DECLARATION

I, Ogochukwu Perpetua Ukwuoma, declare that I am the sole author of this Thesis, and the work is a result of my investigations and research, except where otherwise stated.
All references have been duly cited.

RESEARCH TITLE:

AN INVESTIGATION INTO THE ROLE OF ARTIFICIAL INTELLIGENCE (AI) IN MANAGEMENT DECISION-MAKING WITHIN RETAIL BUSINESSES.

BY

OGOCHUKWU PERPETUA UKWUOMA

STUDENT ID:

A DISSERTATION IN ACCORDANCE WITH THE REQUIREMENTS FOR THE AWARD OF A DEGREE OF MASTERS OF RESEARCH IN MANAGEMENT STUDIES

SUBMITTED TO:
YORK ST JOHN UNIVERSITY

LONDON

SEPTEMBER 2025

DEDICATION

Thanking my Creator for the gift of life, wisdom and the opportunity to pursue this academic journey amidst all odds. The intercession of Blessed Virgin Mary in my life paved way.
To my Love, thank you for believing in me.
To my parents, you are always my inspiration.
To Fr Ollie, thank you for walking with me on this journey.
And to my little sister, Nma, you made this happen.
Finally, I appreciate everyone else not mentioned here for making this journey worthwhile. God bless us all.

ACKNOWLEDGEMENTS

A heartfelt gratitude to Dr Rana Mohsin-Ali, my able Supervisor. Your invaluable guidance, support, and expertise throughout this research journey was instrumental in positively shaping this study.

My sincere thanks to the management of York St John University London, the faculty of Business and Masters in Research and the department of Management Studies, for creating a conducive learning environment as well as allocating resources that aided in carrying out this research work.

I also acknowledge with gratitude the various authors and researchers whose works have contributed to the foundation of this study.

Finally, I would like to acknowledge all the retail managers and decision makers in Nigeria for answering this clarion call of responding to the survey and providing valuable insights into the impact of Artificial Intelligence in management decision making within the retail sector.

Thank you all!

ABSTRACT

This study explores how Artificial Intelligence (AI) impacts decision-making in retail organisations, focusing on perceived benefits, limitations, ethical concerns, and managerial roles. The study also investigates how managers interact with AI systems and how ethics shape trust and acceptance. A quantitative research design was adopted. Data were collected using a structured questionnaire administered to 160 participants across various roles in retail organisations. After data cleansing, 129 valid responses were retained for analysis. The analysis used descriptive statistics, correlation tests, chi-square, and multiple regression to examine relationships between AI use, organisational strategy, and ethical considerations. Findings show that most organisations are already using AI in key areas like inventory control, pricing, customer service, and demand forecasting. Respondents agreed that AI improves efficiency, reduces costs, and speeds up decision-making. However, they also noted key limitations, including lack of contextual understanding, data quality issues, and high costs. Managers felt that AI supports rather than replaces them. Most agreed that AI increases pressure to adapt but also frees them for strategic thinking. Ethical concerns were widespread. Data privacy and algorithmic fairness were viewed as major risks, while trust in AI decisions remained moderate. These concerns were shared across job levels and experience groups. Regression results show that ethical awareness is the strongest predictor of effective AI strategy adoption. The study adds to the literature by highlighting the balance between human judgment and AI capabilities. It also provides practical guidance for retail firms, especially in developing economies, on how to implement AI responsibly. Limitations include the use of self-reported data, a single data collection method and a moderate sample size. Future research should adopt mixed methods and examine how AI use evolves over time.

Table of Contents

List of Tables

List of Figures

Chapter One

Introduction

1.1 Background to the Study

Artificial intelligence (AI) is a vital part of making decisions in corporations in this modern era. It assists companies in processing vast amounts of data, identifying patterns, predicting outcomes, and carrying out automated work (Alenezi and Akour, 2025), making AI an invaluable part in business processes. The retail sector has particularly registered increased growth in adopting AI in the previous decade. Many companies now employ AI to gain increased efficiency, cost savings, and improved customer experience (Madanchian, 2024). Earlier systems in AI used to operate by processing rules in making decisions following explicit instructions and not adapting to new information. Developments in machine learning and deep learning have refined the capabilities of AI. Modern systems can process vast amounts of datasets, detect trends, and adjust their process of making decisions to novel input (Kavakli-Thorne and Dai, 2025). This has enhanced the ability of AI to make complex business decisions.

In retail AI is used to forecast consumer demand, inventory management and marketing optimisation (Madanchian, 2024). Recommendation systems created by AI suggest products to customers in alignment with purchase history to drive sales and consumer satisfaction (Haleem et al., 2022). Additionally, dynamic price algorithms adjust prices in accordance with demand, competitors' prices, and consumers' tastes (Chenavaz and Dimitrov, 2025). Developments in digital retail stores have further increased the significance of AI where online stores leverage AI to personalise user experience and drive sales (Adam, Wessel and Benlian, 2021). Chatbots created by AI provide instant support to customers by answering questions and fixing problems in real time (Adam, Wessel and Benlian, 2021). Predictive analytics support retailers in predicting demand and optimizing inventory management (Falatouri et al., 2022). Despite these benefits, decision making by AI has limitations. AI systems perform better with an extensive amount of reliable data. Biased or incomplete data can return inaccurate or unjust decisions (Pennisi et al., 2025). Additionally, while making work efficient, AI is not always conscious about ethical or social implications (Alawamleh et al., 2024). Hence, organisations need to handle AI cautiously while integrating recommendations with moral judgment.

AI's role in organisational decision making is necessary as businesses now rely on it to scrutinise complex sets of data, determine trends, and guide better decisions (Madanchian, 2024). In the retail sector, AI maximises efficiency in operation, increases customer experience, and drives profitability. Automated processes by AI undertake repetitive work while allowing workers to focus on support to customers and strategy (Zirar, Ali and Islam, 2023). Inventory management is among the most vital uses of AI. Classical inventory systems work through previous sales patterns and static forecasted growth. But AI-powered forecast analytics realise greater accuracy by integrating live changes in patterns of demand, seasonality, and market trends (Amosu et al., 2024).

As an example, in-season demand for products is run by AI to allow retailers to order appropriate products while minimizing overstocking and shortfalls.

AI also enhances customer engagement and personalisation. Customer purchase and browsing patterns are researched by AI-powered recommendatory systems to suggest products (Bunea et al., 2024). This level of personalisation creates bonds between customers and establishes sales. Chatbots fueled by AI keep customers in touch by delivering instant support, fixing repetitive issues, and guiding customers through purchasing (Izadi and Forouzanfar, 2024). Artificial intelligence provides dynamic pricing in which prices change in response to demand, competitors' actions, and buying patterns (Chenavaz and Dimitrov, 2025). This maximises revenues while giving retailers an added layer of competitiveness. Furthermore, AI maximises supply chain efficiency by tracking shipments, predicting potential supply interruptions, and making logistics easier (Riad, Naimi and Okar, 2024). Retailers who integrate AI in supply chains can reduce operation costs while enhancing customers' satisfaction. The growing incorporation of AI in retail highlights its importance in making decisions in today's business. AI reduces errors by humans, optimises efficiency, and enables organisations to react quickly to market changes. Issues related to job displacement, threats to ethics, and biased decisions in AI should be addressed appropriately (Khogali and Mekid, 2024). As AI continues to evolve, organisations adopting AI in an ethical manner will possess an unprecedented competitive advantage.

1.2 Statement of the Problem

Despite increased uses in making decisions in business by AI, several problems linger. AI systems utilise vast amounts of data to guide decisions. However, availability and reliability of data continue to be problems (Aldoseri, Khalifa and Hamouda, 2023). Many retail organisations in developing economies like in Nigeria have no access to vast and reliable datasets (Whyte, 2021). Poor-quality data can lead to inaccurate forecasting, making decisions guided by AI less efficient (Aldoseri, Khalifa and Hamouda, 2023). Lack of infrastructure and experts in AI is yet another major challenge. Demaidi (2023) argues that developed economies have advanced systems in AI with solid infrastructure in technology and experts in working with AI. Many retail organisations in Nigeria have minimal or no access to tools in AI and not enough experts in AI (Mohammed and Shehu, 2023). This raises uncertainty about effectiveness in adopting AI-informed decisions in Nigeria's retail sector.

AI-powered decision making is also bringing about ethical and transparency issues. AI algorithms have a tendency to operate in “black boxes,” making decisions difficult to understand (Mathew et al., 2025). This transparency issue has the potential to lead to mistrust among managers and consumers in companies. Additionally, AI systems have the potential to inherit prejudices in training material to continue discriminatory price policies or biased recommendations to consumers (Chen, Wu and Wang, 2023). All these issues point to the fact that AI-powered decision making in retail companies in Nigeria is in dire need of additional research as regulatory systems in Nigeria continue to develop. Businesses and policy makers can achieve better understanding of these issues by determining ways to take full benefits of AI while reducing limitations.

Several researchers have studied the possibility of AI in making decisions in business. Ali et al. (2024) suggest that AI can lead to increased efficiency and correctness in making decisions. Furthermore, Madanchian (2024) confirmed that companies enjoying benefits through AI-powered decisions achieve optimality in engaging customers and in inventory management. However, most of these studies target developed economies where infrastructure is in place. Research is minimal in developing economies like in Nigeria to confirm the effect of AI in making decisions. This raises uncertainty about whether decisions through AI can have equal benefits in economies where infrastructure is not in place. However, another gap in this body of work is minimal research in addressing challenges in adopting AI in retail companies in Nigeria. Talabi et al. (2024) studied adopting AI in Nigerian Mass Media while Elegunde and Osagie (2020) studied predominantly in the banking sector. Retail chains have various ways in which they operate by basing on consumer-moving products and complex supply lines. Since limited studies have been done in Nigeria's retail sector, uncertainty exists in identifying ways to overcome limitations in accessing appropriate data. Ferrara (2023) discusses fairness and bias in Western economies in AI systems. Research is limited in Nigeria for addressing bias in AI, privacy in data, and transparency. Hence, this study fills these gaps.

1.3 Aim of the Study

The aim of this study is to examine the impact of AI-driven decision-making on the performance and operations of retail chains in Nigeria. Specifically, the study seeks to assess how AI influences key business decisions, operational efficiency, customer engagement, and overall business growth within the Nigerian retail sector. This research aims to provide valuable insights that can guide business leaders and policymakers in making informed decisions about AI integration in retail management.

1.4 Objectives of the Study

1. To explore how organisations are using AI to support management decision-making.
2. To identify the benefits and limitations of AI-driven decision-making in the retail chain.
3. To examine AI's impact on human managers' role in the decision-making process.
4. To investigate the ethical considerations associated with AI-driven decision-making.
5. To provide recommendations for optimising AI adoption and utilisation in management decision-making.

1.5 Research Questions

1. How are organisations using AI to support management decision-making?
2. What are the benefits and limitations of AI-driven decision-making within the retail business?
3. How does AI impact the role of human managers in decision-making?
4. What ethical considerations are associated with AI-driven decision-making in the retail Sector?
5. What strategies can be implemented to optimise AI adoption and utilisation in management decision-making?

1.6 Significance of the Study

Artificial Intelligence (AI) has transformed decision making in most industries, including retail. This study is significant in that it provides an insight on the part played by AI in retail decision making in an emerging market as explained below:

Contributing to improved retail business strategy

Artificial intelligence-informed decisions offer solutions to aspects such as prediction of demand, targeted promotions, and automated supply management. However, most retailers in Nigeria keep relying on traditional methods of making decisions, which can prove to be inefficient. This study will inform retail managers how to leverage AI for informed decisions to drive business performances.

Academic Contribution and Theoretical Progress

The current work contributes to academic work in scholarly literature around uses of AI in management in business. While previous work has researched AI-informed management decisions in advanced economies, not much work has been conducted in this context in Nigeria. This work fills a key gap in literature by introducing novel insights to the manner in which AI is used in emerging economies. Findings in this work will also contribute to debate around AI and management decisions by introducing concrete evidence to support established theory or to posit novel theory.

Implications to Policy and Regulation

In Nigeria, retail sector uptake of AI is in an embryonic stage with no policy in place to regulate adaptation. This research will provide policy makers with required information about where AI is in making decisions in retail to inform necessary policy to encourage adaptation while considering regulatory and ethical aspects. Acknowledgment of both threats and benefits created by AI will empower policy makers to design rules that encourage equal competition and consumer protection in the retail market.

Enhancing Consumer Experience

AI-powered decisions can change customer service by providing personalised recommendations, chatbots to guide customers in real time, and predicting customers' tastes through analytics. Nigerian consumers increasingly adopt digital consumption patterns, while standards in shopping experience keep rising. This study is meant to inform companies about ways to leverage AI to drive increased customers' satisfaction towards better brand equity.

Practical Implications to Nigerian Retailers

Several Nigerian retail businesses, especially small to medium-sized enterprises (SMEs) can be unaware of ways in which AI can drive efficiency in their organisations. This study provides actionable insights regarding value added by AI to decisions to guide retailers in ways in which to incorporate AI solutions. It will also highlight problems in adopting AI, including cost, knowledge gaps, and infrastructural limitations to guide organisations in making informed investments.

1.7 Scope of the Study

The goal of this study is to examine the role of artificial intelligence (AI) in management decisions in the retail sector with emphasis on Nigerian retail chains. This is done within the following scopes.

Geographical

The study is limited to Nigeria, an emerging market where retail management has not adopted AI in full. This study is directed towards retail organisations in major business cities such as Lagos, Abuja, and Port Harcourt where adopting AI in business practices is most likely to be seen. This work provides localised findings about AI-powered decision making in an emerging economy.

Conceptual

The study focuses on AI in management decisions in the context of retail. It involves discussions on key areas such as demand forecast, inventory management, personalised offers, and automated customer support. It also discusses benefits, limitations, and implications in decisions through AI. This study is not about designing AI or programming aspects regarding AI but about implications in management decisions in business.

Methodological

The mono method design is employed in this research where quantitative methods is used. Data is collected from retail managers, business executives, and industry experts through surveys and open-ended questions. The study analyses the extent of AI adoption, the perceived benefits and challenges, and its overall impact on decision-making.

1.8 Structure of the Study

The work is divided into six chapters addressing various aspects of the research. Chapter organisation provides a systematic sequence starting with the background to the results and conclusions.

Chapter One: Introduction

Chapter One provides an introduction to this work, beginning with the background where the importance of artificial intelligence (AI) in manager decision making in general, and in retail in particular is briefly described. This is followed by a statement of the problem where gaps in earlier research have been described to point to the reasons why this work is needed. Chapter One goes further to clarify the aims, objectives, questions, hypotheses, significance, delimitations (scope) and methodology (organisation) of this work.

Chapter Two: Literature Review

The chapter addresses present literature in connection to AI-powered decision making in respect to uses, strengths, and limitations in the retail sector. This chapter initially offers an introduction to AI before proceeding to discuss management decisions in respect to the role played by AI, the impact of AI in business processes, and ethics. This chapter also addresses theoretical foundations employed in this work. This chapter concludes by making an identification of gaps in earlier work.

Chapter Three: Research methodology

The chapter defines the design and methodology used in this research. It explains the methodology, research philosophy, and strategy. It looks at methods adopted in collecting data, sampling techniques, and analytical tools used. Additionally, this chapter addresses aspects related to ethics in conducting the research.

Chapter Four: Presentation and Analysis of Data

The chapter offers results of the research in accordance with collected data. It offers descriptive statistics, inferential statistics, and results interpretations in relation to research aims. Findings are further compared to related literature to establish similarities and differences.

Chapter Five: Summary of findings

The chapter offers discussion of the findings and further draws an overall summation of this study's results and draws inferences.

Chapter Six: Conclusion, Recommendations and future directions

The final chapter concludes the work, provides recommendations to managers, policy makers, and future researchers, and discusses limitations to this work while specifying areas where future work can be carried out.

