.2410 | 0.2540 | 0.1060 | 0.0580 | 0.1490 | 0.1030 | 0.2240 |
| AIDeCpl4 | 0.1320 | **0.8420** | 0.1810 | 0.3340 | 0.7530 | -0.3650 | 0.2600 | 0.2930 | 0.0440 | 0.1360 | 0.0740 | 0.0300 | 0.2260 |
| AIDeFS1 | -0.0350 | 0.4480 | 0.4110 | **0.8320** | 0.3530 | -0.2540 | 0.3780 | 0.2200 | 0.1990 | 0.0010 | 0.3030 | 0.1860 | 0.1890 |
| AIDeFS2 | 0.0870 | 0.4000 | 0.2210 | **0.8700** | 0.3200 | -0.2820 | 0.2570 | 0.1690 | 0.0840 | 0.0560 | 0.1100 | 0.0460 | 0.2280 |
| AIDeFS3 | -0.0170 | 0.3460 | 0.3020 | **0.7800** | 0.2780 | -0.1930 | 0.2060 | 0.0420 | 0.0670 | -0.0450 | 0.1440 | 0.0600 | 0.1320 |
| AIDeFi1 | 0.0550 | 0.1710 | **0.8040** | 0.2560 | 0.1070 | -0.1080 | 0.4250 | 0.1210 | 0.3050 | 0.0750 | 0.3950 | 0.3820 | 0.1890 |
| AIDeFi2 | 0.0810 | 0.2920 | **0.9020** | 0.2980 | 0.2290 | -0.1470 | 0.4290 | 0.0470 | 0.2920 | 0.0600 | 0.3930 | 0.3940 | 0.1750 |
| AIDeFi3 | 0.0760 | 0.2550 | **0.8950** | 0.3340 | 0.1700 | -0.1480 | 0.3920 | 0.0520 | 0.3720 | 0.0910 | 0.4180 | 0.4260 | 0.2080 |
| AIDeFi4 | 0.1190 | 0.3260 | **0.9310** | 0.3870 | 0.2420 | -0.2260 | 0.4320 | 0.1070 | 0.3260 | 0.0910 | 0.3870 | 0.3980 | 0.2080 |
| AIDeRi1 | 0.0900 | 0.7610 | 0.2370 | 0.3430 | **0.8890** | -0.3540 | 0.3180 | 0.2740 | 0.0640 | 0.0770 | 0.1040 | 0.0530 | 0.2030 |
| AIDeRi2 | 0.0950 | 0.7550 | 0.1940 | 0.3780 | **0.9220** | -0.3690 | 0.3210 | 0.2810 | 0.0200 | 0.0810 | 0.1140 | 0.0060 | 0.2230 |
| AIDeRi3 | 0.0990 | 0.7380 | 0.1980 | 0.3500 | **0.9240** | -0.3560 | 0.2840 | 0.2720 | 0.0370 | 0.0560 | 0.1140 | 0.0170 | 0.2020 |
| AIDeRi4 | 0.1280 | 0.6690 | 0.1520 | 0.2810 | **0.8010** | -0.2730 | 0.2470 | 0.2800 | 0.0470 | 0.1370 | 0.0850 | 0.0560 | 0.2770 |
| AIDeVP1 | 0.2160 | 0.2970 | 0.2910 | 0.2720 | 0.2420 | -0.1930 | **0.7890** | 0.2640 | 0.1770 | 0.2690 | 0.2490 | 0.2290 | 0.3530 |
| AIDeVP2 | 0.1570 | 0.3080 | 0.3980 | 0.2860 | 0.2790 | -0.2140 | **0.8900** | 0.2850 | 0.2020 | 0.1670 | 0.3310 | 0.2800 | 0.3170 |
| AIDeVP3 | 0.1530 | 0.2660 | 0.4080 | 0.2730 | 0.2370 | -0.1490 | **0.8210** | 0.2590 | 0.1770 | 0.1890 | 0.2690 | 0.2550 | 0.3060 |
| AIDeVP4 | 0.2150 | 0.3520 | 0.4690 | 0.3120 | 0.3340 | -0.2460 | **0.8500** | 0.2280 | 0.1920 | 0.2090 | 0.3530 | 0.2470 | 0.2930 |
| AITech1 | -0.0420 | -0.3180 | -0.0570 | -0.2090 | -0.3250 | **0.7230** | -0.1550 | -0.4520 | -0.0140 | -0.0470 | -0.0640 | -0.0290 | -0.1120 |
| AITech2 | -0.0200 | -0.3680 | -0.1520 | -0.2820 | -0.3430 | **0.8840** | -0.2020 | -0.5000 | -0.0810 | 0.0190 | -0.1160 | -0.0830 | -0.0950 |

| | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| AITech3 | -0.0210 | -0.3480 | -0.1480 | -0.2430 | -0.3250 | **0.8910** | -0.1580 | -0.4630 | -0.0260 | 0.0140 | -0.0800 | -0.0150 | -0.0310 |
| AITech4 | -0.0660 | -0.3450 | -0.1920 | -0.2700 | -0.3340 | **0.9050** | -0.2690 | -0.5000 | -0.0840 | -0.0530 | -0.0990 | -0.0630 | -0.0910 |
| AITech5 | -0.0440 | -0.3230 | -0.2160 | -0.2590 | -0.3030 | **0.9000** | -0.1920 | -0.4500 | -0.0870 | 0.0070 | -0.1270 | -0.0930 | -0.0460 |
| AITech6 | -0.0880 | -0.3990 | -0.1660 | -0.3050 | -0.3930 | **0.8840** | -0.2740 | -0.5000 | -0.1260 | -0.0540 | -0.1170 | -0.0880 | -0.1560 |
| AITech7 | 0.0110 | -0.2690 | -0.1800 | -0.1740 | -0.2340 | **0.7210** | -0.1800 | -0.3730 | -0.1130 | 0.0100 | -0.1500 | -0.1180 | -0.0100 |
| Comints1 | 0.1480 | 0.2620 | 0.0870 | 0.1590 | 0.2590 | -0.4710 | 0.2570 | **0.9200** | 0.2010 | 0.1900 | 0.1070 | 0.1960 | 0.1880 |
| Comints2 | 0.1120 | 0.3580 | 0.0840 | 0.1930 | 0.3340 | -0.5220 | 0.3260 | **0.9320** | 0.1630 | 0.1390 | 0.1460 | 0.1650 | 0.2040 |
| Comints3 | 0.0990 | 0.2440 | 0.0910 | 0.1290 | 0.2380 | -0.4960 | 0.2720 | **0.9020** | 0.1330 | 0.1160 | 0.0810 | 0.1310 | 0.1500 |
| Comints4 | 0.0440 | 0.3060 | 0.0680 | 0.1840 | 0.2900 | -0.5070 | 0.2400 | **0.8590** | 0.1530 | 0.0600 | 0.1060 | 0.1480 | 0.1160 |
| MMPD1 | 0.0340 | 0.1200 | 0.3190 | 0.1280 | 0.0190 | -0.0820 | 0.2630 | 0.1610 | **0.8010** | 0.0630 | 0.5040 | 0.5900 | 0.1690 |
| MMPD2 | 0.0640 | 0.1360 | 0.3120 | 0.1570 | 0.0500 | -0.1140 | 0.1570 | 0.1830 | **0.9060** | 0.0500 | 0.4810 | 0.6640 | 0.1750 |
| MMPD3 | 0.0560 | 0.1200 | 0.2950 | 0.0830 | -0.0050 | -0.0790 | 0.1610 | 0.1610 | **0.9180** | 0.0460 | 0.4810 | 0.7170 | 0.1920 |
| MMPD4 | 0.0950 | 0.1650 | 0.3280 | 0.1270 | 0.1070 | -0.0350 | 0.1960 | 0.1120 | **0.7960** | 0.0870 | 0.4510 | 0.7030 | 0.1690 |
| MMPL1 | 0.4640 | 0.0540 | 0.0270 | -0.0700 | 0.0220 | 0.0550 | 0.1360 | 0.0670 | -0.0320 | **0.6790** | -0.0330 | 0.0050 | 0.3310 |
| MMPL2 | 0.6750 | 0.1450 | 0.1050 | 0.0300 | 0.1090 | -0.0260 | 0.2620 | 0.1410 | 0.0780 | **0.8830** | 0.0700 | 0.0730 | 0.4520 |
| MMPL3 | 0.7190 | 0.0940 | 0.0680 | 0.0050 | 0.0770 | -0.0050 | 0.2030 | 0.1160 | 0.0560 | **0.8900** | 0.0200 | 0.0270 | 0.4860 |
| MMPL4 | 0.7220 | 0.1420 | 0.0890 | 0.0490 | 0.0930 | -0.0640 | 0.2110 | 0.1520 | 0.1010 | **0.8480** | 0.0880 | 0.0690 | 0.5200 |
| MMPRO1 | 0.0660 | 0.0980 | 0.3940 | 0.1060 | 0.0000 | -0.0400 | 0.2170 | 0.1360 | 0.7630 | 0.0390 | 0.4800 | **0.8320** | 0.1730 |
| MMPRO2 | 0.0510 | 0.1560 | 0.3760 | 0.1230 | 0.0850 | -0.1140 | 0.2270 | 0.1620 | 0.5570 | 0.0500 | 0.4790 | **0.8250** | 0.1280 |
| MMPRO3 | 0.0250 | 0.1320 | 0.3880 | 0.1030 | 0.0560 | -0.0660 | 0.2590 | 0.1380 | 0.6600 | 0.0170 | 0.5080 | **0.8410** | 0.1350 |
| MMPRO4 | 0.1010 | 0.0610 | 0.2630 | 0.0390 | -0.0350 | -0.0460 | 0.2690 | 0.1380 | 0.4850 | 0.0770 | 0.3520 | **0.6870** | 0.1280 |
| MMPr1 | 0.0370 | 0.2060 | 0.3670 | 0.2380 | 0.1120 | -0.1100 | 0.3220 | 0.1160 | 0.4920 | 0.0180 | **0.8800** | 0.4850 | 0.1710 |
| MMPr2 | 0.0480 | 0.1750 | 0.3780 | 0.1930 | 0.1320 | -0.1070 | 0.2840 | 0.0900 | 0.4580 | 0.0510 | **0.8430** | 0.4810 | 0.1710 |
| MMPr3 | 0.0260 | 0.0880 | 0.3910 | 0.1390 | 0.0580 | -0.1090 | 0.3280 | 0.1120 | 0.4780 | 0.0620 | **0.8360** | 0.5000 | 0.1640 |
| MOutC1 | 0.3480 | 0.2810 | 0.2210 | 0.2080 | 0.2280 | -0.1000 | 0.3810 | 0.1740 | 0.2000 | 0.4790 | 0.1960 | 0.1680 | **0.8580** |
| MOutC2 | 0.3930 | 0.2900 | 0.1850 | 0.2050 | 0.2180 | -0.0770 | 0.3200 | 0.1680 | 0.1760 | 0.4520 | 0.1500 | 0.1800 | **0.8790** |
| MOutC3 | 0.4370 | 0.2840 | 0.2030 | 0.2060 | 0.2370 | -0.0740 | 0.3290 | 0.1790 | 0.1580 | 0.5240 | 0.1720 | 0.1650 | **0.9160** |
| MOutC4 | 0.3370 | 0.3000 | 0.1810 | 0.1950 | 0.2410 | -0.0480 | 0.3190 | 0.1180 | 0.1930 | 0.4630 | 0.1720 | 0.1450 | **0.8910** |
| MOutC5 | 0.4210 | 0.2690 | 0.1870 | 0.1940 | 0.1920 | -0.1250 | 0.3210 | 0.1960 | 0.1870 | 0.5090 | 0.1850 | 0.1310 | **0.8950** |

### 4.6.2 Validation of Higher Order Constructs (AI Determinants and Marketing Mix Components)

Given that this study used the higher order construct, there was the need to assess the measurement model at the Higher Order Construct (LOC). AI determinants have six (6) dimensions: Complexity, Risk, Firm Size, Finance, Competitive pressure, and Vendor participation. Similarly, Marketing Mix Components have four (4) sub-dimensions: Pricing, Product Development, Promotion and Place capabilities. These dimensions have indicators or observed variables. In this study, we used the LOC to reduce the number of path coefficients. This, therefore, requires the need to validate the LOC measurement model (Hair et al., 2022). For this part of the analysis, the study reported information about the Loadings, Reliability, Convergent Validity and Discriminant Validity (Tables 4.9 and 4.10).

**Table 4.9: Loadings, Reliability and Convergent Validity for LOC**

**Source: Author's Compilation (2022)**

| Constructs | Loadings | Cronbach's alpha (CA) | Composite reliability (rho_a) | Composite reliability (rho_c) | Average variance extracted (AVE) |
|---|---|---|---|---|---|
| **AI Determinants:** | | 0.733 | 0.813 | 0.830 | 0.649 |
| AI Competitive Pressure | 0.801 | | | | |
| AI Complexity | 0.886 | | | | |
| AI Finance | 0.746 | | | | |
| AI Firm Size | 0.791 | | | | |
| AI Risk | 0.835 | | | | |
| AI Vendor Participation | 0.729 | | | | |
| **Marketing Miix Capabilities:** | | 0.756 | 0.766 | 0.781 | 0.637 |
| Marketing Mix Product Developement | 0.761 | | | | |
| Marketing Mix Place | 0.731 | | | | |
| Marketing Mix Price | 0.898 | | | | |
| Marketing Mix Promo | 0.848 | | | | |

**Source: Author's Compilation (2022)**

As seen in Table 4.9, all the indicator loadings were above the threshold of 0.7, the CA and CR were above the recommended threshold of 0.7, and the AVE values were above the 0.5 threshold (Hair et al., 2022).

**Table 4.10: Discriminant Validity for HOC (HTMT)**

| HTMT HOC | | | | | |
|---|---|---|---|---|---|
| Constructs | AI Determinants | AI Technology Adoption | Competitive Intensity | Marketing Miix Capabilities | Marketing Outcomes |
| AI Determinants | | | | | |
| AI Technology Adoption | 0.480 | | | | |
| Competitive Intensity | 0.409 | 0.593 | | | |
| Marketing Miix Capabilities | 0.615 | 0.147 | 0.272 | | |
| Marketing Outcomes | 0.564 | 0.100 | 0.195 | 0.495 | |

**Table 4.11: Discriminant Validity for HOC (Fornell Larcker)**

| Fonell Larcker HOC | | | | | |
|---|---|---|---|---|---|
| Constructs | AI Determinants | AI Technology Adoption | Competitive Intensity | Marketing Miix Capabilities | Marketing Outcomes |
| AI Determinants | **0.67** | | | | |
| AI Technology Adoption | -0.433 | **0.847** | | | |
| Competitive Intensity | 0.351 | -0.55 | **0.904** | | |
| Marketing Miix Capabilities | 0.327 | -0.093 | 0.228 | **0.661** | |
| Marketing Outcomes | 0.39 | -0.097 | 0.189 | 0.528 | **0.888** |

Tables 4.10 and 4.11 depict the discriminant validity of the higher-order constructs (HOC) using the HTMT and the Fornell Larcker criteria. As guided by the Fornell-Larcker rules, the values in the diagonal and bolded are all greater than the cross-correlation of the construct, as shown in Table 4.11. Additionally, the cross-correlations of the constructs were all below the conservative threshold of 0.85, thus confirming the discriminant validity of the HOC.

## 4.7 STRUCTURAL MODEL ASSESSMENT – LOWER ORDER CONSTRUCTS

Having established the adequacy of the measurement via reliability and validity criteria, the next step or stage of the analysis was to examine the structural model results. As recommended by Shmueli et al. (2019), four (4) steps are suggested in this part of the analysis as follows: (1) collinearity evaluation within the structural model, (2) structural model relationships assessment for significance and relevance validation (3) examine the structural model's explanatory power and (4) examine the model's predictive power through PLS-Predict.

### 4.7.1 Assessing collinearity.

Multicollinearity is a condition which exists when two or more independent variables have a strong linear relationship during regression analysis (Chan et al., 2022). Although having a strong correlation does not mean collinearity, researchers aim to assess collinearity existence to guarantee that each variable is independent of the other and it measures what it is intended to measure. Testing for collinearity meant that each variable inclusion was justified as it measures the intended object and helps avoid issues relating to misleading outcomes. Equally, this collinearity check contributed to the dependency on ordinary least squares (OLS) regression output from the endogenous constructs and the corresponding predictor constructs for path coefficient estimation in structural equation modelling (SEM). Hair et al. (2022) stress the potential biases in path coefficient estimates due to collinearity within the predictor constructs.

Although there are several ways to assess collinearity, such as pairwise correlation and PCA (Abonazel et al., 2022), the study used the variance inflation factor (VIF) for collinearity assessment. VIF is the ratio of variance estimating certain constructs (Asar & Genc, 2018). The existing literature suggests that VIF values above 5 indicate the probability of collinearity within the predictor constructs. However, collinearity can still be present with VIF values as low as 3-5 (Becker et al., 2015). In the study, collinearity statistics of the inner model ranged between 1 to 3.6, as shown in Table 4.12, thus alleviating any collinearity concerns.