Chapter Two

Literature Review

2.1 Overview of Artificial Intelligence (AI)

Artificial Intelligence (AI) refers to computers' ability to perform tasks that are typically dependent on human-intelligence. Such tasks entail learning, reasoning, problem-solving, perception, and language understanding (Boamah et al., 2025). AI systems are designed to analyse information, recognise patterns, and make decisions with minimal human interference. AI has advanced from simple rule-based systems to sophisticated algorithms with self-learning and adapting abilities (Soori, Arezoo and Dastres, 2023). AI has been in existence since the 1950s when computer scientists were searching for ways to make computers intelligent. AI was coined by John McCarthy in 1956 during the Dartmouth Conference (Khadragy, 2022). Early AI systems were created to solve logical problems, and their development was slowed by the insufficiency of computational power and information. However, machine learning, deep learning, and big-data advances have enhanced AI's ability to handle large amounts of information and make credible forecasts (Rashid and Kausik, 2024).

Artificial Intelligence (AI) can be classified into three broad categories: Artificial Narrow Intelligence (ANI), Artificial General Intelligence (AGI), and Artificial Super Intelligence (ASI). Artificial Narrow Intelligence (ANI), or weak AI, is designed to perform specific tasks for a specific field, for instance, speech recognition, image processing, or language translation (Biswal, 2022). ANI systems can be seen in daily usage in voice assistants like Siri and Alexa, anti-fraud systems in banks, and music and video recommendation systems (Rashid and Kausik, 2024). ANI operates on pre-defined rules and patterns of information and is unable to perform tasks outside of its programmable scope. Artificial General Intelligence (AGI), or strong AI, is a system with the ability to know, learn, and apply intelligence to a general set of tasks similar to human cognitive abilities (Datta et al., 2024). Unlike ANI, AGI would possess reasoning ability, creativity, and problem-solving ability and would be capable of adapting to new situations without human intervention. AGI is still hypothetical as existing AI systems are yet to become fully human-like in nature. Beyond AGI is Artificial Super Intelligence (ASI), a hypothetical and future development stage whereby AI would surpass human intelligence in all areas including creativity, decision-making, and emotional intelligence (Raman et al., 2025).

One of the major drivers of AI development is access to big data. Organisations and companies generate big volumes of data on a daily basis, and AI facilitates quick and efficient analysis of this data (Haleem et al., 2022). Machine learning is a subset of AI that allows systems to improve with time by learning through experience without explicit coding (Gligorea et al., 2023). Deep learning using neural networks to simulate human brain functionality has increased AI's ability to identify complex patterns and interdependencies in data (Taherdoost, 2023). AI applications are now used across finance, education, retail, and health. AI is applied to health to diagnose illnesses, predict patient outcomes, and help in developing drugs (Akbulut and Colak, 2024). AI is used to identify fraudulent transactions in finance, automate trades, and enhance customer support through chatbots (Mer, Singhal and Virdi, 2024). AI-powered applications in education offer individualised learning sessions to students by adapting to students' strengths and weaknesses (Adewale et al., 2024). AI has revolutionised the retail sector as well. AI-powered recommendation systems suggest products based on customer interests, and AI-powered chatbots enhance customer support (Haque et al., 2024). AI is also applied to demand forecasting, inventory management, and individualised marketing plans to enable companies to optimise operations and improve customer satisfaction (Madanchian, 2024).

Despite all that it has to benefit humanity, AI also has challenges like job replacement fears, ethical dilemmas, and privacy of data (Babashahi et al., 2024). Task automation by AI has given rise to job replacement fears, particularly in areas that involve a lot of repetitive tasks. AI systems also consume large volumes of data and generate fears of biased decision-making (Kalogiannidis et al., 2024). All these are indications that there is a need for regulations and ethical standards to ensure that AI is used ethically.

2.2 AI Application in Management Decision Making

Artificial Intelligence (AI) is transforming business decision-making. AI enables businesses to make quick decisions with minimal human involvement from enormous amounts of data. AI decision-making is increasing managers' productivity, reducing costs, and responding to changes in the market. Companies have implemented AI-based systems in strategic planning, risk management, and operations management in recent years (Kalogiannidis et al., 2024). AI systems process enormous amounts of information and identifying patterns difficult for humans to recognise. AI systems use algorithms, machine learning, and deep learning techniques in making forecasts and suggesting best actions (Armand et al., 2024). AI decision-making is particularly useful in organisations requiring prompt decision making like in retail, finance, health, and supply chain management. The various areas of applying AI to management decision making in line with previous studies and in line with the objectives and research questions in this study are depicted in the conceptual diagram in figure 1 below.

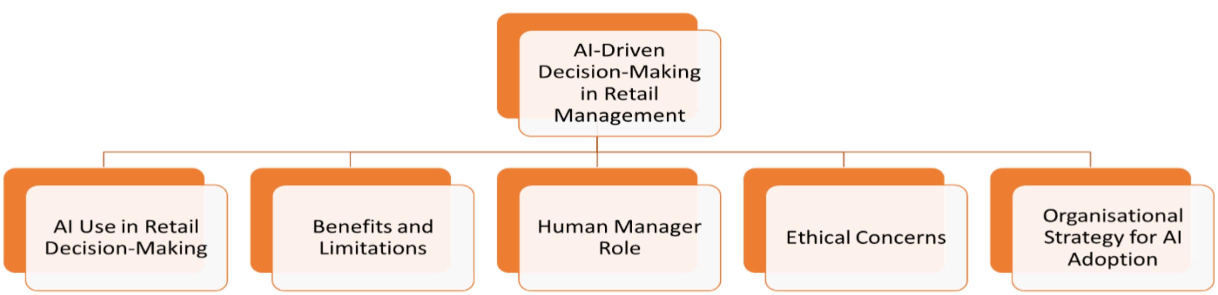

Figure 1: *Conceptual Framework Diagram*

2.2.1 AI in Data-Driven Decision-Making

AI can process huge volumes of data quickly unlike traditional decision-making that relies on human experience and intuition susceptible to biases and inconsistency (Reyna, 2018). AI avoids these pitfalls by processing huge volumes of structured and unstructured data to inform data-driven insights (Kumar et al., 2024). For example, Madanchian (2024) explained that AI analytics software allows firms to uncover customers' tastes, market trends, and operational inefficiencies. In retailing, AI-powered demand forecasting allows firms to predict customer demand and manage inventory to avoid overstocking or stock-outs (Shamsuddoha et al., 2025).

2.2.2 AI in Strategic Decision-Making

AI is utilised by companies to assess risks, analyse investment options and maximise business strategy. AI predictive models and simulations help managers analyse different scenarios before making critical decisions (Madanchian, 2024). In financial management, AI is applied in risk assessment by analysing market trends and historical data to forecast future results (Ozturk, 2024). AI software identifies potential threats and investment opportunities and allows firms to make informed financial decisions. In supply chain management, AI also optimises logistics through demand change forecasting and route optimisation (Riad, Naimi and Okar, 2024).

2.2.3 AI in Operational Decision-Making

Operational decision-making involves day-to-day business operations such as scheduling, resource allocation, and workflow optimisation. Murire (2024) described that AI-powered automated tools make these processes efficient by reducing human intervention and increasing efficiency. An example is AI-powered chatbots that improve customer care by responding to regular inquiries and answering instantly. In manufacturing, AI-powered robots manage manufacturing lines, detect flaws, and modify manufacturing schedules to maximise output (Islam et al., 2025). AI also optimises human resource management by processing employee performance and forecasting workforce demand. Organisations use AI-powered tools to analyse employee engagement, identify areas of skill shortages, and recommend training programs (Murugesan et al., 2023; Murire, 2024). Such applications help organisations to increase employee satisfaction and efficiency.

2.2.4 AI for Decision Making Under Uncertainty

AI is particularly useful in decision-making in uncertain circumstances, whereby managers need to cope with uncertain market conditions and external risks. Machine learning algorithms scan through past information and learn patterns that allow businesses to predict future patterns, asserts Sarker (2021). AI-based detection systems in financial institutions use predictive analytics to identify and block suspicious transactions and prevent financial losses (Pattnaik, Ray and Raman, 2024). AI-based cyber defense products also identify and respond to potential threats in real time to protect businesses against cyberattacks (Jada and Mayayise, 2023). AI-based diagnostic equipment improves accuracy and speed while reducing the likelihood of misdiagnosis (Alowais et al., 2023). All these applications show how AI enhances decision-making in complex and high-stakes circumstances.

2.2.5 Challenges in AI-Driven Decision-Making

Despite all of its advantages for management decision making, AI decision-making is also fraught with challenges. One of them is that AI algorithms are not transparent. Most AI models are "black boxes," and humans do not intuitively comprehend how they make decisions (Mathew et al., 2025). This is an ethical and regulatory issue, especially in fields with high-impact decision-making processes like finance and health. Another problem is that AI can make biased decisions. AI learns from past data (Ferrara, 2023), and this can be biased and lead to unfair or discriminatory decision-making. AI recruitment software has been shown to discriminate in favor of some segments of people and against others and has raised questions about unfairness and lack of diversity. AI systems also require large amounts of quality data to make good decisions. Poor quality or incomplete data can lead to errors in decision-making. Organisations have to invest in data management practices to make AI systems give reliable recommendations. AI is revolutionising management decision-making by providing insights based on data, improving efficiency, and optimising business processes. However, problems like lack of transparency in algorithms, quality of data, and ethics have to be overcome to ensure AI is used responsibly. With AI continuing to evolve, its application in decision-making will become more critical for organisations that have to remain competitive.

2.3 Impact of AI on Human Managers' Role in the Decision-Making Process

Managers previously made decisions using experience and intuition and data processing. AI has introduced new methods of processing large amounts of data and coming up with instant insights (Ali et al., 2024). This has transformed how managers interact with information, make strategic choices, and manage teams. As much as AI improves efficiency and accuracy, it also raises issues about the evolving roles of managers and whether managers are still needed in an AI-driven working environment (Kassa and Worku, 2025). The various uses of AI for this purpose are discussed as follows.

2.3.1 Decision Support Tool

AI sorts through big data, detects patterns, makes recommendations and saves time on analysis (Alowais et al., 2023). Machine learning algorithms make it possible for managers to know market trends, assess risks, and make predictions with greater accuracy (Okeleke et al., 2024). The study also illustrated this in retail by noticing that AI-powered tools study customer behavior and allow managers to maximise prices and inventory management. Pattnaik, Ray and Raman (2024) identified that in financial institutions, AI-based models of risk assessment enable managers to make investment decisions by weighing potential risks and returns. Such applications confirm that AI enhances managerial decision-making and not replaces human managers. AI systems can deal with information speedily, yet human judgment remains crucial in weighing ethical considerations, business goals, and context (Osasona et al., 2024). This refers to managers having to learn new competences that facilitate AI-based decision-making.

2.3.2 Managerial Decision Autonomy

AI automates routine decision-making in some cases to allow managers to focus on strategic activities. Repetitive operations are handled by automated systems such as processing loan applications, screening job candidates or flagging suspicious transactions (Osegi and Jumbo, 2021). Such technologies minimise human biases and maximise efficiency. AI can also limit managerial autonomy by making companies too dependent on algorithm-based decision-making (Alawamleh et al., 2024). Some companies employ AI systems that make business strategy without human intervention. In such cases, managers can get restricted in independent judgment. This is a dilemma in balancing AI automation with human oversight. To address this dilemma, companies must establish directives that make AI aid human decision-making and not substitute it. Managers should still be entrusted with overriding AI advice on some occasions to make sure that decisions are aligned with ethical considerations and company culture (Perifanis, 2023).

2.3.3 Managerial Competency Development

While AI is taking over data processing and routine decision-making, managers must learn new competences to remain effective. Critical thinking, problem-solving, and emotional intelligence are on the rise in an AI-enabled world (Darwin et al., 2023). Leadership is a key function that is transforming. Valdivieso and González (2025) stated that AI is not capable of mimicking human qualities such as creativity, empathy, and moral judgment. Managers must focus on motivating teams, innovation, and adjusting to changes. AI implementation also requires that managers are technologically and analytics literate (Deliu and Olariu, 2024). Managers lacking these competences may fall behind in a dynamic business landscape. Training sessions that enhance AI literacy among managers are required. Organisations should invest in upskilling programs that equip managers with competences to read AI output, make effective choices, and lead in an AI-enabled organisation (Zirar, Ali and Islam, 2023).

2.3.4 Ethical Considerations in Decision Making

Algorithmic bias, data privacy, and transparency are key areas of consideration in AI decision-making (Babashahi et al., 2024). AI models are trained on historical data that may be biased and lead to discriminatory judgments. An example is AI-based hiring platforms that are discovered to favor certain demographic groups and disadvantage others with fears of unfairness (Ferrara, 2023). Cheong (2024) posited that managers should make sure that AI systems are running fairly and ethically. This includes regular checks on AI algorithms for unfairness and biases and imposing mechanisms for avoiding biased decision-making. Organisations should also provide transparency by having AI systems explain how they make choices and allowing human intervention in areas that are important to them such as hiring, lending, and law enforcement. AI-driven job displacement is another ethical concern. AI brings about efficiency since it takes over work in some industries (Babashahi et al., 2024. Ali et al. (2024) acknowledged that businesses should seek methods of AI inclusion without replacing human employees that are creative and relational, hence managers need to act.

2.4 Benefits of AI-Based Decision Making for the Retail Chain

Artificial Intelligence (AI) has transformed decision-making in retail chains efficiently. AI applications devour large amounts of data and provide real-time information to organisations to optimise operations. Retailers use AI to optimise inventories, decide prices, provide customer services, and forecast demand (Haque et al., 2024). The following section discusses AI-based decision-making advantages for the retail business.

2.4.1 Improved Inventory Management

AI simplifies inventory management for retailers by predicting demand and reducing shortages. Traditional inventory management relies on past-selling patterns, while AI systems factor in market trends, weather forecasts, and consumer behavior (Krishnamurthy et al., 2024). Machine learning algorithms identify patterns and recommend optimal inventory levels, reducing waste and optimising availability (Pandey et al., 2023). Amazon uses AI-powered systems helps eliminate overstocking and makes goods available to customers (Li, 2024). AI-powered inventory management optimises logistics and efficiency (Chen et al., 2024).

2.4.2 Better Pricing Strategies and Customer Service

AI creates dynamic pricing strategies based on real marketplace situations and consumer behavior. Gupta (2024) noted that traditional pricing models are based on pre-defined markups or seasonality, while AI considers multiple inputs such as competitor prices, demand trends, and buying behavior. Walmart and eBay use AI-based pricing algorithms to dynamically alter prices to attain optimum revenue and profitability (Gandhimani, 2025). AI-based tools also offer personalised discounting based on individual interests and improve customer loyalty and retention (Dancausa and Millán, 2024).

Bălan (2023) discovered that AI improves customer service through the utilisation of chatbots, virtual assistants, and recommendation engines. Traditional customer service relies on human representatives and is susceptible to delay and inconsistency (Kessel et al., 2025). AI chatbots are used by retailers like Sephora, eBay and Burberry to assist consumers with product inquiries and recommendations (Kokoszka, 2018). AI-based algorithms are used by Netflix and Amazon to recommend movies and products and enhance user experience and generate revenue (Kalyvas, 2025). AI personalisation improves customer engagement and loyalty, as consumers are more likely to purchase products when they are provided with personalised recommendations based on their interests (Chandra et al., 2022).

2.4.3 Accurate Demand Forecasting

AI enhances demand forecasting through the analysis of multiple sources of real-time data (Amosu et al., 2024). Traditional forecasting relies on past sales data that cannot capture abrupt market condition changes (Martins and Galegale, 2023). Predictive analytics by AI systems anticipate demand shifts and allow retailers to optimise supply chain and reduce losses (Khedr and Sheeja, 2024). AI-powered demand forecasting helps grocery retailers to modify orders according to weather, holidays, and the purchasing patterns of customers reducing stockouts or food wastages. AI-based forecasting helps retailers to react to market changes faster and maintain a competitive advantage (Amosu et al., 2024; Okeleke et al., 2024). AI and machine learning for fraud detection and prevention were reviewed by Odufisan, Abhulimen and Ogunti (2025). AI systems utilise machine learning to look for patterns in transactions and identify abnormalities in real time. Companies like PayPal and Mastercard utilise AI-powered anti-fraud systems to reject unauthorised transactions (SDK.Finance, 2021). Odufisan, Abhulimen and Ogunti (2025) contended that AI-powered anti-fraud detection enhances security and protects businesses and consumers against financial losses.

2.4.4 Operational Efficiency and Cost Savings

AI robots and self-checkout are employed by stores to automate operations and reduce manual handling (Wolniak, Stecuła and Aydın, 2024). One example is Amazon that uses AI-powered robots to sort and pack products with efficiency (Li, 2024). It saves time and labor costs and increases overall business efficiency.

2.5 Limitations of AI-Directed Decision Making in the Retail Chain

Artificial Intelligence (AI) has improved decision-making in retail chains to become more efficient, more precise, and less expensive, it is subject to a number of limitations below that can affect decision-making. It is crucial for retailers to be aware of these limitations for effective AI adoption and implementation decisions.

2.5.1 Dependence on Data Quality and Availability

AI systems function well based on the quality, consistency and completeness of data (Kumar et al., 2024). Aldoseri, Khalifa and Hamouda (2023) argue that in most firms especially in retail chains, there can be missing, outdated or inconsistent data and this can lead to inaccurate prediction and poor decision-making. An example is that unless customer buying behavior is documented properly, there can be incorrect inventory recommendations by an AI system and this can lead to shortages or surplus of inventory. Data collection can also be a challenge for retailers in developing economies like Nigeria because there is limited digital infrastructure (Olaghere, Inegbedion and Osiobe, 2023). Biased or inaccurate data can lead to poor decision-making and this can affect business negatively.

2.5.2 High implementation and upkeep costs

AI systems are expensive to create, install, and keep running, this poses a challenge to most retail chains. Stores would require advanced infrastructure, trained personnel, and ongoing system upgrades to keep AI systems in top condition (Wilson, Johnson and Brown, 2024). Madanchian (2024) also mentioned that small and medium-sized retail businesses may not be able to afford AI decision-making tools. Additionally, Aldoseri, Khalifa and Hamouda (2023) observe that AI systems require regular software upgrades and processing power for processing information, which is expensive.

2.5.3 AI Lacks Human Intuition and Emotional Intelligence

Decision-making in retail sometimes requires human emotion awareness, sensitivity to cultures, and customer feelings that AI is incapable of mimicking as it relies on algorithms. AI chatbots can provide automated customer support but may lack the ability to appreciate complex customer grievances that require moral judgment and compassion (Liu-Thompkins, Okazaki and Li, 2022). Leaders in retail management make strategic decisions based on experience and intuition that AI systems cannot replicate with accuracy (Alawamleh et al., 2024). This limitation highlights the need for a balance between AI intelligence and human judgment in decision-making.

2.5.4 Ethics and privacy issues

AI decision-making is ethically objectionable in privacy and consumer rights terms. Data privacy and misuse remain a significant issue (Kalogiannidis et al., 2024). Customer details are collected by retail businesses to optimise marketing initiatives, but privacy violation may result from unauthorised use or misuse of such data (Krafft et al., 2021). Biased AI may also lead to discriminatory pricing or unfair treatment of specific customer segments (Ferrara, 2023). Ethical AI use by retail businesses requires strict policies and regulations for the protection of consumer rights and prevention of misuse.

2.5.5 Risk of Technological Failures

As AI systems are prone to unexpected failures, a failed AI system can bring disruption to businesses leading to losses and customer dissatisfaction (Bylykbashi and Gavranović, 2024). Examples like AI dynamic pricing system and inventory management can produce incorrect price changes and poor forecasts respectively leading to huge business losses. Williams and Yampolskiy

(2021) posit that AI failures can be harmful to business and that backup and human intervention are necessary for AI-based decision-making.

2.6 Ethical Considerations in AI-Driven Decision-Making

AI decision-making enables firms including retail to analyse large volumes of data, make future forecasts on consumer behavior, and manage supply chain operations (Haleem et al., 2022). However, large-scale application of AI has significant ethical challenges. Ferrara (2023) has enumerated some of them such as privacy of information, bias, lack of transparency, accountability, and job replacement that has created controversies around ethical application of AI. Addressing them is important for ensuring equity, trustworthiness, and responsible application of AI to decision-making in retail.

2.6.1 Data privacy and security

AI systems collect and analyse large amounts of consumer data to support decision-making. AI analytics are applied by retailers to track customer behavior, interests, and purchasing patterns (Okeleke et al., 2024). While it aids in providing personalised experiences to businesses, it is a privacy issue. Data breaches, identity theft, and misuse of confidential information are caused by unauthorised access to personal information. Online businesses collect customer information to enhance marketing strategy, for instance, yet there are still privacy issues with how it is stored and distributed (Gupta et al., 2023). Ethical application of AI in retail relies on efficient protection policies for data, compliance with legislation such as the General Data Protection Regulation (GDPR), and transparent disclosure of data collection practices (Adanyin, 2024).

2.6.2 Discrimination and Bias in AI Algorithms

AI relies on historical data and if this historical data is biased, AI systems can reinforce discrimination in decision-making (Ferrara, 2023). Biased AI models in retailing can create unfair pricing policies, exclusionary advertising, or discriminatory hiring. Ferrara (2023) also highlighted that an AI system trained on biased data can benefit some demographic segments while discriminating against others. Similarly, Akter et al. (2021) highlighted that AI-based pricing algorithms can offer discounts to specific customer segments while charging others unfairly which can harm businesses. Bias in AI-based decision-making can be addressed with diversified training data, regular audits of AI models, and ethical oversight in developing algorithms (Chen, 2023; Ferrara, 2023).

2.6.3 Lack of Transparency and Explainability

Most AI systems are "black boxes," and opaque that even developers may not know how they make conclusions (Mathew et al., 2025). Transparency is problematic in retail because managers would need clear explanations for AI-made decisions. If AI systems reject a customer loan application or adjust a product price, companies should be able to offer explanations for such decisions (Davenport and Ronanki, 2018). If AI is not made explainable, it can reduce accountability and trust in automated decision-making. Ethical deployment of AI requires interpretable models and transparent communication of AI-made decisions to stakeholders (González-Arencibia, Ordoñez-Erazo and González-Sanabria, 2024).

2.6.4 Accountability and Legal Responsibility

AI decision-making is making accountability questionable. According to Osasona et al. (2024), it is hard to hold AI accountable for a bad decision that results in injury to customers or employees. AI-enabled stores are required to ensure that legal and ethical guidelines define who is accountable for AI action. If there is an inaccurate AI-powered supply chain system that leads to financial losses, are the developers to blame, the stores, or the data providers? Ethical AI deployment in various sectors particularly retail requires open accountability systems, human oversight, and compliance with legal guidelines that oversee AI technology (Radanliev, 2025).

2.6.5 Job Displacement and Impact on Workforce

AI systems can automate functions such as inventory management, customer support, and pricing optimisation, reducing human workers (Shamsuddoha et al., 2025). This has created controversy surrounding AI and job losses. For instance, automated checkouts have replaced cashiers in many retail stores, displacing thousands of jobs (Tan et al., 2024). While AI creates new job roles in AI management and data science, it also forces companies to retrain workers. Ethical AI adoption in retail has to contend with workforce readiness, retraining, and how to find a balance between human jobs and mechanisation (Gupta, 2016).

2.7 Theoretical Framework

The use of artificial intelligence (AI) in decision-making has grown significantly, and a robust theoretical framework is needed to describe its adoption, implementation, and impact. Theoretical frameworks offer systematic information on how AI is adopted in business practices, how companies react to technological advancements, and what motivates AI adoption. The use of theories enables researchers to evaluate AI-based decision-making in retailing and determine challenges and opportunities. Four theories are used in this research to describe AI-based decision-making in retailing: The Technology Acceptance Model (TAM), Dynamic Capabilities Theory (DCT), Contingency Theory, and Diffusion of Innovations Theory. TAM describes how perceived ease of use and perceived usefulness influence AI adoption. DCT focuses on how companies develop capabilities to integrate AI in decision-making. Contingency Theory highlights that AI is effective depending on situational contingencies. Finally, Diffusion of Innovations Theory describes how AI technologies spread in companies. The use of these frameworks collectively offers multidimensional analysis to ensure a better understanding of how AI enhances business practices and what motivates it to thrive.

2.7.1 Technology Acceptance Model

The Technology Acceptance Model (TAM) was developed by Davis (1989), and it is considered one of the most effective theories applied to study adoption of new technologies. TAM describes how individuals adopt and use technology based on two primary factors: perceived usefulness (PU) and perceived ease of use (PEU) (Wang et al., 2023). In AI-based decision-making in retailing, TAM describes how managers and employees perceive AI tools and how they influence adoption and implementation of AI in decision-making. The Technology Acceptance Model (TAM) is based on the premise that users are more likely to adopt an easy-to-use and useful technology. TAM entails several key factors that influence AI adoption in decision-making.

One is Perceived Usefulness (PU), or the degree to which a user believes AI will enhance decision-making (Davis, 1989). In retail management, AI can be useful to managers if it makes work more efficient, reduces errors, and produces accurate data-based insights. If users understand that AI is positively impacting their work, they are more likely to adopt it in operations. Another key factor is Perceived Ease of Use (PEU), or the degree to which a user believes AI systems are easy to learn and use (Scherer, Siddiq and Tondeur, 2019). If AI tools are easy to learn and apply with less effort, retail managers are more inclined to adopt them. An intricate and difficult-to-use system can slow down adoption while a simple and intuitive AI system encourages adoption. Perceived usefulness and ease of use influence a person's Attitude Toward Use, which is a general perception about AI. If users find AI useful and easy to use, they create a positive attitude toward using AI-based decision-making systems (Scherer, Siddiq and Tondeur, 2019). A positive attitude reinforces their Behavioral Intention to Use AI and encourages widespread adoption in a company.

Studies have established that AI adoption depends on whether retail managers perceive it to benefit them and on ease of implementation (Wang et al., 2023). If AI systems provide clear benefits such as tracking inventory in real time, demand forecasting, and personalised customer experiences, managers are more likely to use them. However, it is problematic for AI systems to be perceived as complex, costly, or hard to integrate with existing processes (Ledro, Nosella and Pozza, 2023). Training and education are crucial for perception and AI adoption rates (Tursunbayeva and Gal, 2024). Although TAM provides a good theoretical framework for AI adoption explanation, it doesn't account for organisational, regulative and cultural factors influencing AI implementation. Moreover, TAM is based on rational decision-making by users to adopt technology while psychological and social factors can also play a role in reality (Malatji, Eck and Zuva, 2020). Yet, despite this limitation, TAM remains a valuable framework for explaining retail managers' perception and determinants driving or preventing AI adoption in decision-making.

2.7.2 Dynamic Capabilities Theory

Teece, Pisano, and Shuen's (1997) proposed the Dynamic Capabilities Theory (DCT). It recognises that organisations need to constantly make adaptations to resources and strategy in order to maintain a competitive advantage. In the case of AI decision-making, DCT can be used to describe how retail businesses use AI to drive business success. DCT is concerned with three capabilities that enable firms to maintain a competitive advantage: sensing threats and opportunities, seizing opportunities, and reconfiguring resources (Teece, Pisano and Shuen, 1997).

Sensing threats and opportunities involve interpreting external developments that are likely to impact business operations (Čirjevskis, 2019). AI plays a crucial role in this exercise by scouring through massive volumes of data to determine market trends, customer demands, and potential threats. AI-powered analytics, for example, help retailers sense changes in consumer purchasing behavior and stock products to meet the demand (Madanchian, 2024).

AI enables the potential for instant decision-making with real-time insights into market trends (Čirjevskis, 2019). AI tools can be applied by retailers in pricing strategy optimisation, personalised marketing campaigns, and customer experience improvement (Haleem et al., 2022). Firms that fail to apply AI in decision-making risk losing market share to firms that employ data-driven approaches to business growth. Organisations have to reconfigure resources to integrate AI in business models. Reconfiguring resources means investing in AI technology, retraining workers, and reorganising processes to allow for automation and data-driven decision-making (Teece, 2018). AI-powered automation optimises supply chain operations and saves costs while enhancing efficiency in retailing.

DCT focuses on agility and responsiveness in retail decision-making. AI forecasting software can be employed by companies to predict changes in demand and control inventory levels to avoid stockouts and surplus inventory. Most retail firms are not capable of adopting AI since it is costly, has risks to privacy and is subject to resistance to change. DCT advises firms to invest in AI development and enhancement to stay competitive. Despite all its merits, DCT dynamic capability doesn't improve business performance and competitive advantage directly (Prester, 2023). There are stores that do not have leadership or vision to invest in decision-making based on AI. Moreover, not every company can reconfigure resources with ease, especially smaller companies with limited technical and financial resources. Nevertheless, DCT is still helpful in explaining that stores can establish AI-based capabilities to improve decision-making, customer experience, and sustainable competitive advantage.

2.7.3 Contingency Theory

Contingency Theory by Burns and Stalker (1961), asserts that there is no best way to manage an organisation. Instead, management practices are effective based on situational factors such as environment, organisation structure, and technology (Pacheco-Cubillos, Boria-Reverter and Gil-

Lafuente, 2024). The Contingency Theory emerged as a critique of management models that was grounded on companies having to adapt to external and internal circumstances. Modern studies expanded on this theory by emphasising that decision-making within organisations has to be context-specific (Mahmud, Soetanto and Jack, 2021). They identified that what is effective for a specific company may not be effective for another company due to size difference, market condition, or technological competences. In AI adoption in retailing, Contingency Theory emphasises that decision-making processes have to be customised to suit specific organisational contexts in order to maximise the implementation and efficiency of AI technologies.

Environmental uncertainty refers to the dynamic nature of the retail environment with ongoing changes in consumer demand, competition, and supply chain disruptions. AI enables firms to analyse market trends in real time and reduce decision-making uncertainty (Perifanis, 2023). Organisational structure has a significant impact on AI implementation speed. Central decision-making structures tend to slow down AI implementation through bureaucratic difficulties, while decentralised structures can expedite implementation (Jerab and Mabrouk, 2023). Large retail chain stores with hierarchical structures can be threatened by AI implementation, while smaller and adaptable firms can easily adapt to technological advancements. Technology fit refers to compatibility between AI solutions and existing goals and capabilities of an organisation. Firms with robust IT infrastructure can better leverage AI to their benefit, while firms with weak technological resources can be threatened to implement AI-based decision-making (Robertson et al., 2025).

Contingency Theory explains how AI adoption varies across different retail firms. Whereas some companies can utilise AI to optimise pricing, supply chain management, and customer support to the best extent possible, others are not in a position to do that due to financial constraints, technical incapacity, or resistance. An example would be that a large multinational retail chain like Amazon is significantly benefited by AI-based decision-making with a strong technological backbone. A locally based retailer with limited resources may find AI implementation costly and unnecessary.

2.7.4 Diffusion of Innovations Theory

Diffusion of Innovations (DOI) Theory by Everett Rogers in 1962 explains how technologies, ideas, and practices are diffused in a social system. It is applied widely to research AI-based decision-making adoption in retail. It explains that AI adoption is not a one-time process but is a process subject to market and organisational contingencies (García-Avilés, 2020). It is a theory explaining how new technologies and ideas are diffused in societies and organisations. In AI adoption in decision-making processes, DOI identifies five factors influencing the rate and extent of adoption: relative advantage, compatibility, complexity, trialability, and observability (Cadarette et al., 2017).