**Table 4.12: Inner Model VIF Statistics**

| Constructs | AI Competitive Pressure | AI Complexity | AI Finance | AI Firm Size | AI Risk | AI Technology Adoption | AI Vendor Participation | Competitive Intensity | Marketing Mix Pdevelopemnt | Marketing Mix Place | Marketing Mix Price | Marketing Mix Promo | Marketing Outcomes |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| AI Competitive Pressure | | | | | | 1.068 | | | | | | | |
| AI Complexity | | | | | | 3.601 | | | | | | | |
| AI Finance | | | | | | 1.387 | | | | | | | |
| AI Firm Size | | | | | | 1.434 | | | | | | | |
| AI Risk | | | | | | 3.179 | | | | | | | |
| AI Technology Adoption | | | | | | | | | 1 | 1 | 1 | 1 | 1.523 |
| AI Vendor Participation | | | | | | 1.462 | | | | | | | |
| Competitive Intensity | | | | | | | | | | | | | 1.59 |
| Marketing Mix Product Developement | | | | | | | | | | | | | 2.678 |
| Marketing Mix Place | | | | | | | | | | | | | 1.042 |
| Marketing Mix Price | | | | | | | | | | | | | 1.579 |
| Marketing Mix Promo | | | | | | | | | | | | | 2.748 |
| Marketing Outcomes | | | | | | | | | | | | | |

## 4.8 MARKETING STRATEGY OUTCOME OBJECTIVE ANALYSIS

Given that the main dependent variable in this study (i.e., Marketing Strategy Outcome) could be objectively measured, the study performed further analysis using objective measures. For this part of the analysis, the marketing strategy outcome was separated into four (4) dimensions as follows: (1) sales increase, (2) profitability increase, (3) market share increase, and (4) return on investment increase. These variables were operationalized: sales increase was measured as the average percentage change in revenue for 2019, 2020 and 2021. Profitability was measured as the average percentage change in operating profit for 2019, 2020 and 2021. Market share increase was measured as the firm's revenue as a percentage of an industry's total revenues on average terms. Return on investment was measured as net income divided by the total cost of the investment.

To perform the analysis, ordinary least square (OLS) regression was performed using the following four equations:

Sales $\text{increase}_i = \beta_0 + \beta_1 AI_i + \beta_2 CI + \beta_3 (AI \text{ x } CI) + \varepsilon_i$ ……………… (1)

Profitability $\text{increase}_i = \beta_0 + \beta_1 AI_i + \beta_2 CI + \beta_3 (AI \text{ x } CI) + \varepsilon_i$ ……………… (2)

Market Share $\text{increase}_i = \beta_0 + \beta_1 AI_i + \beta_2 CI + \beta_3 (AI \text{ x } CI) + \varepsilon_i$ ……………… (3)

Return on Investment $\text{increase}_i = \beta_0 + \beta_1 AI_i + \beta_2 CI + \beta_3 (AI \text{ x } CI) + \varepsilon_i$ ……………… (4)

Where:

AI is the artificial intelligence technology adoption;

CI is the competitive intensity;

$\beta_0 \beta_1 \beta_2 \beta_3$ are the beta coefficient

$\varepsilon_i$ is the error term

**Table 4.13: Descriptive Statistics for Dependent Variable (Marketing Strategy Outcome)**

| Variable | Obs. | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| Sales Increase | 350 | 0.550 | 1.192 | 0.470 | 0.650 |
| Profitability Increase | 350 | 0.510 | 1.043 | 0.460 | 0.570 |
| Market Share Increase | 350 | 0.460 | 0.936 | 0.320 | 0.690 |
| Return on Investment Increase | 350 | 0.620 | 1.396 | 0.250 | 0.720 |

Table 4.13 shows the descriptive statistics of the actual measures of marketing strategy outcome. Sales increase had an average of 55% growth in revenue with a minimum of 47% and a maximum of 65%. Additionally, profitability had a mean of 51% among the firms used in this study. This implies that profit grew by 51% among the study firms. This trend was consistent for both market share and return on investment increase.

**Table 4.14: Dependent Variable (Sales Increase)**

| Constructs | Unstandardized coefficients | SE | T value | P value | 2.50% | 97.50% |
|---|---|---|---|---|---|---|
| | **Dependent Variable: Sales Increase** | | | | | |
| AI | 0.595 | 0.079 | 7.490 | 0.000 | 0.437 | 0.753 |
| CI | 0.354 | 0.119 | 2.980 | 0.004 | 0.118 | 0.590 |
| AI_x_CI | 0.058 | 0.022 | 2.670 | 0.009 | 0.015 | 0.102 |
| Constant | 3.680 | 0.443 | 8.310 | 0.000 | 2.801 | 4.559 |
| $R^2$ | 0.3639 | | | | | |
| Adjusted $R^2$ | 0.3574 | | | | | |
| Prob. > F | 0.000 | | | | | |
| OBS | 350 | | | | | |

Table 4.14 depicts the sales variable regression output. The test was conducted at a 95% confidence interval with a 5% margin of error. As the model was designed, it accounted for the direct influence of AI technologies on marketing strategy outcome constructs, of which the relationship was moderated by competition intensity. From Table 4.14, the moderating effect is confirmed outcomes ($\beta = 0.117$, $p = 0.009$). Equally so, AI's relationship (effect) on sales increase is confirmed ($\beta = 3.680$, $p = 0.000$). The findings overly translate to the views that AI adoption increases sales. The model has an adjusted $R^2$ of 0.36, which can be attributed to a significant proportion in explaining how AI directly influences sales. Although the $R^2$ is acceptable, it is weak/low. This can be attributed to several factors, such as adoption uncertainties, structural issues, implementation challenges, and time lags (Brynjolfsson et al., 2019). Equally so, data integrity and privacy concerns could have been attributed to the weak coefficient.

Table 4.15 shows the regression model output of the profit variable. Using the same guidelines and rules applied to the sales model as proposed by (Hair et al., 2019), the model was conducted at a 95% confidence interval and 5% margin of error. The model confirmed AI-adapted technologies' influence on profit ($\beta$ = 4.903, $p$ = 0.000). The moderating effect was also confirmed ($\beta$ = 0.050, $p$ = 0.000). The extent to which AI explains the variance of profit (dependent variable) (independent variable), which is known as the $R^2$ (Abonazel et al., 2022), was significant (adjusted $R^{2 =}$ 0.1949).

**Table 4.15: Dependent Variable (Profitability Increase)**

| Constructs | Unstandardized coefficients | SE | T value | P value | 2.50% | 97.50% |
|---|---|---|---|---|---|---|
| | | **Dependent Variable: Profitability** | | | | |
| AI | 0.389 | 0.078 | 5.000 | 0.000 | 0.235 | 0.544 |
| CI | 0.223 | 0.109 | 2.052 | 0.041 | 0.112 | 0.458 |
| AI_x_CI | 0.050 | 0.011 | 4.740 | 0.000 | 0.029 | 0.071 |
| Constant | 4.903 | 0.434 | 11.300 | 0.000 | 4.042 | 5.764 |
| $R^2$ | 0.2031 | | | | | |
| Adjusted $R^2$ | 0.1949 | | | | | |
| Prob. > F | 0.000 | | | | | |
| OBS | 350 | | | | | |

Consistent with the rules and guidelines of the model interpretation, AI adoption increases a firm's market share ($\beta$ = 6.023, $p$ = 0.000), as shown in Table 4.16. The moderating influence of competitive intensity was also significant ($\beta$ = 0.029, $p$ = 0.021). The variable variance (market share) was equal to (adjusted $R^{2 =}$ 0.15).

**Table 4.16: Dependent Variable (Market Share Increase)**

| Constructs | Unstandardized coefficients | SE | T value | P value | 2.50% | 97.50% |
|---|---|---|---|---|---|---|
| | | **Dependent Variable: Market Share Increase** | | | | |
| AI | 0.310 | 0.072 | 4.330 | 0.000 | 0.168 | 0.453 |
| CI | 0.176 | 0.080 | 2.195 | 0.029 | 0.182 | 0.273 |
| AI_x_CI | 0.029 | 0.012 | 2.351 | 0.021 | 0.005 | 0.054 |
| Constant | 6.023 | 0.400 | 15.070 | 0.000 | 5.230 | 6.816 |
| $R^2$ | 0.1606 | | | | | |
| Adjusted $R^2$ | 0.1521 | | | | | |
| Prob. > F | 0.000 | | | | | |
| OBS | 350 | | | | | |

Table 4.17 illustrates the regression model findings between AI adoption and the return on investment. The model confirmed that AI adoption increased the company's investment returns

($\beta$ = 5.293, $p$ = 0.000). The moderating effect of competition intensity was also confirmed ($\beta$ = 0.025, $p$ = 0.001). Variable variance ($R^2$ ) was equal to 21%.

**Table 4.17: Dependent Variable (Return on Investment Increase)**

| Constructs | Unstandardized coefficients | SE | T value | P value | 2.50% | 97.50% |
|---|---|---|---|---|---|---|
| **Dependent Variable: Return on Investment Increase** | | | | | | |
| AI | 0.310 | 0.060 | 5.160 | 0.000 | 0.191 | 0.429 |
| CI | 0.331 | 0.112 | 2.950 | 0.004 | 0.108 | 0.553 |
| AI_x_CI | 0.025 | 0.012 | 2.060 | 0.042 | 0.001 | 0.049 |
| Constant | 5.293 | 0.476 | 11.110 | 0.000 | 4.348 | 6.238 |
| R2 | 0.2136 | | | | | |
| Adjusted R2 | 0.2056 | | | | | |
| Prob. > F | 0.000 | | | | | |
| OBS | 350 | | | | | |

On a summative note, Tables (4.15-4.17) depict that AI adoption has a positive and significant relationship with sales increase, profitability, market share and return on investment, even if market strategy outcome is measured objectively from the financials of the individual firms used in this study. Additionally, competitive intensity (CI) moderates the positive relationship between artificial intelligence (AI) technology adoptions. Therefore, this collaborates with the results obtained using perceptual or subjective measures.

## 4.9 STRUCTURAL MODELING RELATIONSHIPS (SIGNIFICANCE AND RELEVANCE)

Consistent with the four-step analysis process, the researcher conducted an evaluation and significance testing procedure on the structural model relationships. This entailed that after assessing collinearity, which was not a concern, the path coefficients were examined in relation to the study's hypotheses. The hypothesized relationships of the study represented an association between the constructs, not the causal effects. Therefore, the positive and significant assessments did not establish the cause-and-effect relationship in this study.

### 4.9.1: Determinants and AI Adoption Relationships

Hypothesis H1a, which states that complexity (ease to use) positively impacts AI adoption at a firm level, was tested. The hypothesis aimed to determine the effect of complexity (ease of use) on AI technology adoption. The results proved that complexity significantly impacts AI technology adoption (β = 0.182, SE = 0.093, T =1.965, P = 0.049), thus supporting H1a.

Hypothesis H1b, which aimed at evaluating if the perceived risk (including market uncertainty, compliance, and regulation) had a positive and significant influence on AI adoption at the firm level, was tested. The results confirmed that the perceived risks associated with AI adoption have a positive and significant influence on AI technology adoption ($\beta$ = 0.161, SE = 0.074, T = 2.176, P = 0.030), thus, supporting hypothesis H1b.

Furthermore, hypothesis H1c aimed to determine if a firm's financial stability positively and significantly influenced AI technology adoption at the firm level. The test results proved that a firm's financial stability has a positive and significant influence on AI adoption ($\beta$ = 0.118, SE = 0.041, T = 2.878, P = 0.004), thus, supporting hypothesis H1c.

More so, hypothesis H1d which states that firm size positively and significantly determines AI adoption at the firm level, was tested. The test results established a positive and significant relationship between firm size and AI technology adoption ($\beta$ = 0.115, SE=0.049, T=2.347, P=0.019). Therefore, the results support hypothesis H1d.

Additionally, Hypothesis H1e, which states that there is a positive and significant relationship between competitive pressure and AI adoption at the firm level, was tested. The test results confirmed a positive and significant relationship between competitive pressure and AI adoption ($\beta$ =0.218, SE=0.062, T= 3.516, P < 0.001). Thus, the results support hypothesis H1e.

Lastly, hypothesis H1f which aimed at evaluating the positive and significant proposition of vendor participation in AI technology adoption at the firm level, was tested. The results show vendor participation positively and significantly influences AI technology adoption ($\beta$ =0.179, SE=0.055, T=3.255, P < 0.001). The findings support hypothesis H1f.

### 4.9.2: Relationship Between Retail Marketing Mix Components and AI Adoption

Hypothesis H2a, which states that AI technology adoption positively and significantly influences marketing mix components (i.e., pricing) capabilities, was tested. The results established that AI technology adoption positively and significantly influences a firm's pricing capabilities ($\beta$ =0.127, SE=0.050, T=2.530, p=0.012). Therefore, the findings support hypothesis H2a.

Equally, hypothesis H2a which states that AI technology adoption positively and significantly influences marketing mix components (i.e., selling/place) capabilities, was tested. The results revealed that AI technology adoption positively and significantly influences a firm's selling/place capabilities ($\beta$ =0.119, SE=0.052, T=2.288, p=0.023). The finding support hypothesis H2b.

Furthermore, hypothesis H2c evaluated AI technology adoption's positive and significant influence on a firm's marketing mix components (i.e., product development) capabilities. This study showed that AI technology adoption significantly and positively influences product development capabilities ($\beta$ =0.178, SE=0.058, T=3.069, p=0.002). The results supported hypothesis H2c.

Lastly, hypothesis H2d predicted that AI technology adoption positively and significantly influences the marketing mix components (i.e., promotional) capabilities. The results established that AI technology adoption positively and significantly influences promotional capabilities ($\beta$ =0.183, SE=0.057, T=3.211, p=0.001). The findings support hypothesis H2d.

#### 4.9.3: Marketing Components Capabilities on Effective Marketing Strategy Outcome

Hypothesis H3, which states that the combined effect of all the marketing mix components capabilities (i.e., price, place, product development, promotion) have a positive and significant influence on marketing outcomes, was tested. The results of the test established that the individual sub-tests for marketing mix components capabilities (price, place, product development, promotion) had a positive and significant influence on marketing strategy outcomes ($\beta$ =0.117, SE=0.057, T=2.053, p=0.041; $\beta$ =0.519, SE=0.050, T=10.380, p<0.000; $\beta$ =0.195, SE=0.071, T=2.746, p=0.006; $\beta$ =0.162, SE=0.063, T=2.571, p=0.011) respectively. Finally, the overall compounding combined positive and significant relationship between marketing mix components capabilities and marketing strategy outcome was confirmed ($\beta$ =0.58, SE=0.045, T=1.972, p<0.049), thus supporting hypothesis H3.

#### 4.9.4: The Moderating Role of Competitive Intensity Retail Marketing

Hypothesis H4 which states that competitive intensity strengthens the positive relationship between AI technology adoption and marketing strategy outcomes was tested. The test established that competitive intensity moderates (strengthens) the positive relationship between AI technology adoption and marketing strategy outcomes ($\beta$ =0.111, SE=0.043, T=2.581, p=0.010), thus supporting hypothesis H4.

Given the positive and significant positive role played by competitive intensity, the study assessed the simple slope magnitude to provide further evidence of the role of competitive intensity in the relationship between AI technology adoption and marketing strategy outcome. Figure 4.3 illustrates the impact.

### 4.9.5: AI Adoption on Retail Marketing Strategy Outcome

Hypothesis H5, which states that there is a positive and significant direct relationship between AI technology adoption and marketing strategy outcome, was tested. The test established a positive and significant direct relationship between AI technology adoption and marketing strategy outcome ($\beta$ =0.172, SE=0.052, T=3.308, $p<0.001$). The findings support hypothesis H5.

Tables 4.18 and 4.19 summarise and present the LOC and HOC results.

**Table 4.18: Summary of Hypotheses test results (Lower Order Constructs)**

| Hypothesis | Path Relationships | *B* | SE | T | P |
|---|---|---|---|---|---|
| H1a | AI Complexity -> AI Technology Adoption | 0.182 | 0.093 | 1.965 | 0.049 |
| H1b | AI Risk -> AI Technology Adoption | 0.161 | 0.074 | 2.176 | 0.030 |
| H1c | AI Finance -> AI Technology Adoption | 0.118 | 0.041 | 2.878 | 0.004 |
| H1d | AI Firm Size -> AI Technology Adoption | 0.115 | 0.049 | 2.347 | 0.019 |
| H1e | AI Competitive Pressure -> AI Technology Adoption | 0.218 | 0.062 | 3.516 | 0.000 |
| H1f | AI Vendor Participation -> AI Technology Adoption | 0.179 | 0.055 | 3.255 | 0.001 |
| H2a | AI Technology Adoption -> Marketing Mix Price | 0.127 | 0.050 | 2.530 | 0.012 |
| H2b | AI Technology Adoption -> Marketing Mix Place | 0.119 | 0.052 | 2.288 | 0.023 |
| H2c | AI Technology Adoption -> Marketing Mix Product Development | 0.178 | 0.058 | 3.069 | 0.002 |
| H2d | AI Technology Adoption -> Marketing Mix Promo | 0.183 | 0.057 | 3.211 | 0.001 |
| H3a | Marketing Mix Price -> Marketing Outcomes | 0.117 | 0.057 | 2.053 | 0.041 |
| H3b | Marketing Mix Place -> Marketing Outcomes | 0.519 | 0.050 | 10.380 | 0.000 |
| H3c | Marketing Mix Product Development -> Marketing Outcomes | 0.195 | 0.071 | 2.746 | 0.006 |
| H3d | Marketing Mix Promo -> Marketing Outcomes | 0.162 | 0.063 | 2.571 | 0.011 |
| H4 | Competitive Intensity x AI Technology Adoption -> Marketing Outcomes | 0.111 | 0.043 | 2.581 | 0.010 |
| H5 | AI Technology Adoption -> Marketing Outcomes | 0.172 | 0.052 | 3.308 | 0.001 |

***Source: Author's Construction (2022)***

Table 4.18 summarises the lower-order constructs hypothesis test results. From the table, all the relationships were supported. The tests were conducted at a 95% confidence interval with a 5% margin of error. The p-values represent the test's significance; as shown in table 4.18, all p-values are less than 0.05, thus indicating significantly strong relationships.

**Table 4.19: Hypotheses test results (High Order Constructs)**

| Hypothesis | Path Relationship | Beta | SE | T | P |
|---|---|---|---|---|---|
| **H1** | AI Determinants -> AI Technology Adoption | 0.433 | 0.046 | 9.492 | 0.000 |
| **H2** | AI Technology Adoption -> Marketing Mix Capabilities | 0.193 | 0.054 | 3.574 | 0.000 |
| **H3** | Marketing Mix Capabilities -> Marketing Outcomes | 0.508 | 0.045 | 11.25 | 0.000 |
| **H4** | Competitive Intensity x AI Technology Adoption -> Marketing Outcomes | 0.111 | 0.043 | 2.581 | 0.010 |
| **H5** | AI Technology Adoption -> Marketing Outcomes | 0.172 | 0.052 | 3.308 | 0.001 |

***Source: Author's Construction (2022)***

Consistent with the rule of thumb for interpreting the hypothesis test, guided by Hair et al. (2017; 2022), all high-order constructs relationships were supported, as shown in Table 4.19. Guided by the 95% confidence interval and 5% margin of error model assumptions, all p-values were less than 0.05, thus supporting the hypothesis tests.

### 4.9.6 The Path Diagrams (SEM output)

Path diagrams are commonly used in social science studies as they aim to show the theoretical constructs relationships investigated. The theoretical constructs are usually shown by latent variables (Jain et al., 2022). As an output of SEM, a path diagram enhances the understanding of the overall study statistical analysis due to its provision of a convenient framework for statistical analysis, including multivariate analysis procedure outcomes like factor analysis, correlations, and regression analysis (Hox & Bechger, 1998; Zhang, 2022). The combined set of metrics is then known as a path diagram. Aligned with Hair et al. (2017) four-step analysis procedure, path diagrams were produced to illustrate findings during the analysis. Path diagrams assist in the overall study analysis explanations and help in providing a basis for the final model accepted. Figures 4.1 and 4.2 are the path diagrams for lower- and high-order constructs. Figure 4.2 also encompasses the moderating effect analysis.

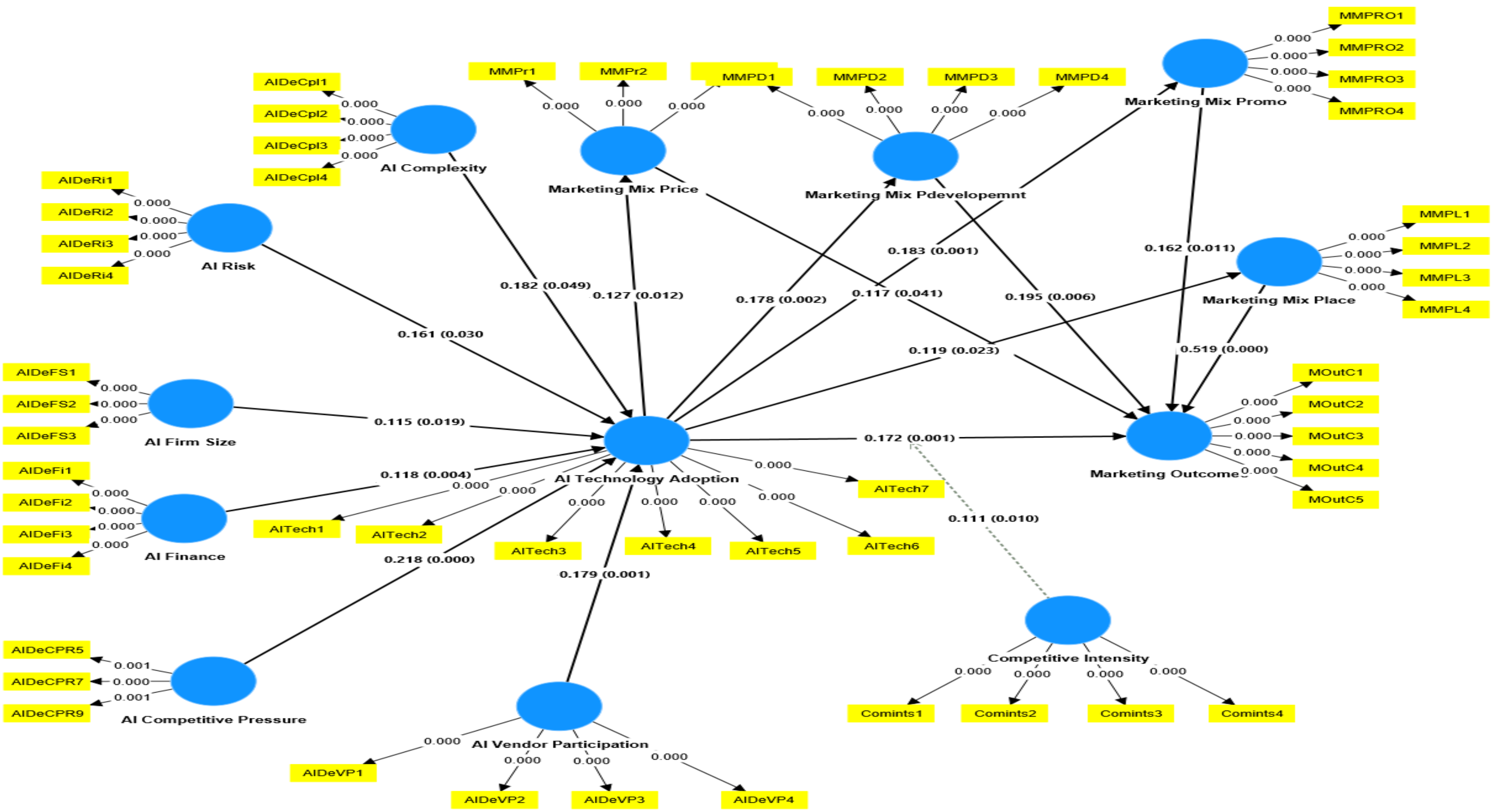


**Figure 4.1: Path Analysis LOC**

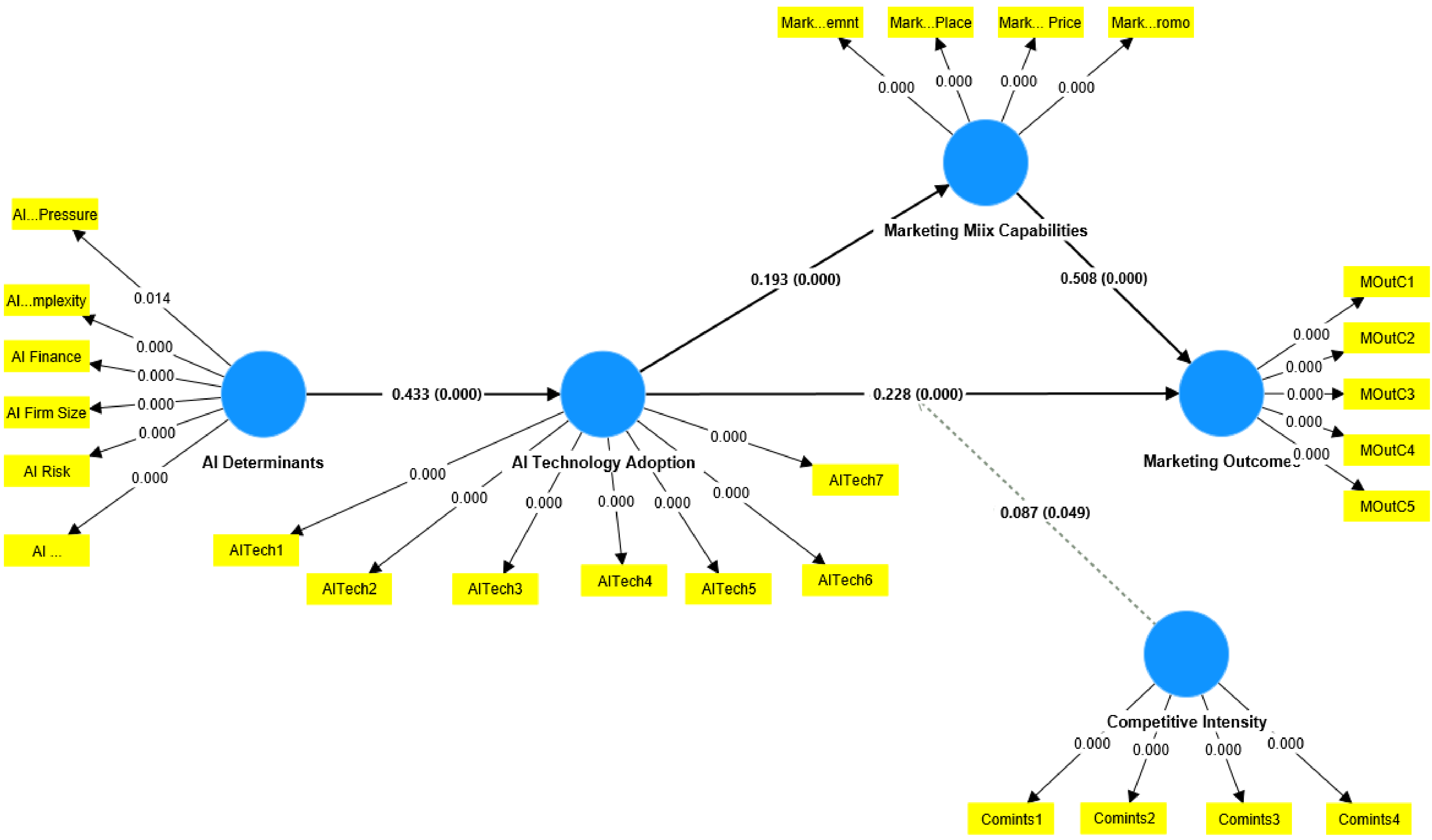


**Figure 4.2: Path Analysis HOC and the Moderating Effect**

*4.9.6.1 Moderating Effect: Slope Analysis*

Figure 4.3 illustrates the moderating effect of competition intensity on the relationship between AI technology adoption and marketing strategy outcomes. From Table 4.3, we observe an interaction between the two variables. With a competitive intensity mean of 0.007, the slope illustrates that when competitive intensity is exerted in the relationship between AI technology adoption and marketing strategy outcomes, it positively influences or strengthens the relationship, denoted with a green line. Considering that the interaction happens on the negative side of analysis, introducing competitive intensity amplifies/increases the positive impact of AI technologies on marketing strategy outcomes.

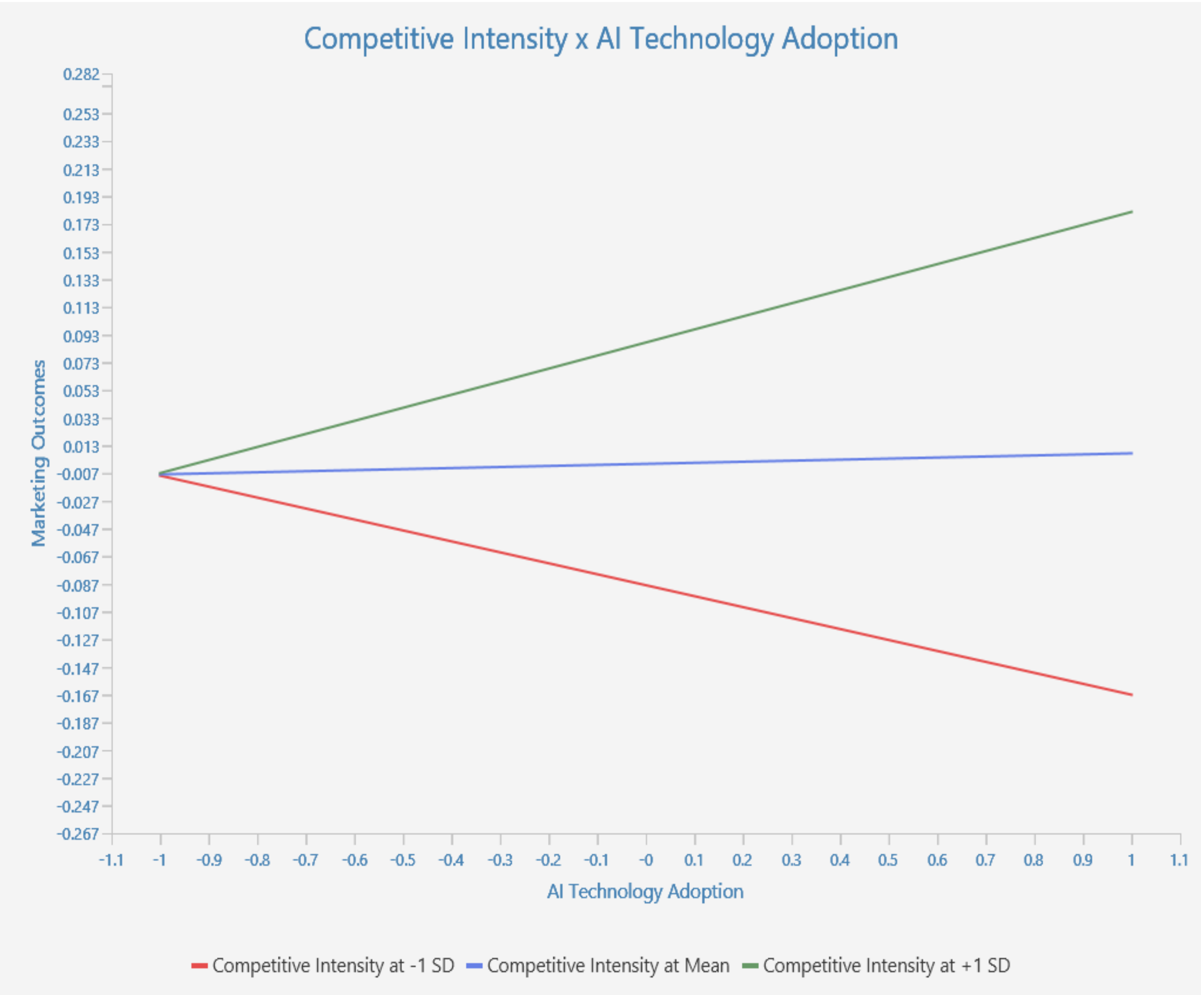


**Figure 4.3: Moderating Effect Slope**

## 4.10 ASSESSING THE MODEL EXPLANATORY POWER

The $R^2$ is used to explain the model's explanatory power. Shmueli and Koppius (2011) express that the $R^2$ mainly explains the variance of every single endogenous construct and is used to quantify the model's explanatory power. There are different recommendations in the literature about the $R^2$ threshold.

For instance, Hair et al. (2011; 2013) have suggested $R^2$ values of 0.75, 0.50 and 0.25 for endogenous latent variables as a rough rule of thumb, respectively described as substantial, moderate, or weak. This study's $R^2$ values for AI technology adoption and Marketing outcomes were 0.187 and 0.291, respectively.

### 4.10.1: Assessing the Models Predictive Power Using PLS-Predict and Q Square

The fourth and last step of the analysis, guided by Hair et al. (2017), was to assess the model's predictive power. Predict relevance was examined using Q Square. Q Square ($Q^2$) is the predictive relevance which measures whether the model has predictive relevance or not (Zhang, 2022). It only establishes the predictive relevance of the endogenous constructs. Q-square values above zero (0) indicate that the values are well constructed and that the model has predictive relevance (Hair et al., 2013).