Relative advantage is the degree to which AI decision-making is an improvement on what already exists. Retailers that perceive benefits in terms of efficiency, accuracy, and customer experience are most likely to implement AI. Compatibility is a measure of how easily AI aligns with what is already in place in terms of processes, culture, and infrastructure. Businesses with robust digital infrastructure are likely to find it simple to implement AI in operations, but traditional businesses may resist due to culture. Complexity is a measure of how easy it is to learn about and implement AI systems. Organisations may be hesitant to adopt AI that is too complicated or that demands technical know-how that they lack, and particularly those without in-house technical resources. Trialability is how easy it is for an organisation to pilot AI on a limited basis before full adoption. Most retailers pilot test programs to determine whether AI can be made to work before widespread adoption. Observability is how clear AI benefits are to others in the field. Success stories by top-performing retailers can be powerful motivators for others to adopt AI (Cadarette et al., 2017).

DOI theory also divides adopters based on how prepared they are to adopt innovations: innovators (2.5%), early adopters (13.5%), early majority (34%), late majority (34%), and laggards (16%) (Smith and Findeis, 2013). Innovators are venturesome individuals or organisations that are quick to experiment with new technologies and are typically leaders in AI adoption. Early adopters are opinion leaders who recognise AI potential and invest in systematic implementation and establish standards for others to adopt. Early majority are cautious decision-making individuals who adopt AI after it has been thoroughly tested and has been proven to be reliable and reduce risks. Late majority are cautious groups that adopt AI out of compulsion, typically by peer pressure or financial reasons, after it has become common in an industry. Lastly, there are laggards who are slow to adopt AI due to costs, lack of know-how, or resistance to change and tend to wait until it is unavoidable (Smith and Findeis, 2013).

It is crucial to understand these factors and adopter groups to apply effective AI adoption in retailing since it allows for customised methods that address specific problems and characteristics of each adopter group. Companies with efficient technological infrastructure and visionary leadership adopt AI faster than those that are slow to do it due to financial constraints or lack of clarity. Alibaba’s AI-powered retail operations can inspire other retail firms to invest in similar tech. However, smaller firms in Nigeria and other emerging economies may lag behind due to limited resources and know-how.

2.8 Empirical Review

The empirical review takes into account available studies on AI-based decision-making in retail and allied sectors.

2.8.1 AI for Retail Decision Making

Studies on AI in retail decision-making were found to uncover potential for transformative effects while also identifying challenges that hamper smooth implementation. Robertson et al. (2025) explored socio-technical challenges that face retailers in AI implementation in value chains. From a qualitative study based on expert interviews, they developed an AI Implementation Compass that addresses challenges on micro-, meso-, and macro-levels and offers a structured framework for AI-led transition in organisations. Their study stresses that there is a need for a balanced strategy to AI implementation that considers internal operational changes and external market forces. Correspondingly, Hashid and Almaqtari (2024) explored AI's role in accounting and auditing and identified AI's potential to enhance efficiency, accuracy, and decision-making. Using a mediation and path strategy to study AI implementation, they found that AI implementation reinforces financial reporting and auditing and offer useful insights for policymakers and practitioners in the field. Contributing to those arguments, Perifanis (2023) surveyed 139 peer-reviewed studies on AI adoption and found that while AI presents tremendous value creation potential, many organisations are faced with strategic implementation. Their study points to complexities in connecting AI capabilities with business strategy and reiterates that structured governance and management of resources are required to maximise AI's value in retail and other fields.

2.8.2 AI and Consumer Behavior Analysis

AI decision-making in influencing consumer behavior in retail. Naz and Kashif (2024) outline ethical challenges in AI-based predictive marketing and identify unintended consequences such as reinforcement of biases, privacy invasion, and manipulation of consumers. The studies emphasise the need for ethical standards in AI-based marketing practices. Wang and Slowik (2024) also propose AI-based modeling of consumer behavior to improve recommendation accuracy in online music retail. By integrating collaborative filtering with a hidden Markov model, their study improves credibility in track recommendations and shows AI's ability to personalise user experience. Gerlich (2023) addresses virtual influencers and demonstrates how AI-generated personas are found to be more credible than human influencers and enhance consumer engagement and purchase intention. Lastly, Esmeli and Gokce (2025) track AI's applications in e-commerce and identify session-based features such as prices and category switches that influence buying behavior.

2.8.3 AI and Supply Chain Optimisation

AI application in supply chain management (SCM) has been extensively investigated in empirical studies that outline its potential to make operations efficient, resilient, and sustainable. Culot, Podrecca, and Nassimbeni (2024) provide a systematic review of empirical studies on AI in SCM and outline themes that range from data requirements and technology deployment to organisation-wide adoption. They warn that the revolutionary potential of AI is overhyped and that there needs to be a realistic balance between its challenges and benefits. Next, Qu and Kim (2024) discuss the AI-enabled technologies for sustainable supply chain management (SSCM) and find AI effective in solving environmental and economic problems but with potential for further development to address social problems like fair labor standards. Chen et al. (2024) introduce AI-based logistics optimisation and illustrate how machine learning and generative models make operations sustainable by reducing carbon emissions and optimizing transport. Finally, Riad, Naimi, and Okar

(2024) introduce an AI-based supply chain resilience framework and illustrate how predictive analytics and automations improve demand forecasting and inventory management.

2.8.4 Impact of AI on Managerial Decision

Bao, Gong, and Yang (2023) explain how AI-powered technologies such as deep learning and natural language processing facilitate human–AI synergy in decision-making. They discuss AI affordances, decision task variations, and human–AI collaboration outcomes and provide a framework for this dynamic that is in development. Marocco, Barbieri, and Talamo (2024) study managers' use of AI in decision-making and identify key impediments and facilitators such as ethical considerations, organisational culture, and psychological factors. They establish that there is a gap between AI's potential and actual implementation in managerial decision-making. Continuing this argumentation stream, Caiza et al. (2024) write about AI's use in government decision-making and attribute efficiency gains to it while cautioning about risks such as bias and lack of transparency.

2.8.5 AI Adoption Obstacles and Ethical Considerations

Ferrara (2023) investigated AI decision-making bias and found that AI systems are biased by training data leading to unfair decision-making in automated hiring and customer segmentation. Hence, constant monitoring and audits of AI needed. Khan et al. (2022) conducted a systematic review of ethical AI challenges. They categorised significant challenges as including privacy of data, job replacement by AI, and lack of transparency in AI decision-making. Findings were, although there is widespread use of AI for efficiency by firms, few of them account for its ethical impacts. Uwagaba, Omotosho and George (2023) also explored barriers to AI adoption in developing economies and found that AI deployment is hampered by high costs, absence of skilled personnel, and weak digital infrastructure in retail.

2.9 Gap in Literature

Despite extensive research on AI decision-making across various domains, key gaps remain. While studies have examined AI in retail (Robertson et al., 2025; Perifanis, 2023), consumer behavior (Naz & Kashif, 2024; Gerlich, 2023), supply chain optimization (Culot et al., 2024; Qu & Kim, 2024), and managerial decisions (Bao et al., 2023; Marocco et al., 2024), few focus on its impact in developing economies—particularly Nigerian retail chains. Empirical evidence on AI's role in managerial decisions within Nigerian retail firms is scarce. Existing studies explore AI-human synergy in advanced sectors, overlooking Nigeria's unique challenges like infrastructural deficits, low digital literacy, and regulatory uncertainty. This study addresses these gaps by exploring AI's influence on decision-making in Nigerian retail, assessing whether it complements or disrupts existing practices.

Another gap concerns AI's practical applications and limitations in retail. While Hashid and Almaqtari (2024) highlight AI's role in financial reporting, its impact on efficiency and growth in Nigerian retail remains underexplored. Robertson et al. (2025) offer a framework for AI-driven change but do not consider Nigeria's structural and economic constraints. This study examines both benefits and drawbacks of AI in Nigerian retail decision-making. Ethical concerns—such as bias and privacy—are also under-researched locally. Though Naz and Kashif (2024) and Khan et al. (2022) discuss these issues broadly, little is known about how Nigerian retailers manage them amid evolving regulations. This research investigates how firms maintain ethical AI use while preserving consumer trust.

Uwagaba et al. (2023) identify cost, technical skill gaps, and weak infrastructure as barriers to AI adoption in developing countries, yet their impact on Nigerian retail decision-making is not well studied. This research fills that void by analysing sector-specific challenges and offering practical solutions. Lastly, while Wang and Slowik (2024) and Esmeli and Gokce (2025) explore AI's effect on consumer behavior, its role in shaping customer engagement strategies in Nigerian retail is largely ignored. Given AI's potential to enhance customer experience, inventory, and delivery, this study provides insights into its deployment in managerial decisions, operational efficiency, and customer engagement—guiding business leaders and policymakers toward sustainable development.

Chapter Three

Methodology

3.1 Introduction

Research methodology provides a systematic approach to investigating a phenomenon through the definition of data collection techniques, strategy, and processes of analysis and interpretation of data. The chapter outlines the research methodology for this study, following the research onion model by Saunders, Lewis, and Thornhill (2019). The research onion, as indicated in Figure 1, provides the systematic manner of investigating design in progressive layers, from philosophical position to data collection procedures. The research is looking into AI-based decision-making in Nigerian retail chain outlets, its influence, limitations, ethical concerns, and managerial implications. To this end, the research procedure is designed to enhance reliability, validity, and objectivity in responding to the research questions. The research method must be maintained in alignment with the research objectives while ensuring data collection methods and analysis are apt to derive feasible results.

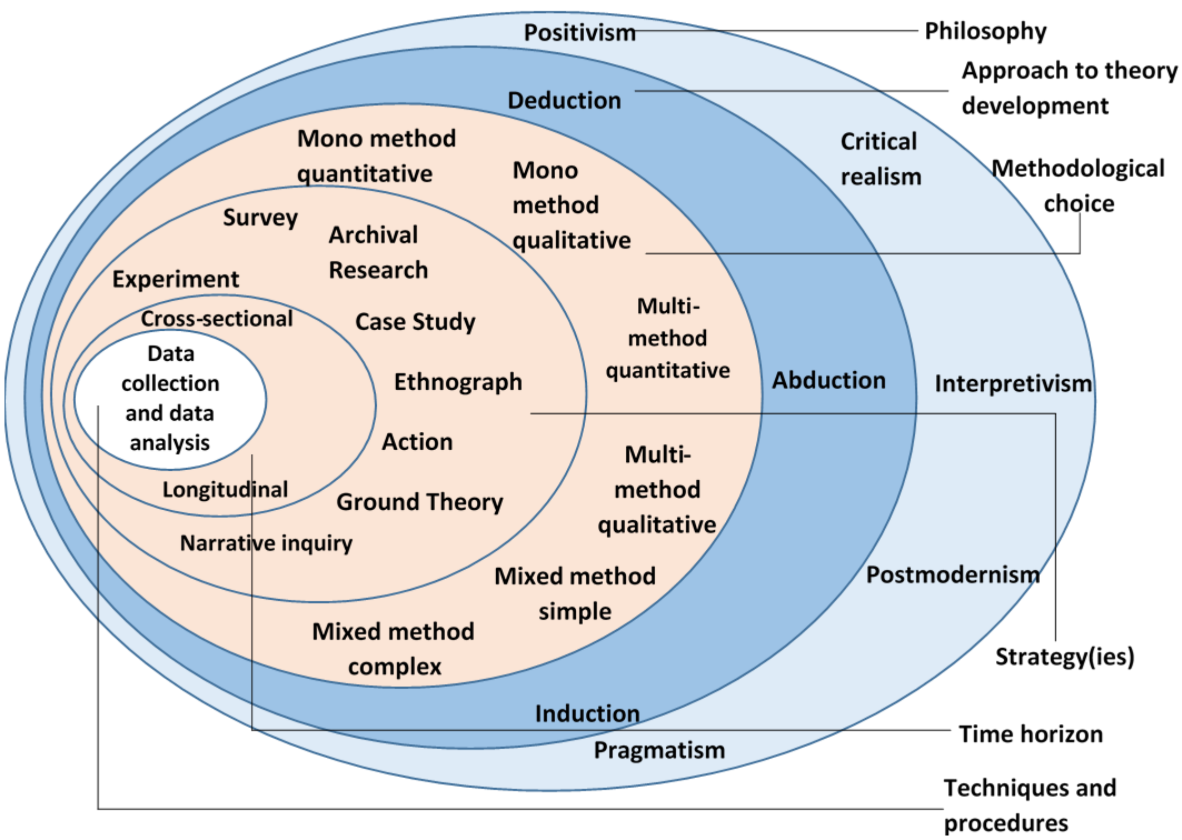

Figure 2: Research Onion (Saunders, Lewis and Thornhill, 2019)

3.2 Research Philosophy

Research philosophy is a set of assumptions and beliefs that guide knowledge creation in a study. Saunders, Lewis and Thornhill's (2019) research onion framework identifies five principal research philosophies: positivism, critical realism, interpretivism, postmodernism, and pragmatism. The selection of an appropriate research philosophy is important due to its influence on research design, data collection, and the style of data analysis.

Positivism is based on the assumption that reality is objective and exists independent of human perception (Saunders, Lewis and Thornhill, 2019). Positivism assumes that knowledge is measurable, testable, and generalisable through scientific methods. Researchers guided by this philosophy use quantitative data and rigorous procedures such as experiments and surveys. Positivist research aims to discover cause-and-effect and is likely to use statistical analysis methods (Creswell and Creswell, 2018).

Critical realism holds that reality exists independently of human perception but is understood through interpretation (Stutchbury, 2021). Unlike positivism, it recognises the influence of social structures and context on knowledge. It supports both quantitative and qualitative methods to explore underlying mechanisms (McEvoy & Richards, 2006).

Interpretivism emphasises the subjective nature of reality, shaped by social interactions and human experience (Bryman, 2016). Common in qualitative research, it focuses on interpreting individual perspectives, motivations, and cultural contexts. Interviews, focus groups, and case studies are typical data collection tools (Saunders, Lewis & Thornhill, 2019).

Postmodernism challenges conventional thinking by asserting that knowledge is socially constructed and influenced by power dynamics (Perera, 2024). It rejects universal truths, emphasising language, culture, and history in shaping reality. Discourse analysis and critical reflection are key methods (Campbell, 2018).

Pragmatism prioritises practical application, asserting that research should be guided by what works in specific contexts (Kaushik & Walsh, 2019). It blends positivist and interpretivist approaches based on research goals and is often linked to mixed-methods research using both qualitative and quantitative techniques (Saunders, Lewis & Thornhill, 2019).

This study adopts positivism as the guiding research philosophy. The choice is suitable because it seeks to examine AI-based decision-making in Nigerian retail chains from the perspective of quantifiable data. Because the study seeks to examine the impact of AI on business operations, it relies on quantitative data, statistical tools, and objective analysis. Positivism ensures results are replicable, generalisable, and free from researcher bias (Creswell and Creswell, 2018). Positivism also aligns with the research objective. The use of structured surveys and statistical models is within the positivist approach in that it enables objective determination of AI impacts on decision-making in Nigerian retail firms.

3.3 Research Approach

Research approach is the manner in which theory is created and tested in a study. The research method shows how data will be collected, analysed, and interpreted. Saunders, Lewis and Thornhill (2019) propose three general research methods: deduction, induction, and abduction. These have their assumptions and are chosen based on the kind of research questions and objectives and data availability.

A deductive approach is a top-down process where research begins with a theory or hypothesis that is then tested by using empirical evidence (Bryman, 2016). This is the approach commonly used in quantitative research, where researchers collect data to prove or disprove pre-established theory. The process is followed in a predetermined sequence: Browse available theory and concepts; create hypotheses or research questions; collect and analyse data to test the hypotheses or address the questions; and confirm, modify, or disprove the initial assumptions Deductive approach is often associated with positivism as it deals with objectivity, measurement, and generalisation (Saunders, Lewis and Thornhill, 2019). The research under this approach is founded on fixed data collection tools such as questionnaires, experiments, or statistical models. The main advantage of deduction is that it allows replication and reliability as researchers can test the same hypotheses or theories in different contexts. Its disadvantage is that it does not allow for much flexibility as the study is limited to test existing theories (Gurukaelaiarasu, 2024).