**Table 4.20: Q-Square**

| Endogenous Constructs | $Q^2$predict | RMSE | MAE |
|---|---|---|---|
| AI Technology Adoption | 0.156 | 0.925 | 0.742 |
| Marketing Mix Product Development | 0.012 | 1.005 | 0.725 |
| Marketing Mix Place | 0.011 | 1.007 | 0.743 |
| Marketing Mix Price | 0.025 | 0.997 | 0.630 |
| Marketing Mix Promotion | 0.010 | 1.004 | 0.760 |
| Marketing Outcomes | 0.029 | 0.992 | 0.753 |

As shown in Table 4.20, the $Q^2$ values above zero indicate the model has predictive relevance.

Additionally, this study assessed the model's predictive power using the Smart-PLS predict (PLS-predict). To handle issues and challenges out of the sample predict parameters, PLS-predict was then introduced (Shmueli et al., 2016). According to Shmueli et al. (2019), when researchers perform the PLS-predict analysis, they estimate the model by training as a split sample, for example, 70% training sample against 30% predictor sample, which is then evaluated for accuracy and performance on the predictor/holdout sample. Therefore, to ascertain the model's predictive power, researchers would examine the prediction error statistics against the sample predicted statistics within certain endogenous constructs. In this case, errors are not mistakes but refer to the residual value between the trained sample error and the handout error. This is the difference between actual values and predicted values. The lower the residual value (error margin), the higher the model's predictive power (Hair et al., 2017). The underlying rule of thumb in the predictive analysis is that the model percentage accuracy should be closer to the handout/test model percentage accuracy, meaning the model standard error will be low or close to zero (0) (Hair & Alamer, 2022). The most common method of assessing prediction error is the Root-mean-square error (RMSE). Danks and Ray (2018) postulate that in case of high non-symmetric prediction error distribution, which is normally visible through a long right or left tail in prediction error distribution analysis, the mean absolute error (MAE) statistics must be used. For accurate metrics interpretation, (Shmueli et al., 2016) stresses the need for the researcher to compare individual indicators' RMSE or MAE values to the actual/naive linear regression model benchmark.

Given that the prediction error distribution was symmetrical, the study used the RMSE metric to assess the predictive power. Shmueli et al. (2019) suggest the following guidelines for accurate model predictive power interoperation.

- The model has high predictive power if all the indicators in the PLS-SEM analysis have lower RMSE or MAE than the naive LM benchmark.
- The model has medium/moderate predictive power when the PLS-SEM analysis outcome on the indicators records smaller prediction errors than the LM.
- Low predictive power is realised when a minority of the dependent construct's indicators record lower PLS-SEM prediction errors than the naïve LM benchmark.
- Lastly, when there is a low prediction error realised from the RMSE or MAE on PLS-SEM analysis compared to the LM benchmark, this assumes that the model lacks predictive power.

Tables 4.21 and 4.22 provide the results of the PLS-predict for this study.

**Table 4.21: Model Predictive Power**

| Indicators | $Q^2$predict | PLS-SEM_RMSE | PLS-SEM_MAE | LM_RMSE | LM_MAE |
|---|---|---|---|---|---|
| AITech1 | 0.093 | 0.861 | 0.683 | 0.903 | 0.750 |
| AITech2 | 0.127 | 0.842 | 0.667 | 0.896 | 0.706 |
| AITech3 | 0.100 | 0.832 | 0.651 | 0.899 | 0.688 |
| AITech4 | 0.125 | 0.842 | 0.660 | 0.907 | 0.698 |
| AITech5 | 0.097 | 0.819 | 0.636 | 0.874 | 0.679 |
| AITech6 | 0.167 | 0.929 | 0.751 | 0.978 | 0.799 |
| AITech7 | 0.059 | 0.762 | 0.594 | 0.768 | 0.603 |
| MMPD1 | 0.009 | 0.752 | 0.566 | 0.767 | 0.583 |
| MMPD2 | 0.010 | 0.713 | 0.487 | 0.731 | 0.520 |
| MMPD3 | 0.006 | 0.718 | 0.523 | 0.746 | 0.547 |
| MMPD4 | 0.011 | 0.753 | 0.571 | 0.767 | 0.586 |
| MMPL1 | 0.001 | 0.841 | 0.684 | 0.919 | 0.801 |
| MMPL2 | 0.002 | 0.632 | 0.457 | 0.869 | 0.666 |
| MMPL3 | 0.001 | 0.558 | 0.388 | 0.773 | 0.539 |
| MMPL4 | 0.001 | 0.574 | 0.377 | 0.794 | 0.506 |
| MMPr1 | 0.023 | 0.606 | 0.350 | 0.630 | 0.448 |
| MMPr2 | 0.019 | 0.661 | 0.465 | 0.677 | 0.486 |
| MMPr3 | 0.013 | 0.553 | 0.375 | 0.582 | 0.412 |
| MMPRO1 | 0.006 | 0.686 | 0.514 | 0.723 | 0.556 |
| MMPRO2 | 0.010 | 0.805 | 0.570 | 0.818 | 0.609 |
| MMPRO3 | 0.009 | 0.719 | 0.538 | 0.746 | 0.570 |
| MMPRO4 | 0.003 | 0.892 | 0.712 | 0.904 | 0.557 |
| MOutC1 | 0.025 | 0.852 | 0.665 | 0.932 | 0.745 |
| MOutC2 | 0.021 | 0.874 | 0.670 | 0.976 | 0.751 |
| MOutC3 | 0.024 | 0.720 | 0.533 | 0.818 | 0.787 |
| MOutC4 | 0.017 | 0.841 | 0.633 | 0.910 | 0.600 |
| MOutC5 | 0.027 | 0.772 | 0.576 | 0.847 | 0.702 |

Table 4.21 shows that the model has predictive powers as the $Q^2$-predict values are all above zero (0). Although some of the $Q^2$-predict values might be closer to zero, the predictive guidelines are applied, hence supporting the model.

**Table 4.22: Model Predictive Power: Q-Square**

| Indicators | Q² predict | PLS-SEM_RMSE | PLS-SEM_MAE | LM_RMSE | LM_MAE |
|---|---|---|---|---|---|
| AITech1 | 0.093 | 0.842 | 0.663 | 0.903 | 0.751 |
| AITech2 | 0.136 | 0.821 | 0.648 | 0.891 | 0.7 |
| AITech3 | 0.111 | 0.83 | 0.638 | 0.894 | 0.682 |
| AITech4 | 0.144 | 0.827 | 0.638 | 0.897 | 0.686 |
| AITech5 | 0.118 | 0.806 | 0.625 | 0.863 | 0.668 |
| AITech6 | 0.18 | 0.904 | 0.722 | 0.97 | 0.793 |
| AITech7 | 0.074 | 0.739 | 0.573 | 0.762 | 0.596 |
| Marketing Mix Product Development | 0.011 | 0.939 | 0.697 | 0.997 | 0.721 |
| Marketing Mix Place | 0.01 | 0.621 | 0.446 | 0.998 | 0.738 |
| Marketing Mix Price | 0.014 | 0.904 | 0.621 | 0.996 | 0.665 |
| Marketing Mix Promotion | 0.011 | 0.897 | 0.666 | 0.998 | 0.757 |
| MOutC1 | 0.024 | 0.842 | 0.656 | 0.933 | 0.749 |
| MOutC2 | 0.018 | 0.878 | 0.679 | 0.977 | 0.786 |
| MOutC3 | 0.022 | 0.725 | 0.539 | 0.819 | 0.6 |
| MOutC4 | 0.015 | 0.834 | 0.636 | 0.911 | 0.702 |
| MOutC5 | 0.026 | 0.756 | 0.566 | 0.847 | 0.641 |

Equally so, as observed in table 4.22, all indicators in the PLS-SEM analysis have lower RMSE or MAE values compared to the naive LM benchmark. Therefore, the model has high predictive power. Aligned with the model findings and predictive power, all relationships can be certified true in this study.

In addition to enhancing the model's predictive power, the research conducted the model's goodness-fit test. This approach aimed to validate the framework and findings, ensuring their reliability and accuracy. For the goodness fit of the model, the researcher utilised the chi-square statistics, SRMR, d_ULS, d_G and the NFI analysis results. Hair et al. (2018) emphasise the need for researchers to be very cautious about reporting and using model fit in PLS-SEM. Furthermore, the same scholars argue that their distinction between saturated (assesses the correlation between all constructs) and estimate model (coined on total effect scheme while considering model structure) remain an ambiguous concept which needs the researcher's critical element when explaining it. Despite the concept's ambiguity, in most cases, researchers have adopted the estimated model results. Hence, guided by Hiar et al. (2018), the study analysed and used the interpretations from the estimated model outcomes.

Additionally, to achieve a model fit, the Normed Fit Index (NFI), also known as the Bentler and Bonett Index, must be close to 1, while the standardized root mean square residual (SRMR) must be less than 0.08 and chi-square significance, with a p-value of less than 0.005 (Henseler et al., 2015). For exact fitness criteria, which are the d_ULS (squared Euclidean distance) and the d_G (geodesic distance), researchers must compare the estimated model value against the original value (saturated model) and should be greater (Dijkstra & Henseler, 2015). Table 4.23 illustrates the goodness of fit of the model.

**Table 4.23 Model Goodness-of-fitness**

| Measurement Technique | Saturated Model | Estimated Model |
|---|---|---|
| SRMR | 0.066 | 0.074 |
| d_ULS | 1.662 | 2.084 |
| d_G | 0.776 | 0.788 |
| Chi-Square | 1484.731 | 1501.639 |
| NFI | 0.813 | 0.811 |

***Source: Author's Construction (2022)***

From the above information in Table 4.23, the model achieved goodness-fit through a SRMR of 0.074, d_ULS of 2.084, d_G of 0.788, Chi-Square of 1501.639 and NFI of 0.811. Having achieved the goodness-fit of the model and the predictive power confirmation, all results were supported with confidence.

**Table 4.24: Summary of Hypotheses Results**

| Hypothesis | Description | Remarks |
|---|---|---|
| H1a | Complexity (ease to use) positively influences AI adoption at a firm level. | Supported |
| H1b | Risk, Compliance and Regulation positively influence AI adoption at a firm level | Supported |
| H1c | Finance positively influences AI adoption at a firm level. | Supported |
| H1d | Size positively influences AI adoption at a firm level | Supported |
| H1e | Competitive pressure influences AI adoption at the firm level. | Supported |
| H1f | Vendor participation influences AI adoption at a firm level. | Supported |
| H2a | AI adoption positively influences the retail marketer's pricing capabilities | Supported |
| H2b | AI adoption positively influences the retail marketer's selling capabilities. | Supported |
| H2c | AI adoption positively influences the retail marketer's product development capabilities. | Supported |
| H2d | AI adoption positively influences the retail marketer's promotional capabilities. | Supported |
| H3 | Marketing mix components with AI-powered capabilities positively relate to a positive marketing strategy outcome. | Supported |
| H4 | Competitive intensity will strengthen the positive relationship between AI technologies adoption and marketing strategy outcomes. | Supported |
| H5 | AI adoption has a direct positive influence on retail marketing strategy outcomes. | Supported |

***Source: Author's construction (2022)***

## 4.10 CHAPTER SUMMARY

The chapter presented the findings and methods or procedures to achieve those results. The chapter was divided into several sections, beginning by presenting respondents' demographic findings. Demographics included the respondents' company background in terms of existence years, number of employees amongst others, and individual background regarding their academics, position held and years of experience. From there, the chapter presented findings on the validity and reliability of the research constructs aligned with the research instrument. Furthermore, from reliability and validity results, the PLS-SEM results were presented together with the hypotheses test results. Additionally, consistent with the study objectives, the results on moderation and mediation were also presented. Overly, all data was presented in graphs, tables and statistical diagrams, enabling the researchers to fully comprehend results, whose interpretation and discussion are in the following chapter.

# CHAPTER FIVE: DISCUSSION OF FINDINGS

## 5.1 INTRODUCTION

The overall study intention was to develop an artificial intelligence adoption framework for food retail marketers in South Africa. The previous chapter, thus chapter four, presented all the analysis and findings to achieve the overall study objective. Hence, this chapter aims to explain, interpret, and clarify the previous chapter's outcomes. The study interprets the outcomes as guided by previous scholarly work and aligns the findings to the existing literature to support or disregard the outcomes as previously proposed (hypotheses). Finally, the researcher will align the findings concerning the proposed framework with its theoretical implications and shortcomings. Consistent and coined on study objectives, the discussion is focused on overall study thematic areas, namely, artificial intelligence determinants, artificial intelligence tools, marketing mix components, marketing strategy outcome and competition intensity within the food retail industry of South Africa.

## 5.2 DEMOGRAPHICS APPROPRIATENESS

As the study survey was conducted through the questionnaire, it had a section for demographics which was broken down into two distinct elements. One section focused on the respondent’s background, while the other focused on the companies. Summarily, considering that 37% of the participants had industrial knowledge/experience between 4-6 years indicates that these were mid-career participants who can relate to industry trends and may appreciate the changes brought by technology and hence have a comprehensive understanding of matters surrounding artificial intelligence in general. Most respondents were employees proving that they are likely to interact with technological tools and are updated with current waves of technology, unlike owners who are likely to have managerial or theoretical knowledge compared to actual interaction with tools. Furthermore, this could translate to the notion that their exposure guarantees actual experiences with AI, which was critical for the study. Additionally, just above a third of the respondents had a degree; marketing or management was more dominant. This indicated that the participants knew about the phenomenon and that the researcher could generalize findings. Additionally, to quantify the respondents and support the generalization of findings, most participants were data analysts, sales personnel, and marketing analysts, meaning they could relate to the investigation as they are exposed to the phenomenon being investigated.

On the company's background, respondents came from marketing and food retail. The companies had existed for over 13 years, had a minimum of 500 employees and were in Gauteng and Cape Town. This can also further ascertain our need to accept the findings and could be generalised as the age of companies indicates experience. The long affiliation to the companies by respondents indicated knowledge and experience. Although most firms are in Gauteng, considering the number of employees and years, most of these companies are nationwide. The probability of these participants providing the researcher with accurate and quality knowledge was high. Equally, the potential of findings depicting the actual conditions was also highly probable.

## 5.3 THE DIRECT EFFECTS OF AI DETERMINANTS ON AI TECHNOLOGY ADOPTION

The study's first objective was to examine the influence of artificial intelligence determinants on adopting artificial intelligence technology. By "determinants", the study aimed at discovering the subjective factors which influence a firm to adopt or not, that is, the hindering or supporting factors of AI adoption. This was a confirmatory exercise for those inconclusive determinants. Given the nature of AI within the retail sector in South Africa and generally, it was imperative to identify the factors that might negatively affect the adoption appetite of food retail marketers when it comes to adoption efforts. Therefore, adopted from the first objective, six hypotheses were developed, that is (H1a, H1b, H1c, H1d, H1e and H1f). All six hypotheses were confirmed to have a significant influence, as postulated. It is worth appreciating that the proposed positive and significant terminology used on the proposed hypotheses relates to the association of constructs rather than causality.

On hypothesis 1a, the study found that the complexity (ease to use) surrounding the use of AI technologies positively impacted the decision-making process around adopting AI technologies. The findings confirm the earlier study findings and theoretical arguments. For instance, Radhakrishnan and Chattopadhyay (2020); Ronaghi (2022) find that due to the rapid development of AI technologies, some systems have become more complicated and difficult to use or integrate within the existing retail value processes or infrastructure. Marr (2019) shares the same sentiments as the previous duo and further expands on the notion that retailers, despite industry affiliation, are the biggest beneficiaries of AI improvements. Still, it has come at the cost of more sophisticated technologies which cannot be staff (employee) friendly. Aligning the findings to theories, Rogers (1995) indicates the complexity of technology innovation (referenced as AI in the study) as one factor affecting a firm's innovation adoption intentions. The findings can be further attributed to the conditions that AI is still a new phenomenon in countries like South Africa. Adopters like food retail marketers lack the right skill set to comprehend and channel AI technology to positive use. They are viewed as very complex, thus resulting in no adoption. Therefore, the study establishes that AI technologies' "ease of use" will encourage adoption, whereas vice-versa is true.

Additionally, on hypothesis 1b, in which the study initially proposed that awareness of the risk, compliance and regulation surrounding AI technologies positively influences the adoption of AI technologies, the study unearthed that risk, compliance and regulation strongly influence AI technology adoption within the food retail sector. Such findings are in support of the existing literature. Theoretically, in any decision-making process to adopt innovation, firms examine the risks and uncertainties surrounding innovation integration (DiMaggio & Powell, 1983; Tornatzky & Fleischer, 1990; Ganguly, 2022). Threats surrounding AI technology adoption arise from a lack of accurate information about certain AI technologies, as most of these are sourced from western countries (Oosthuizen et al., 2021). This has resulted in confusion and frustration for firms considering that AI is still in the infancy stage in the region (Bughin et al., 2017; Kohnert, 2022).