An inductive approach uses a bottom-up method, starting with data collection and observation, followed by pattern recognition and theory development (Creswell & Creswell, 2018). Unlike deduction, it doesn't begin with a hypothesis; instead, researchers explore data to identify trends and build theories. Inductive research typically involves qualitative methods, aiming to understand human behavior, social phenomena, or emerging patterns. Closely linked to interpretivism, it focuses on subjective meanings and lived experiences (Saunders, Lewis & Thornhill, 2019). Its flexibility allows exploration without theoretical constraints, though findings may lack generalisability due to context-specific results (Gurukaelaiarasu, 2024).

An abductive approach involves elements of deduction and induction. It is used where existing theory cannot explain a phenomenon and thus the researcher comes up with new concepts through iterating between theory and data (Dubois and Gadde, 2014). It involves Identifying a research problem, seeking existing theories for possible explanations and collecting new data for the aim of modifying or altering theories. Abduction allows researchers to combine qualitative and quantitative data for the generation of new understandings (Saunders, Lewis and Thornhill, 2019).

This study adopts a deductive approach as it seeks to test existing theories of AI-driven decision-making in retail chains. It is a quantitative data collection-based research, in which statistical models and formal surveys shall be used to examine the impact of AI on business performance. The application of deduction is aligned with the positivist philosophy of the research as it will enable the findings to be objective, measurable, and generalisable.

3.4 Methodological Choices

Methodological choice refers to how a researcher proceeds with data collection and analysis. Saunders, Lewis and Thornhill (2019) identified different methodological approaches based on whether a study uses qualitative, quantitative, or mixed methods. The selection of an appropriate methodology is based on research questions, objectives, and the type of data.

A mono-method quantitative design uses a single quantitative data collection and analysis method. It involves formalised strategies such as surveys, experiments, or secondary numeric data to measure variables and answer the research questions. It is typical in deductive reasoning and positivist philosophy research because it ensures objectivity and replicability (Bryman, 2016). The primary advantage is that it allows statistical testing and generalisation of findings. A limitation is that it may over-simplify complex human behaviours and decision-making processes (Creswell and Creswell, 2018).

A mono-method qualitative design uses only qualitative techniques like interviews, focus groups, or case studies. It's common in research focused on subjective experiences, social interactions, or emerging phenomena (Saunders, Lewis & Thornhill, 2019). It offers rich, detailed insights, making it ideal for exploratory studies, though its subjectivity and limited generalisability make it unsuitable for research needing numerical data (Bell, Bryman & Harley, 2022).

A multi-method quantitative approach applies more than one quantitative technique—such as combining surveys with financial data—to enhance analysis, triangulation, and reduce bias (Saunders, Lewis & Thornhill, 2019). However, it may demand more time and resources, which can be challenging. Similarly, multi-method qualitative design blends approach like interviews, document analysis, and observation to capture diverse perspectives and contexts (Creswell, 2018). Though informative, its subjectivity can make interpretation complex and time-consuming.

A simple mixed-method design uses both qualitative and quantitative methods independently, with one being dominant (Bryman, 2016). For example, surveys may be followed by interviews. It balances statistical precision with contextual depth but requires careful planning to ensure consistency.

The complex mixed-method strategy also combines qualitative and quantitative methods, but both are applied simultaneously and equally (Saunders, Lewis & Thornhill, 2019). It suits interdisciplinary research tackling multifaceted problems but demands advanced skills and large-scale data analysis.

This study follows the mono-method quantitative design as it targets questions regarding AI-based decision-making in retail chains. Through the utilisation of structured surveys and statistical modeling, the study ensures objective measurement and generalisability. The design aligns with the deductive reasoning and positivist research philosophy, making it most suitable for evaluating the effect of AI on business performance.

3.5 Research Methods and Procedures

Research techniques and procedures specify the exact methods of collecting, sampling, and analyzing data in a study. These elements are crucial in making the research valid, reliable, and capable of giving responses to the questions of the study. This study has a structured approach to investigating the impact of AI-based decision-making in retail chains.

3.5.1 Data Collection Methods

Data gathering is a critical aspect of research as it will determine the validity and quality of the results. The research design, objectives, and the type of data required inform the method of data gathering. This study adopts a quantitative approach to data gathering by using structured questionnaires to gather data from decision-makers, managers and professionals in retail. A structured questionnaire is suitable as it will yield answers that are standardised; hence comparison and statistical analysis will be straightforward (Saunders, Lewis and Thornhill, 2019). The questionnaire has closed-ended questions to measure the implementation of AI-driven decision-making, its effectiveness, and pitfalls in retail chains. The participants will rate their AI decision-making experiences on a Likert scale basis. The approach provides measurable data, enhancing the validity and reliability of the study (Bryman, 2016). The questionnaires will be administered electronically via email and online survey platforms. This is to facilitate broader coverage and higher response rates at reduced costs and time compared to physical administration (Creswell and Creswell, 2018). Secondary data in the form of published reports and previous studies will also be used to support or disprove the results from the primary data. These rigorous methods ensure the study is balanced and data-driven.

3.5.2 Sampling Techniques

Sampling involves selecting a representative sample from the population to take part in the study. Since the population size is unknown, a reasonable sample size will be adopted from empirical research. The sample sizes of between 150 and 200 respondents have been used in previous studies on AI adoption and decision-making (Amin and Alanzi, 2024; Lada et al., 2023; Rana et al., 2024). Based on this, the study will use a sample size of 160 retail managers and decision-makers to attain adequate representation for statistical analysis. The study adopts purposive sampling, a non-probability technique used in the selection of participants with specific expertise and experience (Campbell et al., 2020). The technique is suitable considering that AI-based decision-making is not yet used in all retail firms, hence only experts and professionals with working knowledge will be selected. Respondents will be sampled from large retail chains that have adopted AI in their management. The justification of purposive sampling is that it provides the opportunity to collect rich, relevant, and focused data for the study. In contrast to random sampling, where the respondents might not be well-informed about AI, purposive sampling helps to ensure that only experts provide input to the research result. Further, given the constraints of time and resources, a purposely chosen sample adds efficiency without compromising the validity of the research.

3.5.3 Data Analysis

Data analysis involves managing and interpreting data collected to arrive at feasible conclusions. Since the quantitative approach is employed in this research, responses collected will be analysed using descriptive and inferential statistical techniques. Descriptive statistics like mean, standard deviation, and frequency distribution will be employed in summarizing responses and providing an overview of AI adoption by retail chains (Saunders, Lewis and Thornhill, 2019). Data analysis will be done using the Statistical Package for the Social Sciences (SPSS) for computational accuracy and reliable results. In examining how organisations use AI in supporting management decision-making (RQ1) and the benefits and limitations of AI-based decision-making (RQ2), descriptive statistics will be used, including frequency distributions, mean values, and standard deviations. These metrics will provide a clear overview of AI adoption trends, including common applications, perceived benefits, and challenges for retail businesses.

To analyse AI's impact on the decision-making role of human managers (RQ3), inferential and descriptive statistical techniques will be employed. Descriptive statistics will summarise the extent to which AI impacts managerial activities, while correlation analysis will determine the direction and strength of the relationship between AI adoption and change in managerial decision processes. For analysing ethical concerns regarding AI-based decision-making (RQ4) and AI adoption and utilisation optimisation strategies (RQ5), descriptive statistics and cross-tabulation will be employed jointly. Descriptive analysis will unveil the most common ethical concerns mentioned, while cross-tabulation will examine whether company size, industry type, or AI maturity stage have an influence on ethical considerations. In addition, causal analysis techniques such as multiple regression can be employed to explore the relationship between AI adoption approaches and organisational decision quality.

To optimise the validity of the study, the data set will be cleaned and screened for inconsistencies before analysis. The results will be presented in tables and graphical formats to facilitate ease of understanding. The application of both descriptive and inferential statistical methods will facilitate a rigorous, data-driven examination of the adoption of AI and its effects on decision-making in retailing.

3.6 Research Ethical Considerations

Ethical considerations form part of every research study, ensuring data gathering and analysis are in line with established moral and professional standards (Husband, 2020). This study upholds ethical guidelines to protect the rights, privacy, and welfare of all the participants in the research. Ethical clearance for the research has been given by the York St John University Research Ethics

Committee, which attests to the research being ethically acceptable. Among the key ethical considerations in this study is informed consent. The participants will be given a clear explanation of the objectives of the study, their role in the research study, and how their responses will be used. They will be at liberty to accept or decline to participate without any consequences. Each respondent will be requested to read and sign a consent form before answering the questionnaire, which will explain their rights, including their right to withdraw at any stage.

Confidentiality and data protection are also important considerations. No personal details of respondents will be collected, and data will be anonymised so that individual participants will not be identifiable. The study will fulfill the General Data Protection Regulation (GDPR) requirements by storing and using data securely for research purposes only. Electronic files will be encrypted, and only those authorised will have access (Morić et al., 2024). The study also provides non-maleficence in the sense that no harm or risk will be caused to participants by taking part in the study. The questions will be formulated to avoid sensitive or intrusive matters that can cause discomfort. The study will also uphold objectivity and integrity, and findings will be reported accurately without any bias. Plagiarism and data manipulation will be avoided at all costs to ensure academic integrity.

Chapter Four

Data Analysis and Findings

4.1 Introduction

This chapter presents the results of the study based on data collected through the questionnaire. The analysis follows the structure of the research questions and objectives. It includes both descriptive and inferential statistical methods. These are used to understand how retail organisations are using AI in decision-making, and how it affects various areas such as human roles, ethics, and strategy. The first part of the chapter focuses on the demographic information of the respondents. This gives a background to the type of professionals who participated in the study. Understanding their positions and the nature of their organisations helps place the findings in context. After that, the chapter examines how AI is being applied in retail decision-making. It looks at areas such as sales forecasting, pricing, and supply chain decisions. Next, the chapter explores the perceived benefits and challenges of AI use in decision-making. It shows how participants rate AI's speed, accuracy, and possible risks. The findings also explain how AI affects the roles of human managers. This includes whether it supports or replaces traditional managerial tasks. The ethical part of the study is also covered. This section examines how organisations deal with transparency, data protection, and bias in AI systems. It also shows how trust and fairness are viewed by employees. In the final section, the analysis focuses on strategies that may help improve the use of AI in decision-making. These include training, review policies, and human-AI collaboration. All findings are discussed with support from charts, tables, and statistical tests. The aim is to make the data clear and easy to interpret. Where needed, the chapter links the results to existing studies. This allows for a better understanding of how this study compares with what is already known. The goal is to show not only the current state of AI use in retail but also its broader implications for decision-making in the sector.

4.2 Descriptive Analysis

Table 1: Descriptive Analysis of Respondents' Data

Variable	Category	Frequency (n)	Percentage (%)
Position in the Organisation	Senior Management	60	47.0%
	Middle Management	45	35.0%
	Operational Staff	24	19.0%
Organisation Size (No. of Employees)	Less than 20	45	35.0%
	20–49	18	14.0%
	50–99	10	8.0%
	100+	57	44.0%
Years Using AI in Decision-Making	Less than 1 year	37	29.0%
	1–3 years	38	29.0%
	4–6 years	24	19.0%
	More than 6 years	25	19.0%
	Not using AI	5	4.0%
Industry Sector	Grocery & Supermarket Retail	34	26.4%
	Fashion & Apparel Retail	15	11.6%
	Electronics & Appliances	11	8.5%
	E-commerce	20	15.5%
	Others (e.g., Logistics, QSR, FMCG, Domino's Pizza)	18	14.0%

The demographic data from the respondents provides a clear overview of the professional backgrounds and organisational contexts of participants in the study. The aim of this section is to describe these characteristics and highlight their relevance to the study on AI-driven decision-making in retail management. Although 160 participants began the survey, only 129 completed it beyond the first page; the remaining 31 responses were excluded during data cleaning due to missing key sections.

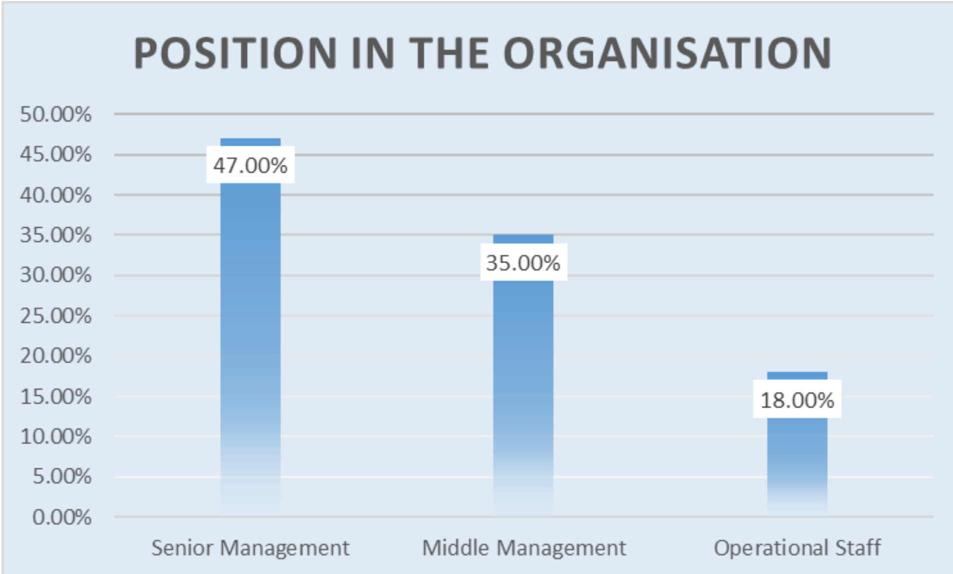

Figure 3: Position in the Organisation

The first variable examined is the position of respondent´ in their organisations. Out of 129 participants, 60 respondents (47.0%) were from senior management. This suggests that nearly half of the participants occupy top-level roles with strategic decision-making authority. These individuals are likely to have significant insight into AI-related decisions within their organisations. Another 45 respondents (35.0%) were from middle management. Middle managers typically implement strategic directives and are often involved in operational decision-making, making their perspectives equally valuable. Lastly, 24 respondents (18.0%) were from operational staff. Though they might not make strategic decisions, their responses offer a ground-level view of how AI is used and how it affects day-to-day operations.

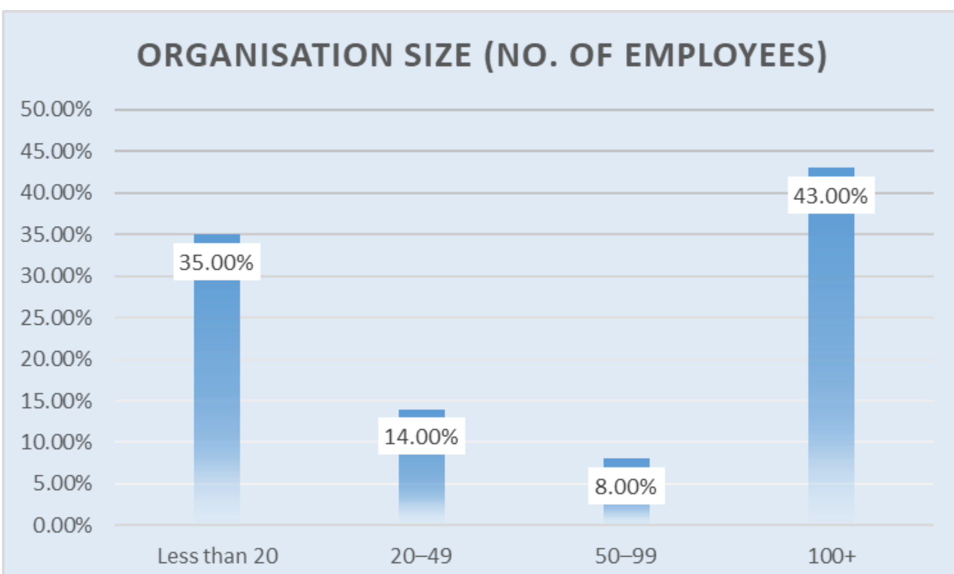

Figure 4: Organisation Size (No. of Employees)

The second variable relates to the size of the organisation in terms of number of employees. Organisations with more than 100 employees formed the largest group, with 57 respondents (43.0%). This is followed by firms with fewer than 20 employees, comprising 45 respondents (35.0%). The presence of respondents from both large and small firms suggests that AI adoption in retail is not limited to large-scale operations. Eighteen respondents (14.0%) were from organisations with 20 to 49 employees, and 10 respondents (8.0%) were from firms with 50 to 99 employees. The diversity in company size is important because firm size can influence the capacity to adopt and integrate AI technologies. Larger organisations typically have more resources to implement complex AI systems, while smaller firms may rely on more basic or third-party AI solutions (Wamba-Taguimdje et al., 2020).

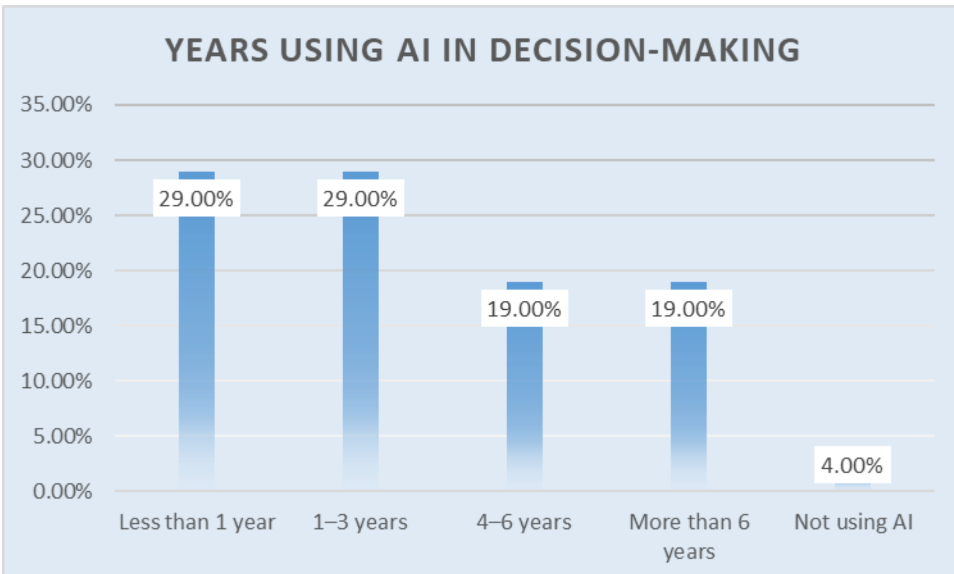

Figure 5: Years Using AI in Decision-Making

The third demographic variable examined is how long the organisations have been using AI in decision-making. The data shows that AI usage is relatively recent for most firms. Thirty-seven respondents (29.0%) indicated that their organisations have used AI for less than one year, while 38 respondents (29.0%) reported AI use between one and three years. This means that a majority of the firms (58%) have adopted AI within the last three years. Twenty-four respondents (19.0%) noted that their organisations have used AI for between four and six years, while 25 respondents (19.0%) have used AI for more than six years. Only five respondents (4.0%) reported that their organisations do not use AI at all. This trend reflects the growing acceptance and integration of AI in retail decision-making, in line with studies showing rapid digital transformation in the retail sector (Dhamija & Bag, 2020).

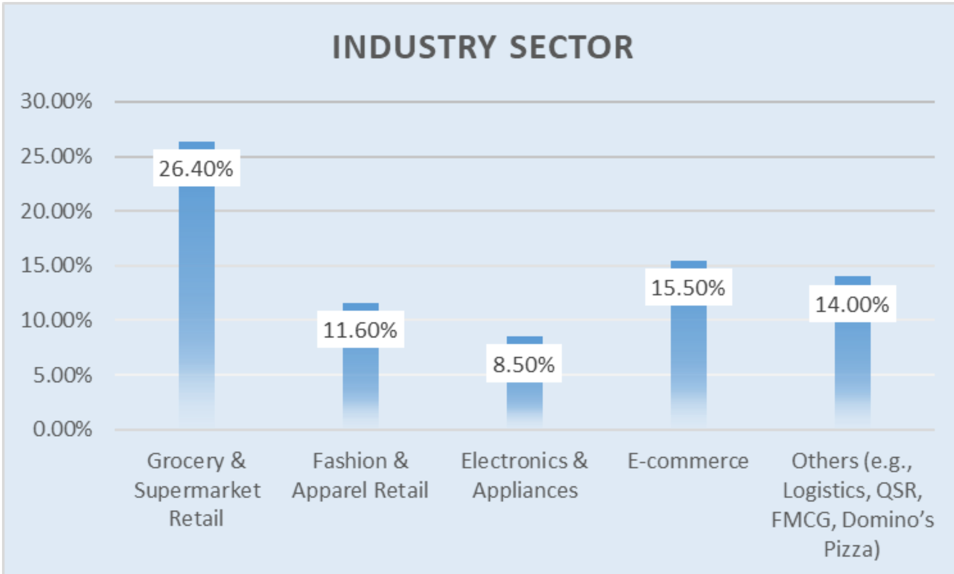

Figure 6: Industry Sector

Finally, the industry sector data provides insights into the types of businesses represented. Grocery and supermarket retail had the highest number of respondents, 34 (26.4%), likely due to the widespread adoption of AI in inventory control, customer insights, and dynamic pricing in this segment. E-commerce followed with 20 respondents (15.5%), reflecting the digital-first nature of such businesses which tend to adopt AI tools early. Fashion and apparel retail had 15 respondents (11.6%), and electronics and appliances had 11 respondents (8.5%). The "Others" category, including logistics, quick service restaurants (QSR), FMCG firms, and restaurant chains like Domino's Pizza, accounted for 18 respondents (14.0%). These sectors are also seeing increased AI usage in logistics, predictive maintenance, and customer service (Chatterjee et al., 2021). This demographic breakdown shows that the study captured data from a wide range of positions, company sizes, AI maturity levels, and sectors. This diversity increases the relevance and generalisability of the findings, as it allows for comparisons across different retail environments and organisational structures.

4.3 Reliability Analysis

4.3.1 AI Adoption in Management Decision-Making

Table 2: Reliability Statistics-AI Adoption

Cronbach's Alpha	N of Items
.907	5

Table 3: Item-Total Statistics-AI Adoption

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
AI analyses customer purchasing patterns	12.29	23.309	.812	.876
AI supports sales prediction and demand forecasting	12.08	25.691	.679	.903
AI reports influence strategic decisions	12.26	23.406	.768	.886
AI is integrated into supply chain decisions	12.39	23.813	.787	.881
AI optimises pricing and promotions	12.41	23.750	.782	.883

The reliability test for the scale measuring AI adoption in management decision-making showed a Cronbach's Alpha value of 0.907. This indicates excellent internal consistency among the five items used to assess this construct. Each item is strongly correlated with the overall scale. The corrected item-total correlations range from 0.679 to 0.812. These values show that all items contribute meaningfully to the scale and none are redundant. The item "AI analyses customer purchasing patterns" had the highest item-total correlation (0.812). This suggests that this item aligns very well with the overall construct. The lowest correlation (0.679) was observed for "AI supports sales prediction and demand forecasting," though it still meets the acceptable threshold for inclusion. The column "Cronbach's Alpha if Item Deleted" helps assess whether removing any item would improve reliability. All values are below the overall alpha of 0.907. This means that deleting any of the items would reduce reliability. The scale, therefore, is best used as it is. These findings support the internal coherence of the items and validate the use of a composite variable to represent AI adoption in management decision-making.

4.3.2 Benefits and Limitations of AI in Decision-Making

Table 4: Reliability Statistics-Benefits and Limitations

Cronbach's Alpha	N of Items
.774	6

Table 5: Item-Total Statistics-Benefits and Limitations

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
AI improves decision-making accuracy	17.64	20.298	.561	.730
AI enhances efficiency and reduces costs	17.34	19.109	.721	.685
AI enables faster decisions than humans	17.44	19.646	.620	.713
AI systems sometimes make errors	17.48	22.489	.505	.745
AI lacks contextual understanding humans provide	17.00	23.828	.411	.765
Difficulty integrating AI with current processes	17.68	24.026	.314	.789

The reliability analysis for the scale measuring the benefits and limitations of AI in decision-making produced a Cronbach's Alpha of 0.774. This value shows acceptable internal consistency across the six items. The corrected item-total correlations range from 0.314 to 0.721, indicating that some items have stronger relationships with the overall scale than others. "AI enhances efficiency and reduces costs" had the highest correlation (0.721), suggesting it closely aligns with the underlying construct. On the other hand, "Difficulty integrating AI with current processes" had the lowest correlation (0.314), indicating it contributes less to the scale's consistency. Similarly, "AI lacks contextual understanding humans provide" had a weaker item-total correlation of 0.411. The column "Cronbach's Alpha if Item Deleted" shows that removing the lowest-correlating item would increase overall reliability slightly. If "Difficulty integrating AI" were removed, alpha would rise to 0.789. However, all six items still contribute meaningful information and reflect both benefits and challenges. The overall reliability is sufficient to support the use of a combined scale for further analysis of this variable.

4.3.3 AI's Impact on the Role of Human Managers

Table 6: Reliability Statistics-Role of Human Managers

Cronbach's Alpha	N of Items
.722	5

Table 7: Item-Total Statistics-Role of Human Managers

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
AI reduces need for human managers	13.92	14.236	.378	.714
AI shifts managers to strategic roles	13.16	11.267	.692	.582
AI frees managers for high-level decisions	12.90	12.758	.517	.661
AI increases pressure to adapt	12.83	12.930	.515	.662
Managers feel confident working with AI	13.07	14.793	.318	.735

The reliability test for the scale measuring AI's impact on the role of human managers shows a Cronbach's Alpha of 0.722. This indicates acceptable internal consistency. The values suggest that the items generally measure the same construct, though with varying strength. The corrected item-total correlations range from 0.318 to 0.692. "AI shifts managers to strategic roles" had the highest correlation (0.692), showing it aligns well with the overall scale. "Managers feel confident working with AI" had the lowest correlation (0.318), meaning it relates less strongly to the rest of the items. The column "Cronbach's Alpha if Item Deleted" helps to assess whether removing an item would improve reliability. Removing the confidence item would raise the alpha slightly to 0.735. This implies it might be the weakest item in the scale, but its removal is not essential, as the overall alpha is already acceptable. The scale mean and variance if deleted also support this. Items focused on role shift and decision-making efficiency had better consistency. These results suggest the scale is suitable for measuring how AI changes managerial roles, though future studies might review the item on manager confidence for clarity or alignment.

4.3.4 Ethical Considerations in AI-Driven Decision-Making

Table 8: Reliability Statistics-Ethical Considerations

Cronbach's Alpha	N of Items
.814	5

Table 9: Item-Total Statistics-Ethical Considerations

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
AI decision-making is transparent and explainable	13.10	14.260	.673	.756
Policies exist for ethical AI decisions	13.11	13.560	.720	.740
AI systems are free from bias and discrimination	13.03	12.822	.742	.731
Employees trust AI-driven decisions	13.13	14.596	.643	.765
AI raises data privacy and security concerns	12.65	18.251	.258	.864

The internal consistency of the scale assessing ethical considerations in AI-driven decision-making is supported by a Cronbach's Alpha of 0.814. This indicates strong reliability and suggests the items are well-aligned in measuring the intended concept. Corrected item-total correlations range from 0.258 to 0.742. Three items—"AI systems are free from bias," "ethical policies exist," and "AI transparency"—show strong correlations above 0.67, indicating they are highly consistent with the overall scale. These items seem to capture the core ethical concerns around AI decision-making. The item "AI raises data privacy and security concerns" has a much lower correlation (0.258), showing weaker alignment. If this item were removed, Cronbach's Alpha would increase to 0.864. This suggests that privacy and security concerns may be conceptually distinct from the other items. However, the item remains important as it addresses a key ethical issue. The scale mean and variance also reflect this trend. The privacy-related item has a notably lower mean and higher variance, indicating more diverse responses. The data suggests respondents see bias, trust, and policy as closely related, while privacy concerns might represent a broader or separate ethical domain in AI use.

4.3.5 Strategies for Optimising AI Adoption in Management Decision-Making

Table 10: Reliability Statistics-Optimising AI Adoption

Cronbach's Alpha	N of Items
.873	5

Table 11: Item-Total Statistics-Optimising AI Adoption

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
Organisation provides AI training	12.77	19.159	.675	.853
Clear policies for AI in decision-making	12.78	19.344	.705	.845
AI adoption is regularly reviewed	13.01	18.521	.726	.840
Collaboration between AI and humans is encouraged	12.33	19.946	.652	.858
Organisation invests in ethical AI for better decision-making	12.82	19.212	.748	.835

The reliability statistics for strategies aimed at optimising AI adoption in management decision-making show a high internal consistency, with a Cronbach's Alpha of 0.873. This suggests that the items reliably measure a single underlying concept. All five items fall within acceptable corrected item-total correlation values, ranging from 0.652 to 0.748. This indicates each item contributes meaningfully to the overall construct. The item with the strongest contribution is "Organisation invests in ethical AI for better decision-making" with a corrected correlation of 0.748. This suggests that ethical investment is a central part of AI optimisation strategies. The item "AI adoption is regularly reviewed" also shows strong alignment (0.726), indicating review processes are key in optimising adoption. The item "Collaboration between AI and humans is encouraged" has the lowest correlation (0.652), but it still remains within a strong range. The scale means and variances are relatively consistent, showing that respondents viewed all strategy elements as important. The results suggest that policy clarity, ongoing training, regular reviews, collaboration, and ethical investment are essential to effective AI integration in managerial decision-making.

4.4 Findings and Analysis

This section presents the results of the data analysis conducted using SPSS. The analysis was guided by the study's research questions, and it is structured accordingly to maintain clarity and focus. Each subsection addresses a specific research question, using appropriate statistical techniques to interpret the responses collected through the structured questionnaire. Both descriptive and inferential methods were applied where necessary to uncover key patterns, relationships, and differences in the data. The aim is to provide a comprehensive understanding of how AI is adopted and utilised in retail decision-making, including the associated benefits, challenges, ethical considerations, and strategies for optimisation. Tables and summaries are used to support interpretation and highlight the most relevant findings.

4.4.1 AI Adoption in Management Decision-Making

Table 12: Descriptive Statistics-AI Adoption

	N	Minimum	Maximum	Mean	Std. Deviation
AI analyses customer purchasing patterns	104	1	5	3.04	1.454
AI supports sales prediction and demand forecasting	102	1	5	3.25	1.367
AI reports influence strategic decisions	101	1	5	3.13	1.488
AI is integrated into supply chain decisions	96	1	5	2.96	1.421
AI optimises pricing and promotions	92	1	5	2.93	1.428
Valid N (listwise)	90				

The descriptive statistics for AI adoption in management decision-making provide insight into how retail organisations are currently using AI technologies across various strategic functions. The item with the highest mean score is the use of AI for sales prediction and demand forecasting (Mean = 3.25, SD = 1.367), indicating that this is the most common area where AI supports decision-making. A mean above 3 suggests that most respondents moderately agree that AI is used for this purpose. This result reflects AI's growing role in demand planning, where predictive analytics help managers respond proactively to market trends. The second-highest item is the use of AI-generated reports for strategic decisions (Mean = 3.13, SD = 1.488). This suggests that AI contributes to higher-level decision-making processes, although the relatively high standard deviation points to variability in adoption levels across organisations. The use of AI to analyse customer purchasing patterns also received moderate support (Mean = 3.04, SD = 1.454). This function is foundational in retail analytics and customer segmentation. Its moderate mean suggests that while some firms use AI for this purpose, others may still rely on manual methods or simpler tools. On the lower end, the integration of AI in supply chain decisions scored a mean of 2.96 (SD = 1.421), while optimising pricing and promotions recorded the lowest average at 2.93 (SD = 1.428). These means suggest a generally cautious or uneven adoption in these areas. This may be due to the complexity or cost of integrating AI into operational systems like logistics or dynamic pricing. The responses show that AI is being adopted in various aspects of management decision-making, but with varying intensity across functions. The standard deviations, which are all above 1.3, indicate diverse practices and differing levels of maturity in AI implementation among respondents.