Additionally, Brynjolfsson et al. (2019) elaborates on how the mismatch between the actual gains and hype surrounding AI adoption has fuelled uncertainties towards adoption. The AI technology adoption paradox is a major source of risk and uncertainty. More practical and scientific findings which support the study findings of the mismatch between reality and hype are Rust and Huang (2022). More so, when considering the regulatory framework which regulates the use of specific technologies or other attributes of technology, consistent regulation is required. Considering that AI is data-driven, regulation surrounding data protection, the privacy of information and security has been subject to fierce regulation. Recently in South Africa, the passing of the POPI Act, which protects 3$^{rd}$ parties, has had a negative effect on data mining. Consultations with stakeholders would have been ideal as this contradicts what the government preaches on encouraging technology adoption. As the biggest beneficiaries of the 41R, particularly data usage, marketing divisions need to understand the consistency and volatility of regulation around data protection. Equally, ethical applications of AI have become a concern as most firm decision-makers are unaware of the AI ethics boundaries (Feuerriegel et al., 2022). Therefore, adopters will examine the threats, uncertainties, and regulations before innovation adoption.

Furthermore, hypothesis 1c, where the study predicted that firm size was a crucial factor in determining the adoption of AI tools, was supported. Previous studies also confirm the findings of the study. For instance, Kinkel, Baumgartner, and Cherubini (2022) emphasise firm size as a critical component many adopters will examine before integrating any innovations for compatibility purposes. However, Baker (2012) long expressed his concerns and indicated his lack of conviction as he refers to firm size as a crude proxy for adoption as it is subject to other elements. The subjective narrative closely aligns with Marr's (2019); Dora et al. (2022) findings which postulate that due to rapid AI innovation inventions and the dynamic demands of customers and firms, companies have taken the tailor-made route, meaning they adopt technologies which meet their demands regardless of size; thus, size can be discharged as vital determinant which might hinder adoption. However, because large firms dominate the food retail industry in South Africa, predictions on size being an important factor are relevant as companies intend to adopt technology which will be easy to infiltrate in their already existing infrastructure. Although still a subjective conclusion, larger firms adopt AI more efficiently than small firms due to their economies of scale, this is supported by the study findings.

Hypothesis 1d, in which the study initially proposed that industry and government pressure positively influences AI adoption within the marketing food retail industry of South Africa, was supported. The findings were also supported by past studies' findings and theories too. For instance, the findings align with those of Dubey et al. (2019), who unearthed that due to AI technologies' hype and potential, the government and industry boards have exerted pressure directly or indirectly to encourage AI-powered technology adoption. Equally, Sun et al. (2018); Ukpabi et al. (2019) identified industry pressure as one of the major reasons for digital adoption since failure to adopt certain technologies may be deemed unadvanced or an incompetent player. Chen et al. (2022), in their study of AI adoption determinants, place external pressure as a major source of adoption. In South Africa, currently, this is visible with AI and machine learning online applications being adopted by companies for digital trading, for example, the Checkers 360 (Three-

Sixty) grocery application and the ‘Pick n Pay’ ASAP! for online grocery shopping. In their “Institutional Theory” of innovation adoption, DiMaggio, and Powell (1983) emphasise how external pressure leads to innovation adoption, which aligns with the study findings that external pressure influences adoption. In South Africa, this is expected as the fourth industrial revolution (4iR) subject has been making noise in all business corridors.

Moving on to hypothesis 1e, the study predicted that a company’s financial stability positively influenced AI technology adoption. The prediction was strongly supported. Furthermore, the findings were also supported by other previous scholarly works. Considering the theoretical contributions made by Rogers (1995), who explicitly laments that innovation integration is costly, most potential adopters must examine their finances before adopting any innovation. The theoretical contributions align with the study findings.

Additionally, Phuoc (2022); Ronaghi (2022) agree that under the “organizational factors” which influence innovation adoption, finance is one important attribute. Studies on AI adoption determinants collectively find that finance determines the adoption of AI tools. Marr (2019) finds that with the rapid increase in AI technologies development and or advancements, the cost is not solely on the actual tool(s) purchased but also on maintenance, staff training (upskilling) and technology infrastructure. Chen et al. (2022) ascertains this view and elaborate on the need for extensive funding to integrate digital technologies within a firm. For South Africa, where the country is deemed a user rather than the actual producer of these AI technologies (Accenture, 2018; Schoeman & Seymour, 2022), the importation of AI tools and skills have been on the rise (Oosthuizen et al., 2021). This means that the cost associated with AI adoption is high, thus the need to examine the financial stability of food retailers. Therefore, the findings are consistent with those of the researchers mentioned above and others (e.g., Danquah et al., 2017; Dekimpe, 2020; Dwivedi et al., 2021; Dubey et al., 2019; Esteve et al., 2020) who emphasise on a favourable financial position when deciding to adopt AI technologies.

Lastly, hypothesis 1f predicted that vendor participation in food retail marketing technologies positively influences the adoption of those technologies. The study found that the appropriate vendor participation ecosystem influences AI technology adoption within the food retail sector. The findings align with past studies and theories. For instance, Roger (1995), in his theory of innovation diffusion, postulates that due to the complex nature of technology innovation integration, adopters tend to assess the existing support structures regarding innovation adoption in case they face challenges. Similarly, Phuoc (2022) asserts the IDT theory contribution and further laments the need for a healthy digital ecosystem amongst adopters which aims at continuous training by ICT service providers due to the ever-changing landscape of innovations. Ronaghi (2022) shares the same sentiments and contributions as they emphasise on innovation vendor platforms' existence to ease the magnitude of impact in case, they face challenges during integration. Viewed with practical lens on the South African food retail marketing landscape, the findings align with the current conditions, which require retailers to always support their online platforms while ensuring it serves their clients conveniently. The reliability of online platforms can act as a basic marketing technique. In their study on AI determinants, Rosero et al. (2020) discovered that to contain the challenges surrounding AI technologies adoption, the proximity of vendor participants (Information Technology consulting firms) is encouraged for potential adopting firms. The findings are accurate for economies like South Africa, where AI is still in its infancy stage hence there is so much uncertainty and lack of guidance towards technology adoption (Accenture, 2018; Chen et al., 2022); supporting structure from experts is crucial.

## 5.4 AI TECHNOLOGY ADOPTION ON MARKETING MIX COMPONENTS

Consistent with the conceptual framework and study objective number two, which examines whether AI technology adoption influences the marketing mix components' capabilities, the proposed hypothesis was supported. Furthermore, aligning with the definitions and boundary discussions of marketing mix components in chapter two, i.e., Pricing, Selling, Promotion and Product Development, the study conducted a hypothesis test to examine the significance of AI technologies adoption on the marketing mix components. The proposition was to statistically prove if AI adoption influences the food retail marketing mix components capabilities around product development, promotion, selling and pricing. The hypotheses proposed are denoted as H2a (pricing capabilities), H2b (selling capabilities), H2c (product development capabilities) and H2d (promotional capabilities).

On hypothesis 2a, the study found that adopting AI technologies significantly and positively influenced the pricing capabilities of food retailers. The findings confirm the earlier studies' findings. For instance, Bauer and Jannach (2018) postulate that due to the rapid use of big data tools to improve pricing strategies for e-commerce, the recent upward trajectory of e-commerce is justified by efficient and competitive pricing. Bolton et al. (2019), in their study of digital harnessing strategy for marketing, found that AI tools can improve adopters' pricing, thus overly becoming more competitive. Similarly, Cannella (2018), in his scientific study of AI in marketing, discovered that AI technologies could predict accurate prices for products with minimum error powered by data analytics of previous customer purchasing behaviour. On a more contextual lens, that is, on food retail studies, Huang, and Rust (2022) found that food retailers are one of the biggest beneficiaries of AI technology overlap to their industry as it powers improvements on marketing mix components, particularly with pricing where big data analytics is involved. Chandramana (2017) believes that due to the nature of the oligopoly (price competitive prone) nature of the food retail industry, retail analytics will drive success as retailers are likely to adopt AI technologies that improve their pricing initiatives. The pricing strategies overly contribute to the success of the overall marketing strategy for a firm. Researchers such as Dimitrieska et al. (2018); Dzybura and Hauser (2019); Dekimpe (2020) all share the same sentiments that the adoption of AI for marketing purposes will improve the marketing activities; this is inclusive of pricing, which is a marketing mix component. Thus, as observed, the study's findings are also confirmatory to those of previous studies.

On hypothesis 2b, in which the study proposed that adopting AI technologies positively influences marketers' selling capabilities within food retail, the findings significantly supported the proposition. This finding supports Chen's (2019) findings, which empirically found that AI technologies can improve and empower salespeople with the capabilities to close sales efficiently, faster, and reliably. Likewise, Grewal et al. (2018; 2020); Guha et al. (2021); Haenlein et al. (2019); Huang and Rust (2022), in their studies of AI, AI evolution and retail marketing, found that AI technologies pose as a strategic selling tool which can outsmart humans through machine learning capabilities. The researchers found that AI recommendation powers and product range filtering makes the shopping experience easy; hence customers are likely to purchase without much persuasion. The sentiments can be applied to physical and online shopping. Marketers now apply robots and sales agents to respond to sales matters such as order processing, queries, and delivery issues. For robots in retail, western countries have been championing that (Huang & Rust, 2021;2022) and credit to their innovation capabilities. However, in some markets, such as South

Africa, AI-driven sales (automated selling) have increased, evident with the high use of chatbots to boost sales (Hildebrand & Bergner, 2019). Therefore, based on the study's findings, it is imperative to note that adopting AI tools improve food retailers' selling capabilities.

Furthermore, hypothesis 2c predicted that adopting AI technologies positively influences the product development capabilities of food retailers. The findings significantly confirmed the proposition. Additionally, the findings aligned with other past studies' findings. For instance, Wen et al. (2019) empirically found that within the retail supply chain, product development is a critical phase that retailers should aim to achieve as it will imply that they are supplying what customers demand. The authors further attest that the birth of AI within the product development stage has improved research models and techniques, resulting in improvement in product development exercises. Dekimpe (2020) finds that integrating AI within the research and development phase has resulted in companies obtaining useful insight for product development. The accuracy and quantity of products produced for customers have improved due to AI (Ali-Abbasi et al., 2022; Jarek & Mazurek, 2019). However, Marr (2019) emphasizes that AI adoption doesn’t necessarily impact the product. Instead, it improves the channels for research and development. AI has facilitated an easy way of gathering information which is important for product development (Jarrahi, 2018; Ameen et al., 2022). Wilson and Daugherty (2018) find that humans and AI machines join forces to enhance collaborative intelligence for marketing activities, particularly in research and development. This entails those marketers can gather series and multiples of data easily, which has become a key component of product development. Wirth (2018), in his study on what AI does for marketing, discovered that marketing experts are channelling the data harnessed to good use, for example, on product development and sales predictions. Thus, based on the findings, it is evident that AI technologies directly influence food retailers' research and product development.

Lastly, hypothesis 2d predicted that adopting AI technologies positively influences food retail marketers' promotional capabilities. The results supported the proposition. As expected, the findings align with other previous study findings. For instance, viewed as the exposure weapon which identifies the company and secures sales of the company products (Hartmann et al., 2019), Ashfaq et al. (2020) indicate how AI has revolutionised the marketing (promoting) of retailer’s products. AI has facilitated the erosion of dependency on physical store advertising to online promotional activities, leading to improvements in promotional quality as well (Fajoye, 2021). Avery (2018) elaborates on his findings about AI-driven branding and advertisement, which have changed the marketing dynamics for the better. Kietzmann et al. (2018) find that marketers leverage AI technologies to enhance their user experience and customer journey with quality promotional activities. On another angle, considering South Africa's volatile socio-economic landscape, which is Covid-19 stricken, online retail has since been on the rise as businesses adopted a new way of doing business (Stats SA, 2021). The move made online retailing highly competitive. The results of the pandemic have encouraged innovative ways of product promotion. Crediting AI, food retail marketers have managed to adopt some AI technologies to promote their products and fend off competition (Anakpo & Mishi, 2021). Chen (2018), in his study on drivers for online shopping by examining the 4Ps (Price, Place (selling), Promotion and Product), discovered that there is a strong positive correlation between shopping intentions and promotional campaigns. The author cites 3D advertisements as a major digital transformer and a game changer in retail marketing. It is, therefore, evident that the study's findings align with supporting previous studies' findings.

## 5.5 AI-POWERED MARKETING MIX COMPONENTS ON MARKETING STRATEGY OUTCOME

Consistent with study objective three, the study aimed to examine the influence of AI-powered marketing mix components on achieving a positive marketing strategy outcome.

The study proposed the hypothesis that:

*H3: Marketing mix components with AI-powered capabilities positively affect marketing strategy outcomes.*

The above prediction that a positive relationship exists between AI-powered marketing mix components and marketing strategy outcome (H3) is supported. This finding aligns with other previous study findings. For instance, since AI enables retailers to improve their pricing strategies, firms will likely offer competitive pricing, which hypothetically increases sales (Lindsay, 2017; Ameen et al., 2022). Liozu and Hinterhuber (2021) discovered that since pricing is a prominent driver for profitable growth, firms are resorting to AI-powered pricing strategies based on data analytics to increase profit. Davenport et al. (2019) finds that since AI has the power to influence marketing mix components and results in designing an effective marketing strategy, the outcomes of the marketing strategy will be successful as prices are likely to be competitive, accurate products which meet the needs of customers are to be supplied. The distribution channels are likely to be effective, resulting in costs of production reduction. Huang and Rust (2022), in their studies of AI technology-driven marketing strategy and AI robotics studies, find that AI enhances the strategy creation process as it can change promotional activities and reach greater markets, attributed to an increase in revenue collection. The marketing strategy outcome records increased revenue, and AI-powered marketing mix components can reach new markets, thus gaining a larger market share (Jarek & Mazurek, 2019). As most retailers aim to reduce production costs, once AI is adopted at the research and product development stage, the firm can find efficient production methods that reduce production costs and credit to AI (Kroll et al., 2018). For example, Lewandowski et al. (2021) find that retailers are likely to increase sales through engagements in "Search Engine Optimization" (SEO), which has extended features and the ability to track customers who visited the website and recommend products according to their previous purchasing behaviours. Ma and Sun (2020), in their attempt to examine how computing power exceeds human insights and leads to effective marketing strategies, found that through machine learning and AI, marketers will exceed their expectations and meet their objectives. Roetzer (2017), in his analysis of the 5Ps of marketing artificial intelligence, found that AI transforms all marketing mix components hence strategically changing the marketing strategies for the better, where the outcome of those strategies is always positive. Lastly, as Martinez-Lopez and Casillas (2013) present their study findings on AI-based systems applied in industrial marketing, they discovered that AI plays a critical role in overall marketing strategy success as it empowers all marketing mix components with some predictive, diagnostic, prescriptive and descriptive power. The findings are consistent based on the study findings and other scholarly works outcomes.

## 5.6 DIRECT INFLUENCE OF AI TECHNOLOGIES ON MARKETING STRATEGY OUTCOME

To achieve the overall study objective, which is to develop an adoption framework for marketers within the food retail industry, the study exploratively proposed a hypothesis on how the adopted tools directly influence marketing strategy outcomes. This meant that this hypothesis aimed to examine how the identified technologies impact the overall marketing strategy without first powering the marketing mix components. The proposition would prove the influence of AI tools on sales, profit, and cost of service delivery, amongst other factors of marketing strategy outcome, as contextualised in the study. Thus, the study proposed the hypothesis that:

*H5: AI adoption has a direct positive influence on retail marketing strategy outcomes*.

The above prediction that AI technologies adoption directly positively influences retail marketing strategy outcome (H4) is supported. This finding aligns with other previous study findings. For instance, Calof et al. (2017) found that business intelligence powered by the adoption of AI tools for machine learning is positively correlated to the strategic positioning objective of corporates which is mainly to increase sales, revenue and or improve operational efficiencies. Chen (2019), in his study of analysing the augmenting effects of AI on marketing performance, discovered that when companies adopt AI within their operations for marketing purposes, the marketing performance of that corporate improves, which is evident through improvement in profitability, sales, and revenue. The disruptive nature of AI technologies has changed the overall marketing landscape such that marketers have improved their performance which is recognised through sales increase (Chowdhury et al., 2022; Davenport et al., 2019). Using chatbots directly as dummy salespeople who can assist clients more effectively and efficiently compared to humans is evidence of improved customer servicing, which marketing teams strive for (Ameen et al., 2022; Jarek and Mazurek, 2019). A study by Infosys in 2017 found that AI promises to take over all marketing activities to the point that it will outshine human performance and potentially double the retailers' sales in the next few years. Although the relationship was confirmed with an adjusted R-squared of 0.36 in the South African food retail context, the significance was low due to some possible factors. Literature indicates that South Africans are still in the infancy stages of AI adoption; hence profits on sales and other marketing strategy outcomes cannot be instantly realized (Accenture, 2018). Additionally, the effectiveness of AI adoption in driving sales may be influenced by various contextual factors specific to the South African market. Factors such as consumer preferences, cultural differences, economic conditions, or competitive dynamics may mitigate the impact of AI on marketing strategy outcomes (sales) (Huang and Rust, 2022).