4.4.2 Benefits and Limitations of AI in Decision-Making

Table 13: Descriptive Statistics-Benefits and Limitations

	N	Minimum	Maximum	Mean	Std. Deviation
AI improves decision-making accuracy	104	1	5	3.20	1.477
AI enhances efficiency and reduces costs	102	1	5	3.56	1.376
AI enables faster decisions than humans	102	1	5	3.41	1.465
AI systems sometimes make errors	101	1	5	3.42	1.227
AI lacks contextual understanding humans provide	103	1	5	3.89	1.179
Difficulty integrating AI with current processes	99	1	5	3.20	1.309
Valid N (listwise)	94				

The descriptive statistics for RQ2 explore the perceived benefits and limitations of AI in organisational decision-making. Six items were assessed, each using a 5-point Likert scale from "Strongly Disagree" to "Strongly Agree". The results present a balanced view, showing both optimism and concern about AI capabilities. The highest mean score is for the statement "AI lacks contextual understanding humans provide" (Mean = 3.89, SD = 1.179). This indicates strong agreement that AI, despite its capabilities, struggles to grasp the nuanced contexts that human managers naturally consider. This perception reflects a commonly cited limitation of AI systems in qualitative and complex decisions. The next highest is "AI enhances efficiency and reduces costs" (Mean = 3.56, SD = 1.376). This suggests that many respondents believe AI leads to improved performance and savings. Efficiency is one of the major selling points for AI adoption, especially in industries like retail where speed and accuracy matter. Similarly, "AI enables faster decisions than humans" received a relatively high mean (3.41, SD = 1.465). This shows that AI is appreciated for its speed, a useful trait in fast-moving industries. Yet, the high standard deviation implies different experiences or levels of use across organisations. Interestingly, the item "AI systems sometimes make errors" had a mean of 3.42 (SD = 1.227), which shows that many agree AI is not infallible. This reinforces the need for oversight and human intervention to verify or interpret results, especially when mistakes could affect key business outcomes. Statements about improving decision-making accuracy and difficulty integrating AI with current processes both had the same average (Mean = 3.20), but different standard deviations—1.477 and 1.309, respectively. These responses show that while some believe AI adds accuracy, others face challenges embedding it within legacy systems. The variation in responses across all items, reflected in standard deviations above 1.2, highlights diverse levels of AI maturity and confidence. These findings reveal that while many appreciate AI's benefits, concerns about limitations, especially its lack of context and integration issues, remain widespread.

4.4.3 AI's Impact on the Role of Human Managers

Table 14: Descriptive Statistics-Role of Human Managers

	N	Minimum	Maximum	Mean	Std. Deviation
AI reduces need for human managers	104	1	5	2.52	1.231
AI shifts managers to strategic roles	102	1	5	3.29	1.347
AI frees managers for high-level decisions	100	1	5	3.57	1.305
AI increases pressure to adapt	101	1	5	3.63	1.271
Managers feel confident working with AI	101	1	5	3.41	1.218
Valid N (listwise)	100				

Table 15: Correlations-Role of Human Managers

		AI adoption	Perceived human impact
AI adoption	Pearson Correlation	1	.521**
	Sig. (2-tailed)		.000
	N	104	104
Perceived human impact	Pearson Correlation	.521**	1
	Sig. (2-tailed)	.000	
	N	104	104

**. Correlation is significant at the 0.01 level (2-tailed).

The analysis for RQ3 explores how AI adoption influences the role of human managers. Five key statements were used to assess respondents' perceptions, using a 5-point Likert scale. The responses show a mixed perspective. Some respondents view AI as a support tool, while others express concern about role displacement and adaptation stress.

The item “AI increases pressure to adapt” has the highest mean score (Mean = 3.63, SD = 1.271). This indicates that many respondents believe managers face significant pressure to adjust to AI systems. This pressure could stem from the need to learn new technologies, adopt new workflows, or make faster data-driven decisions. The variation in responses also suggests that the impact may differ depending on individual roles and organisational context. The next highest mean score is for “AI frees managers for high-level decisions” (Mean = 3.57, SD = 1.305). This implies that AI helps reduce routine tasks, allowing managers to focus on strategic and creative aspects of their roles. This aligns with the broader idea that AI can complement human intelligence rather than replace it. The statement “Managers feel confident working with AI” had a mean of 3.41 (SD = 1.218). This suggests that while confidence levels are generally positive, there may still be reservations, particularly in settings where training or system transparency is limited. Building trust in AI is essential, especially in decision-making environments where human judgment is still needed. “AI shifts managers to strategic roles” recorded a mean of 3.29 (SD = 1.347), showing moderate agreement. This supports the idea that AI is gradually changing what managers focus on. Instead of handling operational details, many are now engaging more with strategic planning, data interpretation, and policy alignment. On the other hand, the lowest-rated item was “AI reduces the need for human managers” (Mean = 2.52, SD = 1.231). This shows that most respondents do not believe AI is replacing human managers. It appears they see AI more as an assistant than a substitute. This could reflect current industry practice where decision authority still resides with humans, especially in complex or high-risk scenarios.

The correlation analysis adds more insight. A significant positive correlation was found between AI adoption and perceived human impact ($r = .521$, $p < 0.01$). This suggests that as AI adoption increases, respondents are more likely to perceive changes in managerial roles. The correlation strength is moderate, meaning that while AI adoption plays a role, other factors also influence how managerial functions evolve. These may include organisational culture, training opportunities, or existing digital maturity. The data shows that AI is not making managers obsolete but altering their responsibilities and introducing new pressures. Managers must stay adaptive and technologically literate to remain effective in AI-driven environments. The responses highlight both optimism and caution, pointing to a gradual shift rather than a dramatic change.

4.4.4 Ethical Considerations in AI-Driven Decision-Making

Table 16: Descriptive Statistics-Ethical Considerations

	N	Minimum	Maximum	Mean	Std. Deviation
AI decision-making is transparent and explainable	103	1	5	3.14	1.229
Policies exist for ethical AI decisions	101	1	5	3.16	1.286
AI systems are free from bias and discrimination	98	1	5	3.24	1.370
Employees trust AI-driven decisions	99	1	5	3.13	1.192
AI raises data privacy and security concerns	98	1	5	3.59	1.120
Valid N (listwise)	97				

Table 17: Summary of Ethical Considerations and Demographic Associations

Ethical Item	N	Mean	Std. Dev.	Associated Demographic	χ^2 (df), *p*-value	Stat. Sig.?
AI systems are free from bias and discrimination	98	3.24	1.370	Position	$\chi^2 = 9.862$ (8), p = .275	No
				AI Duration	$\chi^2 = 22.189$ (16), p = .137	No
AI raises data privacy and security concerns	98	3.59	1.120	Position	$\chi^2 = 2.986$ (8), p = .935	No
				AI Duration	$\chi^2 = 12.427$ (16), p = .714	No

The analysis for RQ4 focuses on understanding ethical concerns in AI-driven decision-making within the retail sector. Five variables were assessed to capture different ethical dimensions. These include transparency, policy availability, fairness, trust, and data privacy. Responses were measured on a 5-point Likert scale. The results provide insight into how participants perceive the ethical alignment of AI in their organisations. Among all the items, the statement "AI raises data privacy and security concerns" had the highest mean score (Mean = 3.59, SD = 1.120). This shows that privacy concerns are a major issue for respondents. Many participants agreed that AI systems create risks related to data handling, which aligns with ongoing debates in the literature about AI's reliance on large-scale data collection and the risks of misuse or breaches (Zeng et al., 2021). The relatively low standard deviation suggests a moderate level of agreement among the participants. "AI systems are free from bias and discrimination" had a mean score of 3.24 (SD = 1.370). This result shows uncertainty. Participants do not strongly believe AI is unbiased. Fairness in algorithmic decision-making is a major topic in AI ethics, especially when AI systems are used in hiring, pricing, and customer segmentation. The high standard deviation implies a wide range of views, likely shaped by varying levels of exposure to AI or different applications in use. The item "Policies exist for ethical AI decisions" recorded a mean of 3.16 (SD = 1.286). This score indicates that organisations may have some ethical frameworks in place, but their presence is not strongly confirmed. This may reflect either lack of awareness among staff or incomplete policy development. The result is important because having clear ethical policies is necessary for accountability and compliance. "AI decision-making is transparent and explainable" also had a low mean of 3.14 (SD = 1.229). Many AI models are black boxes, especially when they rely on deep learning algorithms. This makes it hard for users and stakeholders to understand how decisions are made. The lack of transparency can reduce trust and lead to resistance in implementation. Similarly, "Employees trust AI-driven decisions" recorded a mean of 3.13 (SD = 1.192). This suggests a neutral to slightly positive perception. Trust is a key factor in technology acceptance. A moderate mean and standard deviation show mixed views across the sample.

To explore whether these ethical views differ by background, cross-tabulation and chi-square tests were run. Focus was placed on bias and privacy concerns, as these are highly discussed in ethics literature. These two items were tested against position in the organisation and duration of AI use. This was done to see if job level or AI experience shaped ethical views. The test for "AI systems is free from bias" by position showed $\chi^2 = 9.862$ (df = 8), p = .275. The result is not statistically significant. Similarly, the cross-tab with AI use duration yielded $\chi^2 = 22.189$ (df = 16), p = .137. This also was not significant. For "AI raises data privacy concerns," the position-based test gave $\chi^2 = 2.986$ (df = 8), p = .935. Again, this is not significant. The duration-based test had $\chi^2 = 12.427$ (df = 16), p = .714. These values show that views on ethics do not significantly vary by job level or years of using AI. The lack of statistical significance suggests that ethical concerns are broadly shared across roles and experience levels. This may mean that ethical risks of AI are seen as common organisational issues, not limited to any one group.

4.4.5 Strategies for Optimising AI Adoption in Management Decision-Making

Table 18: Descriptive Statistics-Optimising AI Adoption

	N	Minimum	Maximum	Mean	Std. Deviation
Organisation provides AI training	103	1	5	3.14	1.387
Clear policies for AI in decision-making	98	1	5	3.13	1.321
AI adoption is regularly reviewed	98	1	5	2.92	1.397
Collaboration between AI and humans is encouraged	97	1	5	3.63	1.294
Organisation invests in ethical AI for better decision-making	97	1	5	3.09	1.275
Valid N (listwise)	95				

Table 19: Summary of Multiple Regression Analysis Predicting Strategies to Optimise AI Adoption

Model Component	Result/Value
Dependent Variable	Strategies to Optimise AI Adoption
Independent Variables	AI Adoption, Benefits of AI, Ethical Considerations
Model Fit	$R = 0.751$; $R^2 = 0.564$; Adjusted $R^2 = 0.550$
ANOVA (F-statistic)	$F(3, 99) = 42.619$, $p < 0.001$
Significant Predictors	- AI Adoption ($\beta = 0.232$, $p = .012$) - Ethical Considerations ($\beta = 0.465$, $p < .001$)
Marginally Significant	Benefits of AI ($\beta = 0.169$, $p = .052$)
Constant (Intercept)	$B = 0.139$, not significant ($p = .640$)
Standard Error of Estimate	0.746

The analysis for RQ5 investigates strategies that can enhance AI adoption in management decision-making. Five items were measured using a 5-point Likert scale to assess key organisational practices that may support effective AI integration. The results provide an overview of how organisations are approaching this goal. Among the items, the statement “Collaboration between AI and humans is encouraged” had the highest mean score (Mean = 3.63, SD = 1.294). This indicates that most organisations are promoting synergy between human judgement and AI systems. Encouraging collaboration can improve acceptance and help managers feel supported rather than replaced by AI tools. The relatively high mean also reflects a broader trend in which human-AI interaction is positioned as complementary rather than competitive. The item “Organisation provides AI training” recorded a mean of 3.14 (SD = 1.387), suggesting that training efforts are present but not widespread. AI adoption requires employees to understand how to interpret outputs, use tools, and apply results. Lack of adequate training may hinder adoption and reduce the benefits of AI investments. Similarly, "Clear policies for AI in decision-making" had a mean of 3.13 (SD = 1.321). This shows that many organisations may not have fully developed formal guidelines. Policies are necessary to guide ethical, transparent, and consistent use of AI in business processes. Without them, adoption may be uneven or problematic. The statement "Organisation invests in ethical AI for better decision-making" had a mean score of 3.09 (SD = 1.275). Ethical investment in AI includes using responsible algorithms, reducing bias, and complying with regulations. This result suggests a moderate effort, though more improvement may be needed to meet industry standards. The lowest-rated item was "AI adoption is regularly reviewed", with a mean of 2.92 (SD = 1.397). This indicates that few organisations consistently evaluate AI performance and impact. Regular review is essential for making improvements, identifying failures, and aligning AI with changing goals. The low score highlights a potential gap in AI governance.

A multiple regression analysis was also conducted to determine which factors predict the implementation of effective strategies for AI adoption. The dependent variable was overall strategy, while the predictors included AI adoption, perceived benefits, and ethical considerations. The model produced an R value of 0.751 and an R^2 of 0.564, indicating that 56.4% of the variance in strategy implementation is explained by the three predictors. The adjusted R^2 of 0.550 shows that the model is robust and generalisable beyond the sample. The model's F-statistic ($F(3, 99) = 42.619$, $p < 0.001$) confirms that the regression is statistically significant. This means the predictors together contribute meaningfully to understanding what drives organisations to adopt better AI strategies. The strongest predictor was ethical considerations ($\beta = 0.465$, $p < 0.001$). This suggests that organisations that prioritise fairness, transparency, and data protection are more likely to adopt strong AI strategies. Ethics plays a key role in building trust and gaining support for AI implementation. AI adoption also had a significant effect ($\beta = 0.232$, $p = .012$). This means that organisations that already use AI in key decision-making are more likely to put structured strategies in place. Experience with AI likely informs better planning and management. Benefits of AI had a borderline effect ($\beta = 0.169$, $p = .052$), meaning its influence is weaker and only marginally significant. While benefits are important, they may not drive action unless supported by practical structures or ethical concerns. The intercept ($B = 0.139$, $p = .640$) was not significant, meaning that when all predictors are zero, the baseline level of strategy implementation is minimal. Overall, the results show that ethical awareness and existing AI use are the key drivers for effective AI strategies in management decision-making.

Chapter Five

Discussion and Summary of Findings

5.1 Discussion of Findings

5.1.1 AI Adoption in Management Decision-Making

The findings for RQ1 show that AI is actively supporting data-driven decision-making in retail, particularly in sales prediction, strategic planning, and customer analysis. The highest mean score was recorded for AI use in sales prediction and demand forecasting (Mean = 3.25), which supports literature by Shamsuddoha et al. (2025) that highlights AI's role in anticipating consumer demand and improving inventory decisions. Respondents also reported moderate use of AI-generated reports for strategic decisions (Mean = 3.13), consistent with Madanchian (2024), who explained that AI helps simulate different business scenarios to guide strategic choices.