Similarly, Oosthuizen et al. (2020) indicate that fewer larger firms dominate the South African market and small firms (also part of the participants) would struggle to realise benefits compared to the bigger companies hence a possible justification of low coefficients found on the direct impact of AI on marketing strategy outcomes. More so, implementation challenges will likely affect the gains of AI adoption. Adoption within the food retail sector can be very complex and challenging; thus, companies fail to recoup adoption gains Marr (2020). For example, considering the POPIA, issues around data protection, ethics, quality, integrity, and the systems used may not align with the purpose of adoption, thus posing potential risks instead of providing benefits. Furthermore, the time frame gaps used to measure adoption benefits may vary according to companies; hence, collectively may not reflect AI gains. Brynjolfsson et al. (2019) indicate that some rush to quantify the influence of AI integration, which may cause a mismatch between the expected results and reality. Therefore, arguments for weak coefficients could be due to time lags.

Despite the weak relationship findings, Manyika et al. (2017) postulate that in their findings on automation and the future, automation will reduce the cost-of-service delivery and improve product offering as it can determine future demands at a limited cost. Increasing sales and revenue while reducing costs are some of the major objectives of retailers (Al-Surmi et al., 2022; Miklosik et al., 2019), hence corporates who adopt AI and machine learning will finally solve some of these problems which traditional methods have been long lagging in solving (Mintz et al., 2021). Thus, the study findings affirm that the technology directly impacts retailers' marketing activities where its adoption can impact sales, revenue, service delivery and customer interactions.

## 5.7 THE MODERATING EFFECT OF COMPETITION ON AI ADOPTION AND MARKETING STRATEGY OUTCOME RELATIONSHIP

The study predicted a positive relationship between AI adoption and marketing strategy outcome. Based on the study findings on hypothesis H4, and previous studies, they confirmed the relationship. Although not formally hypothesized, the study found a positive and significant relationship between competitive intensity and marketing strategy outcome. The findings are also supported by other previous empirical studies. For instance, the two competitive advantage strategies (cost-leadership and differentiation) have produced positive outcomes as the former tends to attract customers through reduced prices which increases sales, while the latter is more coined on product uniqueness which may increase revenue as customers buy value instead, of price (Porter, 1985; Duanmu et al., 2018). Additionally, competitive advantage is gained through price accuracy for markets like South Africa, which are very price sensitive, translating to positive marketing strategy outcomes in terms of improved sales. Examining the direct relationship between competition and strategy outcome enabled the researcher to quantify the moderating role of competition in the study. Since this relationship was confirmed, the study initially proposed that competition plays a vital role in strengthening the relationship between the two (competition and positive marketing strategy outcomes). Thus, the study proposed the hypothesis that:

*H4: Competitive intensity will strengthen the positive relationship between AI technologies adoption and marketing strategy outcome.*

The study accepted the proposition that competitive intensity strengthens the positive relationship between AI adoption and marketing strategy outcome. The finding aligns with past scholarly findings. Haddaram and Elragal (2015); Ndoro et al. (2020) find that adopters of AI have used competition as the source of adoption. This influences the relationship between adoption and marketing strategy outcome as the aim is underpinned by achieving the strategic goals through technology. Additionally, if competitors use AI technologies for whatever prescribed reasons, it brings excitement around industry peers, resulting in them leaning towards adoption (Youssef et al., 2022). Thus, overly competition will strengthen the relationship between adoption and marketing outcomes. Observed through the lens of typical competition methods available in the industry, which are mainly promotional wars, price, product differentiation and closeness of substitutes, these are likely to strengthen the relationship as past literature findings postulate that technology leads to competitive advantage (Manyika et al., 2017b; Rust & Huang, 2021;2022). Although, Milliou and Petrakis (2011) find that if companies pre-commit to adoption, despite the fierceness of competition, it will affect the commitment to technology adoption to achieve their strategic goals. Equally, Cao and Li (2018) argue that the relationship between AI adoption and marketing strategy expectations cannot be strengthened by competition intensity as there tends to be lower pre-adoption and post-adoption incentives and gains, thus, resulting in reduced adoption appetite. However, Marr (2019) asserts that innovation is now utilised as a fighting tool against stiff competition.

## 5.8 CHAPTER SUMMARY

The chapter aimed to discuss in detail the main empirical findings of the study, as presented in chapter four, as the study aimed to develop a framework for adopting AI technologies within the food retail marketing sector in South Africa. The study has proposed several hypotheses to help the researcher formulate the framework. As the findings confirmed and supported by the literature, the identified determinants influenced AI adoption. Collectively, the six determinants overall significantly influenced the adoption of AI technologies. Furthermore, the study confirmed that food retailers adopt different AI technologies for marketing purposes, and the nine identified technologies were confirmed. Additionally, those AI technologies positively impacted the marketing mix components, which were important for powering the company to design an effective marketing strategy.

Similarly, AI technologies had a direct positive impact on the marketing strategy. The study found that AI-powered marketing components lead to positive strategy outcomes, where sales and revenue, amongst others, are likely to increase due to the influence of AI. Lastly, the study found that competition does strengthen the relationship between AI adoption and marketing strategy outcome, as initially proposed. All the findings had supporting literature.

# CHAPTER SIX: SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

## 6.1 INTRODUCTION

This chapter details an overview of the critical aspects discussed in the earlier chapters of the research. The chapter emphasizes the vital findings of the study upon which conclusions are derived. The section also details the study's implications, recommendations, and suggestions for future studies. The recommendations are purely based on the findings. It is beyond doubt that the results found in the study appropriately answer the research questions as indicated in the first chapter. Having analysed the data collected through a survey and going through the phase of presenting and interpreting the findings, AI has several factors which affect its adoption within the food retail marketing sector. Equally, it is important to understand the technologies adopted for food retail marketing, the marketing mix components which are a huge part of marketing strategy, and the influence of AI can be measured through the success of the marketing strategy outcomes put in place. As a result, the study develops a framework for AI adoption within the food retail marketing industry.

## 6.2 SUMMARY OF THE REPORT

The study aimed to develop an artificial intelligence adoption framework for the food retail marketing industry in South Africa. The whole thesis comprises six chapters. In chapter one, the researcher described the research problem. The problem was derived from a detailed, deep setting outlining the study's background, stating the problem statement, the study objectives, research questions which seek to achieve the objective and finally, detailing how the thesis was structured. Although many studies exist around the subject of AI and not forgetting to acknowledge the efforts made by past scholars in South Africa on AI and retail marketing regardless of industry, it was discovered that the country and industry players are yet to harness the benefits or gains of those scholarly discoveries, particularly on the frameworks available for adoption as it isn’t many. The ones available are not tailor-made for the food retail marketing industry. As the aim was to develop an adoption framework, the study guided by literature should first identify the critical determinants influencing adoption within the food retail marketing space. The second objective was to identify the country's most common AI technologies food retail marketers use. The third objective was to examine the influence of the adopted technologies on the marketing mix components, which in past popular literature has been referred to as the 4Ps of marketing. The fourth objective examined the moderating role of competition magnitude on the relationship between AI technologies adopted and how they influence the anticipated marketing strategy outcomes. It is important to indicate that answering the research questions fully would enrich the research to establish the framework as the overall objective.

In chapter two, the researcher conducted and presented a comprehensive review of past literature on AI and the food retail marketing industry in South Africa. Under the chapter, the author operationalized “artificial intelligence”, “marketing mix components”, “retailing”, and “marketing strategy outcome”. Literature was reviewed on the determinants of AI adoption, the types of AI tools potentially used in food retail marketing, the marketing mix components and the major strategic goals set by food retail marketers. While reviewing literature, the researcher took an investigative and interrogative route which aimed at critiquing some debates and identifying gaps due to the evolution around the subject whilst adding value to the “body of knowledge”.

Guided by past scholarly work and theories, the literature reviewed established that there are many determinants of AI adoption. The literature revealed that some of these factors are interlinked and dependent on each other, while others are independent. The underpinning theories which were synchronised to form the theoretical background were “*Innovation Diffusion Theory (*Rogers, 1995), the “*Technology-Organisation-Environment framework*” (Tornatzky & Fleischer, 1990), “*Institutional Theory*” (DiMaggio and Powell, 1983) and “*Productivity Paradox Theory (PPT)*” (Solow, 1987). Based on the theoretical findings, these theories are common and offer a basis for identifying the determinants of any innovation adoption. Although the theories differ in their structural construction, they offer similar conclusions. The determinants for AI adoption could be grouped into different categories, i.e., technological, organisational, environmental, and technical.

Additionally, with an extensive literature review, the chapter acknowledged the changes in the marketing field. There is an evident shift from traditional retailing to digital retailing, and how most of the AI tools used are mostly suitable for firms with a strong digital footprint. Despite the formidable strides made by the marketing teams in utilizing AI tools to improve physical stores' marketing initiatives, most tools are suitable for digital or online marketing, where most data can be easily obtained. Regarding the marketing mix components, the literature reviewed acknowledged their evolution. Some scholars have expanded the 4Ps (Price, Place, Promotion and Product) to 7Ps (Price, Place, Promotion, Product, People, Process and Physical evidence). However, literature still argues that the 4Ps are sufficient for marketing studies and debates as the 7Ps are a breakdown of the 4Ps, not an entire discovery of other marketing mix components. Nevertheless, the marketing mix components examination is critical for any marketing strategy formulation and measurement. Some studies also indicated how effective AI can influence the marketing mix components and how a positive influence can yield positive marketing strategy outcomes. Furthermore, the literature indicates that an industry's competitiveness may influence companies to adopt AI technologies. However, interestingly, the relationship between the adopted technologies and marketing strategy outcome would be strengthened by competition intensity. Although this debate had inconclusive answers, it was worth noting the points. Theory and past studies' contradictory arguments surrounding competitive intensity and AI motivated the inclusion of the concepts in the study. Furthermore, based on past studies, the proposed theoretical framework constituted competitive intensity, which was a moderating factor. Finally, guided by the theories and extensive systematic past studies reviewed, the researcher developed the study's theoretical framework and proposed several hypotheses to confirm the model's accuracy and validity (framework).

In chapter three, the researcher detailed how the study was conducted. Firstly, the researcher indicated the research paradigms and philosophies. The study was based on theories and past scholarly literature. The study adopted positivism and objectivism paradigms from the ontological and epistemological philosophies. To answer the research questions and achieve the objectives, the researcher adopted the quantitative research method primarily guided by the nature of the research and the philosophies adopted. Data was collected through a self-administered questionnaire. The study adopted already existing constructs guided by past literature. The researcher used the common Cronbach's Alpha technique to test for the internal consistency and reliability of results. The results were above Cronbach's Alpha coefficient rule, which stipulates that any coefficient above 0.7 indicates the reliability of results and that internal consistency is achieved amongst items included in the questionnaire and as applied in the research instrument Likert scale. Critical to every research, the chapter also detailed how the research ethics were adhered to ascertain that the research was conducted ethically. Of paramount importance was obtaining the research clearance letter from the University, which was granted (Ethics clearance number: **H21/11/39**). Once the letter was granted, the chapter details how the researcher followed other critical aspects of the research ethics, namely, seeking consent from individuals to participate in the survey, ensuring privacy and confidentiality on their participation and making sure their responses are kept safe, with the commitment that the data will be destroyed after five years. Data was analysed through the Statistical Package for Social Sciences (SPSS) version 27. Smart-PLS enhanced analysis for data modelling and predictive and diagnostic analytics. Procedures for confirmatory and exploratory factor analysis were explained. Using the PLS-SEM, it enriched the study's findings by confirming the relationships.

In chapter four, the researcher gave a detailed account of the study results, depicted the data discussed, and analysed the findings. Since the study was quantitative, data were reported on and rigorously analysed and presented. The chapter was structured so that the researcher presented the demographics and inferential and descriptive statistics. The aim was to ensure that the participants were well-defined and their participation in the study was justified by presenting their characteristics. The pivotal of the chapter, mainly based on, was to indicate the iterative flow of how the overall model will be determined. This began by examining every construct, filtering out statistically insignificant items, and confirming and exploring relations guided by the proposed conceptual framework. This step-by-step process allowed the researcher to identify the determinants of AI adoption, examine how the adopted technologies would affect the marketing mix components, how the marketing mix components influence the marketing strategy outcomes and examine the direct influence of AI tools on strategy outcomes while quantifying the moderating impact of competition on the former relationship. The chapter discussed the model fit indices for structural equation modelling using Smart-PLS. Finally, the hypotheses results were presented. The hypotheses established an association between the different high-level and low-level constructs. The strength and direction of the association were measured using correlation coefficients. Equally so, the association was not causal; hence no cause-and-effect relationship was established; instead, it was purely association.

In chapter five, the researcher discussed the findings and results in chapter four. The discussions were guided by the theories, literature and knowledge reviewed in chapter two. Most importantly, guided by the research objectives, chapter five first discussed AI's determinants. Aligned with objective number one, which was to identify the determinants of AI through the hypotheses tested, the chapter discussed the confirmations of the hypotheses that size, finance, complexity, vendor participation, risk/compliance/regulation and competitive pressure does influence AI adoption. Moving along, using the same thematic format, the commonly adopted tools for retail marketing were confirmed. Furthermore, various past studies confirmed the under-scrutiny hypotheses that AI tools significantly impact marketing mix components, particularly pricing, place, promotion, product research and development. These findings aligned with the hypotheses on AI-powered marketing mix components influencing the marketing strategy outcomes.

Similarly, the findings on the relationship between AI technologies adopted and marketing strategy outcomes were confirmed. Lastly, the chapter confirmed the moderating effect of competitive intensity on the relationship between AI technologies adoption and marketing strategy outcome. This meant that competition strengthened the relationship.

In chapter six, the last chapter, the researcher gives a detailed overview of the study. This is done by documenting the empirical research findings, which tackle the research questions to achieve the overall study objectives. Emphasis on the results and findings is pivotal in the chapter since this is where the research conclusions are drawn from. The research further emphasizes findings as they form a basis for recommendations and suggestions for future studies. Lastly, the research states the study's limitations, a critical aspect of the study's boundaries.

**6.3 CONCLUSIONS**

The study aimed to tackle the five research questions as indicated in chapter one: What factors influence AI adoption in food retail marketing in South Africa? What are the AI technologies adopted for food retail marketing activities in South Africa? What is the influence of AI in designing a food retail marketing strategy in South Africa? What is the moderating effect of competitive intensity on the relationship between AI technologies adoption and marketing strategy outcome? What AI adoption framework can the South African food retail marketing sector adopt? These research objectives gave a basis for the research questions, which were extensively addressed accordingly.

### 6.3.1 AI technologies adopted (Objective 1)

⇒ The study concludes that Artificial Intelligence (AI) is a broad phenomenon being channelled to use in different industries. AI adoption within the food retail marketing industry is also applied. There are wide and common technologies that can be used for retail marketing. The technologies range from content creation to direct advertising initiatives, from product development to product placement and pricing. Such technologies included big data analytics systems, which most AI tools rely on (big data), automated customer relationship management systems, recommendation filtering applications, social media marketing, virtual chatbots, automated sales agents, and cloud computing. We are noticing the rise of Chat-GPT, which uses AI algorithms to act or respond to inputs. It is tipped to destroy the marketing space through content creation, visual designs, and response accuracy. For effective use of these systems, there is a need for data and a unique skill set to help organizations harness the benefits of adoption.

### 6.3.2 Artificial Intelligence Determinants (Objective 2)

⇒ The study concludes that several factors influence or determine their adoption. Based on the literature, the study finds that other determinants are conclusively discussed on how they determine innovation adoption, particularly AI. However, some determinants have contradictory outcomes, and continued debates on whether they influence AI adoption willingness within the retail marketing sector still exist. Therefore, these determinants formed a basis for examining their influence when AI is adopted in the food retail marketing space in South Africa. Based on empirical findings, the study concludes a positive relationship between successful AI adoption and financial stability. Based on high-order constructs, the study concludes a positive and statistically significant relationship between AI determinants and adoption ($\beta = 0.433, p=0.000$). This relationship is established through understanding and analysing AI technologies' complexity (ease of use), perceived risk magnitude, firm’s financial stability, size, vendor participation and external competitive pressures. The following empirical findings on lower-order constructs (relationships) endorse the high-level conclusion.

On lower order construct, the study concludes that AI technologies complexity (ease of use) positively influences AI adoption. Due to a lack of internal skills, difficulties in operating AI technologies, and lack of guidance or support in adoption procedures, AI technology complexities would negatively impact AI adoption willingness. Thus, having user-friendly technologies that are easy to integrate within the marketing functions and require less reliance on IT support personnel would lead to AI adoption. This positive relationship was statistically supported with ($\beta = 0.182, p=0.049$), hence significant.

Equally so, the study concluded a positive and significant relationship between perceived (compliance and regulation) and AI adoption ($\beta = 0.161, p=0.030$). The findings transfer to proper regulation of AI applications, and the government continued support is likely to increase the chances of AI adoption. Consistency in regulation and market risk management from policymakers would positively influence AI adoption considering the past empirical findings that AI success is data-dependent in most scenarios (Nozari et al., 2022). Given the recently passed POPI Act, which regulates 3rd data protection, which could be detrimental to data mining for marketers within the food retail sector, such regulations can be deemed contradictory to the heavy emphasis on 4IR adoption by the government despite protecting users.

Additionally, the study concludes a positive and significant relationship between a stable firm financial position and AI adoption ($\beta = 0.118, p=0.004$). Due to the costs associated with AI integration, such as reskilling, up-skilling or hiring qualified human capital, and the purchase and maintenance of AI technologies, the adopters must be financially stable to adopt AI successfully. Har et al. (2022) indicate how finance is a critical component of AI adoption, particularly in developing economies where they are regarded as adopters instead of innovators; hence costs associated with the adoption are likely to be high.

Furthermore, the study concludes that a positive and statistically significant relationship exists between firm size and AI adoption ($\beta = 0.115, p=0.019$). Firm size measured by the number of employees and geographically spread means the firm will likely adopt AI technologies successfully. This is based on the findings that companies aim to reduce operational costs such as those of human capital and hence will be eager to automate processes and, in most circumstances, such characteristics are associated with large companies that have many employees and are national wide such as fast-moving consumer goods (FMCG).

More so, the study concludes that competitive pressures positively and significantly influence AI adoption (*β = 0.218, p=0.000*). The positive relationship between the two emanates from the empirical evidence that firms in the same industry will compete; hence early adopters play a pivotal role in influencing other industry peers to adopt AI for survival, continued health competition and industry acceptance. AI technology has facilitated competition fighting ammunition. Past literature evidence suggests that internal pressure leads to adoption, and external pressures from governing bodies and the government can lead to AI adoption (Chen et al., 2022).

Lastly, the research concludes a positive and significant relationship between vendor participation and AI adoption (*β = 0.179, p=0.001*). This relationship is established through the availability of independent support units or firms locally to help the adopters have a smooth transaction towards successful adoption and integration. The study establishes that when there is a healthy digital ecosystem where industry experts and consultants advise on adoption, firms are likely to feel comfortable with adoption, considering the backup plan of existing support structures in case of failure.

### 6.3.3 Artificial Intelligence adoption on marketing mix components (marketing strategy design/outcome): (Objective 3)

⇒ The study concludes a positive and significant relationship between AI technology adoption and marketing mix components (*β = 0.193, p=0.001*), relative components of marketing strategy design. Huang and Rust (2021) agree that for strategic marketing purposes, price, place, promotion, and product are critical marketing mix components which marketers must always consider, particularly in this 4IR, where the dimensions and boundaries of marketing have drastically shifted. Therefore, the study reveals that AI positively influences the marketing mix components as they target improvements in pricing accuracy, accurate product development, appropriate placement, and enhanced product promotion.

The findings presented below are consistent with the high-order findings presented above: A positive and significant relationship exists between AI adoption and the food retail marketer's pricing capabilities (*β = 0.127, p=0.012*). Considering the predictive power of

AI, supported by machine learning (ML) and reading algorithms, marketers can predict accurate prices for their products accounting for all other factors of production. Compared with past/traditional methods, advanced machine learning algorithms can interpret models from observational data toppling past practices and professional humans, hence realising improved accuracy.

Equally, the study concludes a positive and significant relationship between AI adoption and selling (*placement*) capabilities (*$\beta$ = 0.119, p=0.023*). Since this is a combinative process that uses skills, knowledge, information, and a unique set of resources, AI has brought the conglomeration aspect all at once. Data processing power and the skills set to carry out the process promptly. The ability to do repetitive tasks continuously, accurately portraying humans and the efficient rate, has positively impacted AI in strategic selling, proving that AI adoption positively influences selling capabilities. Virtual agents and automated chatbots are now commonly applied for repetitive tasks as they are programmed to mimic humans more effectively (Cheng & Jiang, 2022).

Additionally, the study concluded that there is a positive and significant relationship between AI adoption and product development capabilities (*$\beta$ = 0.178, p=0.002*). The use of AI in product development has opened a wealth of possibilities and new methods for conducting research. With data availability, the research and development stages have become automated, allowing companies to create more accurate products for their customers. Marketers have also been able to leverage AI to allocate resources more effectively for advanced modelling and creativity, bringing more insight into the research and development phase of products. AI has played a key role in driving these initiatives. Thus, the study confirms the positive impact it has had.

Furthermore, the study concludes a positive and significant relationship between AI adoption and the promotional (marketing) of goods and services within the food retail marketing sector (*$\beta$ = 0.183, p=0.001*). AI has drastically changed the marketing space for goods and services, where advertising has become tailor-made due to previous purchases or friends' alignment; last searches enable recommendations of products and programmed email marketing to engage with customers continuously. The most common way to gather past behavioural experiences is through "cookies" online. In physical stores, clustering (grouping) of products due to association and purchase trends has been evident. More importantly, past studies emphasize social media impact, which has also increased as online trading continues to grow (Cheng & Jiang, 2022).

- ⇒ Lastly, on the combined marketing strategy outcome, the study concludes that there is a direct positive and significant relationship between AI adoption and marketing strategy outcome (*$\beta$ = 0.172, p=0.001*). As empirical evidence suggests, AI does improve the marketing initiatives of any organization. This has been centred on big data analytics, the use of social media and the increase in online shopping, which generates data. The findings give a basis for the continued influence of data in the fourth industrial revolution, the rapid rise of the influence of social media, robots, and how the shift from traditional (physical) to online shopping is moving the boundaries of retailing. AI thus directly improves sales by realising new markets, potentially increasing revenue, ROI, and market share. Although the findings have a weak/low regression coefficient, the statistics can be accepted. Based on past literature, the issues around adoption levels, implementation concerns, time lag and contextual factors (data issues, ethics, and integrity) are realistic justifications for the weak coefficient. Despite the possible reasons for the weak coefficient on AI technologies influencing sales, the earlier counterarguments support the study findings affirm that AI adoption directly influences marketing strategy outcomes.

### 6.3.4 The moderating effect of Competition Intensity on the relationship between AI adoption and marketing strategy outcome (Objective 4)

- ⇒ The study concluded that competitive intensity would strengthen the positive between AI adoption and marketing strategy outcome (*$\beta$ = 0.111, p=0.010*). As the moderating factor, competition intensity will enable firms to find creative ways to fight competition and stay relevant in the industry. Creative ways are possible through innovation adoption. More interestingly, customer appreciation of digital ways of trading is on the rise, thus meaning a positive impact of AI. Considering the intense competition within the food industry, the price and promotional wars, product differentiation and daily marketing initiatives, AI adoption has given the firm ammunition to curb competition while being creative and adding value to its customers. Thus, the relationship between the two prodigies is reinforced by competition intensity.

### 6.3.5 Other conclusions:

⇒ The study concludes that there is a positive and significant relationship between AI-powered marketing mix and overall marketing strategy outcome (*$\beta = 0.508, p=0.000$*). The results provide evidence that when AI enhances these capabilities, it leads to better performance in terms of sales, profit, revenue, and market share, which are critical goals for any firm or marketing department. AI has become a driving force in shaping overall marketing strategy.

The following data findings presented below provide evidence of the assertion:

- A positive and significant relationship exists between AI-powered pricing capabilities and marketing strategy outcomes (*$\beta = 0.117, p=0.041$*).
- A positive and significant relationship exists between AI-powered selling (place) capabilities and marketing strategy outcome (*$\beta = 0.519, p=0.000$*).
- A positive and significant relationship exists between AI-powered product development capabilities and marketing strategy outcomes (*$\beta = 0.195, p=0.006$*).
- A positive and significant relationship exists between AI-powered promotion (advertising) capabilities and marketing strategy outcome (*$\beta = 0.162, p=0.011$*).

## 6.4 RECOMMENDATIONS

Based on the research findings, the following suggestions/recommendations were offered to retail marketers as ways to implement AI at their companies successfully:

### 6.4.1 Staff training and development

Management should engage in staff training and development to assist in honing and developing a more comprehensive skillset. AI adopted for marketing purposes requires an exceptional skill set and expertise, which is insufficient in the South African market. Therefore, there is a need for reskilling and/or upskilling employees, as most of the systems used require unique skills. If well handled, this can potentially contribute to new employment creation in the economy.

### 6.4.2 Invest in Infrastructure

Internal and external AI infrastructure is critical for success and sustained integration. Hence, industry players need resource sharing, as some resources might be costly when individually absorbed. The government can offer incentives to companies pivoting towards adoption as it is part of their strategic aims to encourage technology adoption within the country. This will ensure every company can adopt and harness AI benefits while dealing with the digital divide (inequalities) that are becoming visible.

### 6.4.3 Promote continuous learning on new AI technologies and boundaries.

Artificial Intelligence has evolved over the years, and its boundaries have widened; hence, adopters need a clear understanding of what AI integration means. Properly defining AI according to their demands and what it can do for them is the first critical step to successful AI integration. Learning about the best practices of AI to stay up to date is important for food retail marketers. This can be achieved through enrolment in academic institutions and joining other industry professional bodies which invest in technology advancement. Alternatively, firms collaborate with governments and academic institutions to set up information dissemination centres to transfer news and knowledge so that companies can make informed decisions. Information is key. AI applications have so much uncertainty. AI volatility and continued rapid advancement are not making it easy as information easily becomes redundant.

### 6.4.4 Promote Local and International expert networking.

In this fourth industrial revolution, there is so much hype surrounding AI, but some findings state the mismatch between hype and actual gains of AI; hence adopters must consult with industry experts to help quantify the potential benefits and risks associated with AI adoption. Companies must ensure leaders attend local and international seminars, workshops and industry trade fairs for networking and knowledge sharing.

### 6.4.5 Invest in Customer Education Programmes

The companies must engage in research and customer educational programmes which might benefit their technology acceptance levels. Every innovation has its challenges and gains, particularly in customer acceptance. Thus, there is a need for educational programmes for market acceptance. This can be done in stores (physical), which could increase the reach and comprehension of customers. This recommendation is in line with the findings of Wood and Lynch Jr. (2002), who indicate the significant role of advanced knowledge in learning new products or innovations, ultimately leading to adoption.

### 6.4.6 Adopt AI Risk Management Framework

Companies must develop a contingency or risk management plan to curb any eventualities when adopting AI. Since AI is mostly imported in South Africa, so much risk is involved, which is unexplained due to different adoption environments, hence the need for a risk management plan. AI adoption is expensive; thus, there is a need to guard against risks in case they occur.

### 6.4.7 Adopt Policy-Compliant Technologies

The study confirmed that AI is data-driven, particularly for marketing purposes. Therefore, firms need to adopt AI technologies which align with national policies and regulations. Adopting AI innovations against policies is illegal and may result in penalties. AI technologies must align with AI ethics and cyber security policies. Most AI tools haven't reached a level of acting as humans fully or having that sense of feeling; thus, there is a need to address ethical issues surrounding the use of AI technologies. Automated virtual agents may respond to customers unethically, leading to customer violation. More importantly, what if the customer is also an AI robot? Hence security can be easily at the breach.

## 6.5 CONTRIBUTION TO BODY OF KNOWLEDGE

Despite acknowledging that some studies have been conducted elsewhere, the researcher believes and is very confident that the study warrants adoption for economies like South Africa or other developing economies as this could be an enduring solution to the problems the food retail marketing players face, which is lack of guidance (frameworks) for sustainable AI adoption. Providing a feasible adoption framework which is the last objective for the study and overall study main, will yield more positives, particularly in realising the benefits of AI within the food retail marketing division. In reality, the majority of past studies have focused on the developed economies and the systems which are used over there (e.g. Marr, 2019; Brynjolfsson et al., 2019; Calof et al., 2017; Bughin, LaBerge & van Zeebroeck; 2017; Chen, 2019; Davenport et al., 2019), with a few studies focusing on South Africa (e.g. Oosthuizen et al., 2020; Ridge et al., 2015) whereas some studies focus on the benefits of AI, hyping its potential as well as highlighting few drawbacks (e.g. Raisch & Krakowski, 2021; Rao & Verweji, 2017; Schwab, 2017). The few existing studies do not provide adequate information on AI and the technologies adopted for food retail marketing in South Africa. The literature is too broad and lacks context to the South African market. AI literature has been criticised for being too technologically focused and neglecting business, marketing, and organisational needs (Haddara & Elragal, 2015). There is a need for robust and relevant research to contextualise the technologies according to divisions within different marketing spaces. Equally, the literature must focus on business and organisational needs to indicate the combinative nature of AI and retail marketing. Literature has been limited on proper technologies for environments like South African food retail marketing. The underlying discovery that most African countries are adopters than developers of most of the technologies has been at the centre of this gap.

Therefore, the current research consolidated perceptual issues within food retail marketing and identified the accurate and relevant AI technologies or affiliates that could be used within the food retail marketing space. The aim was to ensure that the subject players realise the full potential of those systems as they speak to their demands with limited risk or costs associated with adoption. On the AI technologies used by retail marketers, although the most sought-after are for data analytics and that is what most firms attempt to adopt, however, it seems "data management tools" have not yet commanded credible attention internally as companies still struggle with data storage and are dependent on external sources. In that regard, the research weighs through unearthing the need for investment in data management centres tailored to suit their data analytics structures and available systems. Investment in In-House built data analytics systems can be an added advantage.

Additionally, when it expands to what determines the adoption of those identified AI technologies and systems, the study adds value to existing literature subjecting to the arguments that adoption of innovation can be placed into three distinct categories, i.e., Technological, Environmental and Organizational factors (e.g., Rogers, 1995; Baker, 2012; Bloom et al., 2021; Herath et al., 2020; Dora et al., 2022). Although the study acknowledges that these are the main categories of determinants, some of the elements within those categories have been outdated or are rather obvious without considering the current changes and different geographic locations of potential adopters. The study adds to the list of those elements and unearths the trade-offs associated with technology adoption, considering the determinants in existing theories. Data privacy has become a major factor in AI adoption, and policymakers centre their arguments on 3rd party data protection. Additionally, the study unlocks value by confirming the critical determinants which in the past have been contradictory to adoption. More so, "vendor participation and regulation" have been core in determining adoption specifically in the South African context as most of the systems are imported hence need for a healthy ICT ecosystem (consultants) who can assist in successful integration locally, whereas for regulation, continued refinement of policies is needed to help successful integration considering the fact data is the catalyst for this fourth industrial revolution and AI success. However, few studies have touched on privacy, regulation and ethics surrounding AI tools, as they might be more harmful than helpful if not well handled. The study contributes to the extension of AI determinants of AI adoption, contextualizing the impact of AI if not properly integrated and defining the boundaries of possible adoption within the food retail sector. The study also adds value by defining the different levels of AI adoption based on the characteristics of the technologies under consideration. Such levels contribute to the theoretical literature.

AI is a new phenomenon in most parts of the world, specifically African countries. Most of the AI technologies adopted are imported from the likes of the USA, India, China, and the UK, just to name a few, as most studies denote (e.g., Huang & Rust, 2021; Huang, Rust & Maksimovic, 2019; Manyika et al., 2017), lack of guidance and literature around how AI should be successfully integrated into the marketing division in the food retail sector exists. Therefore, possibly the outright contribution of the study is the final framework for AI adoption, as presented in Figure 6.1.

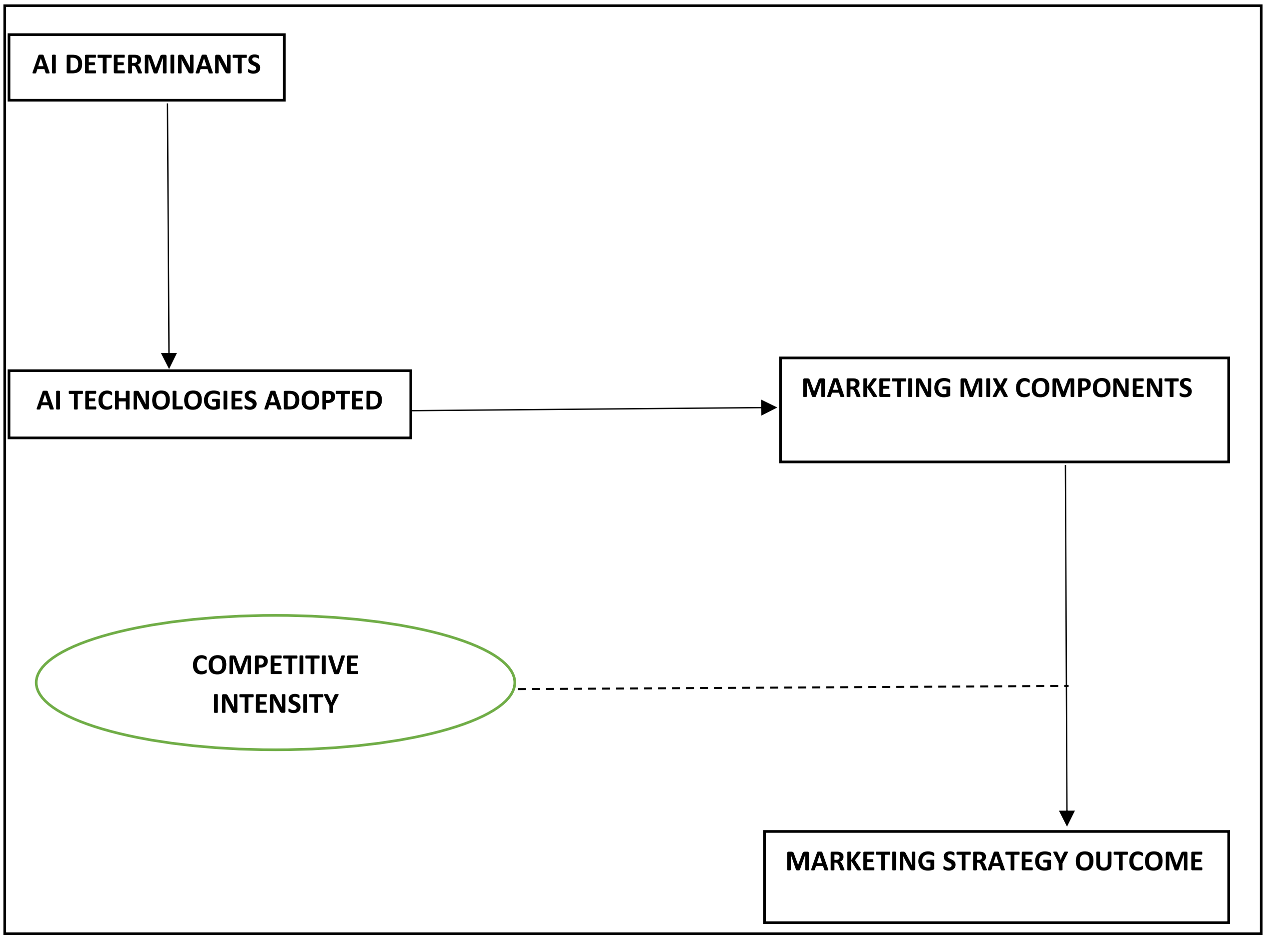


**Figure 6.1: Artificial Intelligence Adoption Framework for Food Retail Marketers in South Africa**

After qualifying and quantifying variables through the Structural Equation Modelling (SEM), the models summarized the significant steps (guidelines) that food retail marketers in South Africa can adopt when pivoting towards AI adoption. Guided by statistical outcomes from SEM, firstly, to achieve their overall marketing strategic goals (outcomes), retail marketers must examine the determinants of AI adoption (complexity, vendor participation, size, finance, competition, and risk/compliance/regulation). The framework then denotes the types of AI technologies adopted for food retail marketing (Big Data Technologies, Customer Relationship Management, Advertising tools, Content Generation Technology, Lead Generation, and Customer Retention Technology). Moving along, having identified the potential AI technologies which can be adopted, the model quantifies how the identified technologies can influence marketing strategy outcome, measured through improvements of sales, market share, profitability and return on through marketing mix components (price, promotion, product, and place) which are elements of marketing strategy. Lastly, the model allows adopters to use competition to strengthen the direct relationship between AI technology and marketing strategy outcome.

## 6.6 IMPLICATIONS OF THE STUDY

### 6.6.1 Practical Implications

Given that the research aimed to provide a real-world solution to the industry, there was a need to deduce practical solutions from the findings. For example, as much as it is imperative for retailers to continuously train their personnel and upskill them, adopting the proposed framework will be a practical solution as it allows a once-off adoption phase and forms a basis for continuous improvement. The framework brings forth extended benefits of understanding that AI has demand forecasting powers which can reduce waste and improve inventory management. Additionally, AI improves physical store shelf management, which can optimize the placement of products in stores based on consumer preferences, sales data, and other factors, which can increase sales, revenue, and customer satisfaction.

Furthermore, another practical extended benefit of the model is the ability to enable food retail marketers to recommend accurate products to potential buyers due to past purchase behaviour trends insights and other information, which can improve customer loyalty and sales. Additionally, price optimization becomes feasible as marketers can assist in price adjustments in real-time based on demand within the digital trading platforms, competitors' prices, and other factors, which can increase competitiveness and profitability. While physical stores may not change prices as frequently as online stores, retailers still rely on data-driven insights to make necessary adjustments. Lastly, AI-powered chatbots for customer service can be integrated as they can provide customers with quick, accurate and personalized assistance, improving customer satisfaction and reducing the workload of customer service representatives.

### 6.6.1 Methodological Implications

Considering the nature of the study and appreciating how the methodology used (quantitative methodology) enhanced the study while achieving the objectives. The research acknowledges the methodology drawbacks in the form of the findings’ representation as doubts are cast on whether they will represent the views of the general audience and the legitimacy of results through reliability and validity concerns. Elicited from the strengths of the quantitative approach, the research challenges future researchers on AI adoption within the food retail sector to utilize both the quantitative and qualitative approaches to gather a more comprehensive view of the concepts under investigation. Since this is a cross-sectional study, limitations on the failure to reflect the primary prior and post determinants effects if inaccurately identified calls for the mixed approach adoption to realise compelling results.

## 6.7 LIMITATIONS AND FUTURE STUDIES

Given the research objectives, questions and design, there are various limitations which future studies could examine and further explore. Firstly, the determinants of AI differ according to industry and company location, considering the socio-economic characteristics of a country; hence future scholars can devise a comparative mechanism to align the determinants according to the host country or company characteristics.

Additionally, the determinants are theoretically grouped into Technology, Organizational and Environmental without any acceptable grouping model. Therefore, future studies can explore the mechanisms and processes used to group the determinants considering that the theories don’t account for current market dynamics. The Technology Readiness Index (TRI) can help account for the market dynamics and how AI technology can be integrated into other business functions. Considering that the study was undertaken assuming that companies have evaluated their readiness, future scholars may begin one step back and use the TRI to examine the optimism levels, discomfort, innovativeness, and insecurity concerns as assessment tools for technology adoption readiness.

Based on the overall study objective, the study does not provide testing parameters to quantify the framework's success if adopted. Future studies can further explore the framework and device measurement parameters of success. In that case, it will enable adopters (food retail marketers) to measure their investment returns.

Although the study confirmed that AI adoption affects dynamic marketing mix components' capabilities, it is worth it for future studies to explore each technology against each marketing mix component to examine its strength. This may enable adopters to channel each technology where it optimises outcomes strategically.

The study covered all food retail companies regardless of size; hence future researchers may focus on distinguishing the retail companies through size and examine the adoption of large corporations against SMEs. In that case, more meaningful outcomes will be observed, considering that most of the companies in South Africa are SMEs and a few large firms dominate the retail sector. The comparative domain between SMEs and large corporations on AI adoption integration and marketing would be interesting.

Furthermore, as the study focused exclusively on participants from Gauteng and Western Cape, it is recommended that future scholars expand their research to include the entire country. This would ensure broader geographical representation and coverage of other regions within the country. Questions around the generalization of findings would have been addressed.

Additionally, the study adopted the purposive sampling technique and a purely quantitative approach. Future scholars may expand research by using different research methods, ideally, a mixed approach to understand the phenomena in-depth. Equally so, future researchers can focus on using a different sampling technique, such as snowballing or random sampling, since technology has become part of life, so almost everyone can participate.

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**APPENDIX A: Research Instrument**

This aims at developing an artificial intelligence adoption framework for food retail marketing in South Africa. We have identified knowledgeable and experienced professionals like yourself because your views are paramount to this study. The questionnaire will take up to 10 minutes to complete, and as a thank you, we are giving you the option to receive a report of the findings. You are kindly reminded that there are no right or wrong answers, and the questionnaire is not a review of individual employee performance. All responses will be treated anonymously. Any email address and name of the organization given by participants will be kept separate from other responses, and findings will not be reported in a way that makes the participants identifiable. Hence, please answer honestly. Thank you in advance for participating; your cooperation is greatly appreciated. By continuing, you are consenting to participate.

**<u>Section A: Respondent's Background</u>**

1. Number of corporate/industrial experience?
   0-3☐ 4-6☐ 7-10☐ 11 +☐

2. Are you the owner ☐ or employee ☐?

3. What is your highest level of education completed?
   High School (Matric)☐ Diploma ☐ Degree ☐ Honours ☐ Masters ☐ PhD ☐

4. Qualification? Computer Science ☐ Supply Chain ☐ Marketing ☐ Management ☐ Operations Research ☐ Statistics ☐ other……………………

5. Job or Corporate Title? Director ☐ Supply Chain Manager ☐ Sales Executive ☐ Data Scientist ☐ Data Analyst ☐ IT technician ☐ Software developer ☐ Marketing Manager ☐ Marketing analyst ☐ Market researcher ☐ other …………

6. Which Department? Marketing/Sales ☐ IT ☐ Operations ☐ other ………………

**<u>Section B: Firm Background</u>**

1. Which option best describes your company affiliation or activities?
   Marketing ☐ Food Retailors ☐ IT ☐ other ……………………

2. Approximately how old is the company?
0-3 years ☐ 4-8years ☐ 9-12 years ☐ 13 + ☐

3. How many employees does the company have?
1- 100 ☐ 101-250 ☐ 251-500 ☐ 500 + ☐

4. Please indicate the location of the firm?
Gauteng ☐ Western-Cape ☐ Both Gauteng & Western-Cape ☐

**Section C:**

***For the following statements please use the scale below:***
***Overall Scale- 1= Strongly disagree (SD), 2= Disagree (DA), 3= Slightly disagree (SLD), 4= neutral (N)***
***5 = Slightly agree (SA), 6 = Agree (A), 7 = Strongly agree (SA).***

| ***Please indicate the extent to which you agree with the below statements:*** ***AI Determinants*** | ***SD*** | ***DA*** | ***SLD*** | ***N*** | ***SLA*** | ***A*** | ***SA*** |
|---|---|---|---|---|---|---|---|
| **AID01**- I find AI technologies easy to use. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| **AID02-** I find AI technologies very risky and uncertainty about their application. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| **AID03-** Firm size influenced adoption of AI technologies. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| **AID04-** I find **e**xternal pressure from industry peers or government very crucial for the adoption of AI technologies. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| **AID05-** I find financial position very important for AI technologies adoption. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| **AID06-** I find vendor participation or external support structures important for AI adoption. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| | | | | | | | |
| ***Please indicate the extent to which you agree with the below statements:*** ***Marketing-Components Capabilities*** | ***SD*** | ***DA*** | ***SLD*** | ***N*** | ***SLA*** | ***A*** | ***SA*** |
| **MCC01**- AI technologies adoption increases pricing accuracy. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| **MCC02**- AI technologies adoption increases product offering accuracy. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| **MCC03**- AI technologies adoption increases product reach. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| **MCC04**- AI technologies adoption increases supply/delivery efficiencies. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| ***Please indicate the extent to which you agree with the below statements:***<br>***Types of AI Technologies adopted*** | ***SD*** | ***DA*** | ***SLD*** | ***N*** | ***SLA*** | ***A*** | ***SA*** |
| **AIT01-** My company uses AI technologies for data analytics purposes. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| **AIT02-** My company uses AI technologies for customer targeting/ new markets search purposes. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| **AIT03-** My company uses AI technologies for predicting future sales. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| **AIT04-** My company uses AI technologies for effective resource allocation tasks. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| **AIT05-** My company uses AI technologies for recommending similar products to our clients. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| **AIT06-** My company uses AI technologies to enhance our brand. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| **AIT07-** My company uses AI technologies to identify customer interconnectedness/similarities. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| **AIT08-** My company uses AI technologies to conveniently chat with our customers. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| **AIT09-** My company uses AI technologies to maintain the relationships with our clients. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| | | | | | | | |
| ***Please indicate the extent to which you agree with the below statements***<br>***Competitive Intensity Moderating role*** | ***SD*** | ***DA*** | ***SLD*** | ***N*** | ***SLA*** | ***A*** | ***SA*** |
| **CIRM01-** Competition in our industry is very intensive. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| **CIRM02-** There are many promotional wars in the industry. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| **CIRM03-** Products/anything that one competitor can offer, others can match it too with ease. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| **CIRM04-** Price competition in our industry is very intense. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| **CIRM05-** Competition for market share in our industry is very intense. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |

| ***Please indicate the extent to which you agree with the below statements:***<br>***Marketing Mix Components on marketing strategy outcome*** | ***SD*** | ***DA*** | ***SLD*** | ***N*** | ***SLA*** | ***A*** | ***SA*** |
|---|---|---|---|---|---|---|---|
| **MXMS01-** Customer management (CRM) technologies improve the relationship between the company and clients. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| **MXMS02**- Integrating data analytics technologies enhances the overall company marketing activities. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| **MXMS03-** Utilizing customer targeting/ segmenting systems significantly increase distribution efficiency of the company. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| **MXMS04-** Recommendation and filtering applications within AI systems increase product reach. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| **MXMS05-** Predictive analytics/modelling improves overall company sales. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| **MXMS06-** Resource allocation systems improve optimization procedures. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| **MXMS7-** Digital marketing applications improve the quality of marketing material. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| | | | | | | | |
| ***Please indicate the extent to which you agree with the below statements:*** ***AI adoption on marketing strategy outcome*** | ***SD*** | ***DA*** | ***SLD*** | ***N*** | ***SLA*** | ***A*** | ***SA*** |
| **MSD01**- AI technologies adoption increases sales growth rate. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| **MSD02**- AI technologies adoption increases profit margins. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| **MSD03**- AI technologies adoption reduces increase the return on investments. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| **MSD04**- AI technologies adoption has increases market share. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| **MSD05-** AI technologies adoption reduces the cost-of-service delivery. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |

# APPENDIX B: Ethics Approval

UNIVERSITY OF THE WITWATERSRAND, JOHANNESBURG

Research Office

**HUMAN RESEARCH ETHICS COMMITTEE (NON-MEDICAL)**
R14/49 Mpunzi

| | |
|---|---|
| **CLEARANCE CERTIFICATE** | **PROTOCOL NUMBER: H21/11/39** |
| **PROJECT TITLE** | The development of Artificial Intelligence adoption framework for food retail marketing in South Africa |
| **INVESTIGATOR(S)** | Mr S Mpunzi |
| **SCHOOL/DEPARTMENT** | Wits Business School/ |
| **DATE CONSIDERED** | 19 November 2021 |
| **DECISION OF THE COMMITTEE** | Approved<br>Risk Level: Minimal |
| **EXPIRY DATE** | 14 December 2024 |

**DATE** 15 December 2021 **CHAIRPERSON** (Professor J Knight)

cc: Supervisor : Dr F Saruchera

**DECLARATION OF INVESTIGATOR(S)**

To be completed in duplicate and **ONE COPY** returned to the Secretary at Room 10004, 10th Floor, Senate House, University. Unreported changes to the application may invalidate the clearance given by the HREC (Non-Medical)

I/We fully understand the conditions under which I am/we are authorized to carry out the abovementioned research and I/we guarantee to ensure compliance with these conditions. Should any departure to be contemplated from the research procedure as approved I/we undertake to submit an amendment of the protocol to the Committee. **I agree to completion of a regular progress report. For Minimal and Low studies, this is due annually on 31 December. For Medium and High Risk studies, this is due twice annually on 30 June and 31 December.**

Signature

15 / 12 / 2021
Date

PLEASE QUOTE THE PROTOCOL NUMBER ON ALL ENQUIRIES

**APPENDIX C: Plagiarism Declaration**

# Sinenhlanhla Mpunzi (1730520)-PhD Thesis Final-1.docx

*by* Sinenhlanhla Mpunzi

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## APPENDIX D: Language Editing Confirmation

# EDITING CONFIRMATION

To whom it may concern:

This memo serves to confirm that the manuscript/research project detailed below has been language-edited and/or proof-read.

Regards,

*-IETS-*

------------------

IET Innocent *(Cert. Lang. Ed.)*
*Language Editor*

**************

**Manuscript Title:**

THE DEVELOPMENT OF AN ARTIFICIAL INTELLIGENCE ADOPTION FRAMEWORK FOR FOOD RETAIL MARKETING IN SOUTH AFRICA

**Author:**

SINENHLANHLA MPUNZI

**Issued on:**

25/02/2023

Disclaimer:
The editor/proofreader makes no claim as to the accuracy of the manuscript contents nor the objectives of the author. While all possible efforts have been made to ensure the text as edited is readable and grammatically correct, the author(s) have the option to accept or reject suggestions and trackable changes made to the document before submission.

*** Professional Editors ***

sarchcot@gmail.com