The mean score for using AI to analyse customer purchasing patterns (3.04) indicates moderate application, aligning with Kumar et al. (2024), who noted that AI assists in understanding consumer behavior through large-scale data analysis. However, AI adoption was lower for supply chain decisions (Mean = 2.96) and for pricing and promotions (Mean = 2.93). This cautious use reflects Kalogiannidis et al. (2024), who acknowledged that full AI integration into operational logistics remains a challenge due to technical and financial barriers. The high standard deviations across items indicate varied AI maturity levels among organisations. This supports findings by Murire (2024), who argued that while some firms adopt AI aggressively, others remain in early stages. These patterns reveal uneven adoption, where AI is used more in strategic and analytical roles than in automated pricing or logistics. The findings echo broader trends reported by Armand et al. (2024), showing that while AI is transforming decision-making, adoption levels differ across business functions.

5.1.2 Benefits and Limitations of AI in Decision-Making

The findings for RQ2 show that respondents recognised both the benefits and the limitations of AI in decision-making. The highest-rated concern was that AI lacks human contextual understanding (Mean = 3.89), confirming the view of Liu-Thompkins, Okazaki, and Li (2022) that AI cannot fully replicate human emotion, intuition, or cultural awareness. This aligns with Alawamleh et al. (2024), who explained that AI may support decision-making but cannot entirely replace human judgment. The efficiency and cost-saving benefits of AI (Mean = 3.56) are widely supported in literature. Haque et al. (2024) and Chen et al. (2024) described how AI improves productivity and operational efficiency in retail by automating tasks and reducing costs. The ability of AI to make faster decisions than humans (Mean = 3.41) also support findings by Amosu et al. (2024), who highlighted the usefulness of AI for rapid decision-making in high-speed environments like inventory or pricing management. The perceived issue that AI systems sometimes make errors

(Mean = 3.42) reflects the views of Bylykbashi and Gavranović (2024), who reported that technological failures can disrupt operations. Respondents also agreed that integrating AI into existing systems is difficult (Mean = 3.20), a concern raised by Madanchian (2024) and Aldoseri, Khalifa, and Hamouda (2023), who noted the cost and complexity of AI implementation. The responses show optimism about AI's potential but reveal concerns about its limitations, especially around human understanding, error rates, and integration. These match both practical concerns in industry and the themes explored across recent literature.

5.1.3 AI's Impact on the Role of Human Managers

The findings for RQ3 show that AI is influencing the role of human managers, but not eliminating them. Most respondents disagreed that AI reduces the need for human managers (Mean = 2.52). This supports the view of Ali et al. (2024) and Osasona et al. (2024) who noted that AI supports, but does not replace, managerial roles. AI helps in data processing and analysis, but human judgment remains important for ethical and contextual decision-making. Managers reported increased pressure to adapt to AI (Mean = 3.63), aligning with Kassa and Worku (2025) who explained that AI adoption requires new skills and mindsets. The need for technological literacy and adaptation to AI-driven systems creates stress for many managers. Deliu and Olariu (2024) also highlighted that managers need training to remain effective in AI-integrated environments. Many respondents agreed that AI frees managers for higher-level tasks (Mean = 3.57) and shifts their focus to strategic roles (Mean = 3.29). This is supported by Alowais et al. (2023), who stated that AI handles routine decisions, allowing managers to work on planning and innovation. AI also requires that managers develop new competencies in leadership and interpretation, as noted by Zirar, Ali and Islam (2023). The significant correlation ($r = .521$) between AI adoption and perceived human impact suggests that greater AI use leads to more changes in managerial roles. This aligns with Perifanis (2023), who emphasised balancing automation with human oversight. As AI adoption grows, managers must evolve their roles rather than step aside.

5.1.4 Ethical Considerations in AI-Driven Decision-Making

The findings for RQ4 show that ethical concerns in AI decision-making are widely recognised in retail. The highest-rated concern was about data privacy and security (Mean = 3.59), which reflects strong agreement. This aligns with Gupta et al. (2023) and Kalogiannidis et al. (2024), who stressed that AI systems collect large volumes of consumer data, often raising concerns about misuse and breaches. Participants expressed consistent worry across different roles and levels of AI use, supporting Adanyin (2024), who recommended clear policies for data protection. The low mean score for transparency (Mean = 3.14) suggests that many AI systems are still seen as black boxes. This matches the concerns of Mathew et al. (2025) and González-Arencibia et al. (2024), who noted that explainability in AI is limited. Without clear explanations, trust and accountability are weakened, especially in sensitive decisions like pricing or hiring. Respondents were unsure about AI being free from bias (Mean = 3.24), reflecting concerns seen in Ferrara (2023) and Akter et al. (2021). These studies explain how biased data leads to unfair treatment of customers. The findings support calls for regular audits and diverse training datasets to reduce algorithmic bias. The low trust in AI (Mean = 3.13) is consistent with literature suggesting that ethical risks reduce employee confidence (Cheong, 2024). The lack of significant difference in views across job roles or AI experience also confirms Ferrara's (2023) claim that ethical concerns are shared organisation-wide and require collective action, including policy and oversight.

5.1.5 Strategies for Optimising AI Adoption in Management Decision-Making

The findings for RQ5 show that collaboration between humans and AI is the most supported strategy for improving AI adoption (Mean = 3.63). This aligns with Murire (2024), who explains that AI should complement human work by reducing manual tasks. Studies like Alowais et al. (2023) and Riad, Naimi and Okar (2024) also support human-AI collaboration for improving decision speed and accuracy in areas like logistics and customer service. The emphasis on collaboration helps reduce fears about replacement and encourages acceptance. Training had a moderate score (Mean = 3.14), suggesting that while some organisations train staff on AI, many still fall short. This supports Murugesan et al. (2023), who stress that upskilling is critical to successful AI adoption. Without proper training, employees may struggle to use AI tools or misinterpret outputs. Low scores for clear AI policies (Mean = 3.13) and regular review (Mean = 2.92) point to weak governance. Mathew et al. (2025) emphasise that black-box models require oversight to ensure ethical use. Lack of policies increases risk and limits trust. The regression analysis shows that ethics ($\beta = 0.465$) is the strongest driver of strategy adoption. This agrees with Ferrara (2023) and Jada and Mayayise (2023), who link ethical awareness to trust and responsible use. AI experience ($\beta = 0.232$) also matters, suggesting that hands-on use helps organisations refine their strategies. The weak effect of perceived benefits ($\beta = 0.169$) suggests that practical and ethical readiness may matter more than theoretical gains when driving real action.

5.2 Summary of Key Findings

5.2.1 AI Adoption in Management Decision-Making

The findings for RQ1 show that AI is actively used in many areas of retail decision-making. Respondents confirmed AI helps in operations like inventory, logistics, and customer service. Strategic use of AI is also growing. This includes pricing, forecasting, and market analysis. AI tools are also used in high-risk or uncertain situations. Examples include fraud detection and financial planning. However, operational use is more common than strategic use. Most participants said their companies have started using AI, but some are still in early stages of adoption.

5.2.2 Benefits and Limitations of AI in Decision-Making

For RQ2, the results show both the benefits and the limitations of AI in decision-making. Many participants agreed that AI improves efficiency, saves costs and helps decisions happen faster.

However, the highest agreement was with the idea that AI lacks context meaning it does not understand human situations well. Some people also believed AI makes mistakes and is hard to integrate into older systems. These views suggest that while AI helps a lot, it cannot fully replace human judgment.

5.2.3 AI's Impact on the Role of Human Managers

The findings for RQ3 reveal that AI changes the role of managers but does not remove them. Participants agreed that AI helps managers focus on big decisions and reduces routine work. However, they also said it increases pressure to learn new tools and adapt quickly. Many managers feel somewhat confident using AI, but not all. Few people believed AI will fully replace human managers. These responses show that AI support is welcome, but human insight is still needed.

5.2.4 Ethical Considerations in AI-Driven Decision-Making

For RQ4, most participants had concerns about ethics in AI. The strongest concern was about data privacy. Many people felt that AI systems may misuse personal data. Responses were also uncertain about bias and fairness. Some thought AI may treat people unfairly in hiring or pricing. There was also low confidence that ethical policies are clearly in place. Views on transparency were mixed, and trust in AI decisions was not very high. Tests showed that concerns were shared across job levels and experience, suggesting the concerns are organisation-wide.

5.2.5 Strategies for Optimising AI Adoption in Management Decision-Making

In RQ5, the findings focused on how to support AI use in decision-making. The strongest agreement was that human-AI collaboration is encouraged. This means AI is seen as a tool that works alongside people. Other areas like training and ethics investment were rated moderately. Few organisations review their AI use regularly. This suggests limited monitoring. The regression analysis showed that ethical awareness is the strongest factor that drives effective AI strategy. AI experience also matters. Perceived benefits were less important. This shows that good AI use depends more on ethical planning than just expected advantages.

Chapter Six

Conclusion, Recommendations and Future Directions

6.1 Conclusion

This study explored how AI is used in decision-making within retail organisations and supports operations, strategy, and complex decisions. The study also assessed perceived benefits, limitations, human roles, ethical concerns, and organisational strategies for adoption. The findings show that AI tools are being adopted in many retail firms, mainly to improve speed, efficiency, and customer service. Managers are learning to work with AI rather than being replaced by it. Ethical concerns remain important, especially about data privacy and fairness. The study adds to theory by showing how AI is shaping decision structures, leadership roles, and trust in automation. It highlights the balance between machine logic and human judgment. Practically, the study helps managers understand where AI helps most and what challenges may arise. It shows that success depends not only on the tools used but also on staff training, ethical rules, and human-AI collaboration. Many participants wanted better policies and regular system reviews. This implies that organisations should not just invest in AI tools but also build support systems around them. The regression results suggest that ethical awareness is the strongest driver of good AI strategy. This finding is useful for decision-makers who aim to create effective and fair AI systems. The research used a quantitative approach. A structured questionnaire was shared with retail professionals, and data were analysed using descriptive and inferential statistics. One limitation is that the study was based on self-reported data, which may not always reflect actual practices. Also, the sample may not cover all types of retail organisations, especially smaller firms or those in early stages of AI adoption. Future studies could explore the topic using mixed methods. Interviews or case studies may add richer insight into how AI systems are actually used. Researchers may also focus on specific areas like hiring, pricing, or customer service. This will help understand how AI impacts different parts of retail decision-making.

6.2 Recommendations

The following recommendations are suggested to improve AI adoption in retail decision-making and guide future research:

1. Enhancing AI Use in Organisational Processes: Retail firms should invest in training staff to use AI tools in strategic, operational, and uncertain environments. This will help improve productivity, decision speed, and data use across departments.
2. Balancing AI Benefits with Limitations: Firms should combine AI insights with human review to avoid overreliance on algorithms. Routine audits of AI outcomes should be carried out to reduce risks linked to bias, errors, or data quality problems.

3. Supporting Human Managers in AI Environments: Managers need new skills such as AI literacy, critical thinking, and ethical reasoning. Retail firms should offer regular upskilling programs to help managers stay effective in AI-supported roles.
4. Building Ethical AI Frameworks: Organisations should adopt clear policies on AI ethics, including fairness, transparency, and data privacy. Firms should carry out regular checks on algorithms to reduce bias and gain employee trust.
5. Improving Organisational Strategy and Policy for AI: Retail firms should develop structured AI strategies that include collaboration guidelines, training plans, policy enforcement, and review cycles. Future research could assess how such policies affect AI performance in different types of retail businesses.

6.3 Suggestions for Future Research

1. Future studies should explore how AI adoption differs between small retail firms and large chains. This study mainly involved medium to large organisations.
2. Researchers can use qualitative interviews to get deeper insights into employee experiences with AI. This study used mainly survey data.
3. Future work may focus on industry-specific AI applications such as fashion, food retail, or electronics. This study treated retail as one broad sector.
4. Longitudinal research could track how attitudes toward AI change over time as adoption increases and systems improve.
5. Further research is needed on the effect of AI failures on customer satisfaction and recovery strategies used by managers.

6.4 Contribution to Knowledge

1. This study gives new insights into how AI affects decision-making in retail organisations, using both human and technological perspectives.
2. It highlights the importance of ethical factors like transparency, fairness, and trust in shaping AI strategy and acceptance.
3. It shows that while AI brings many benefits, human managers still play a key role in judgement and ethical oversight.
4. The research links AI adoption with organisational strategies and identifies ethics as the strongest driver for successful integration.
5. It contributes new data from a developing economy perspective, where digital infrastructure and experience with AI vary widely.

Reference list

Adam, M., Wessel, M. and Benlian, A. (2021) 'AI-based Chatbots in Customer Service and Their Effects on User Compliance', *Electronic Markets*, 31(2). Available at: https://doi.org/10.1007/s12525-020-00414-7.

Adanyin, A. (2024) 'Ethical AI in Retail: Consumer Privacy and Fairness', *European Journal of Computer Science and Information Technology*, 12(7), pp. 21–35. Available at: https://doi.org/10.37745/ejcsit.2013/vol12n72135.

Adewale, M.D., Azeta, A., Abayomi-Alli, A. and Sambo-Magaji, A. (2024) 'Impact of artificial intelligence adoption on students' academic performance in open and distance learning: A systematic literature review', *Heliyon*, 10(22), p. e40025. Available at: https://doi.org/10.1016/j.heliyon.2024.e40025.

Akbulut, S. and Colak, C. (2024) 'Next-Generation Healthcare: Artificial Intelligence Applications in Disease Management', *Diagnostics*, 14(11), p. 1087. Available at: https://doi.org/10.3390/diagnostics14111087.

Akter, S., Dwivedi, Y.K., Biswas, K., Michael, K., Bandara, R.J. and Sajib, S. (2021) 'Addressing Algorithmic Bias in AI-Driven Customer Management', *Journal of Global Information Management*, 29(6), pp. 1–27. Available at: https://doi.org/10.4018/jgim.20211101.oa3.

Alawamleh, M., Shammas, N., Alawamleh, K. and Bani Ismail, L. (2024) 'Examining the limitations of AI in business and the need for human insights using Interpretive Structural Modelling', *Journal of Open Innovation: Technology, Market, and Complexity*, 10(3), p. 100338. Available at: https://doi.org/10.1016/j.joitmc.2024.100338.

Aldoseri, A., Khalifa, K.N. and Hamouda, A.M. (2023) 'Re-Thinking Data Strategy and Integration for Artificial Intelligence: Concepts, Opportunities, and Challenges', *Applied Sciences*, 13(12), p. 7082. Available at: https://doi.org/10.3390/app13127082.

Alenezi, M. and Akour, M. (2025) 'AI-Driven Innovations in Software Engineering: A Review of Current Practices and Future Directions', *Applied Sciences*, 15(3), p. 1344. Available at: https://doi.org/10.3390/app15031344.

Ali, M., Khan, T.I., Khattak, M.N. and Şener, İ. (2024) 'Synergizing AI and Business: Maximizing Innovation, Creativity, Decision Precision, and Operational Efficiency in High-Tech Enterprises', *Journal of Open Innovation Technology Market and Complexity*, 10(3), p. 100352. Available at: https://doi.org/10.1016/j.joitmc.2024.100352.

Alowais, S.A., Alghamdi, S.S., Alsuhebany, N., Alqahtani, T., Alshaya, A., Almohareb, S.N., Aldairem, A., Alrashed, M., Saleh, K.B., Badreldin, H.A., Yami, A., Harbi, S.A. and Albekairy, A.M. (2023) 'Revolutionizing Healthcare: The Role Of Artificial Intelligence In Clinical Practice', *BMC Medical Education*, 23(1). Available at: https://doi.org/10.1186/s12909-023-04698-z.

Amin, H.A. and Alanzi, T.M. (2024) ‘Utilisation of Artificial Intelligence (AI) in Healthcare Decision-Making Processes: Perceptions of Caregivers in Saudi Arabia’, *Cureus* [Preprint]. Available at: https://doi.org/10.7759/cureus.67584.

Amosu, O.R., Kumar, P., Ogunsuji, Y.M., Oni, S. and Faworaja, O. (2024) ‘AI-driven demand forecasting: Enhancing inventory management and customer satisfaction’, *World Journal of Advanced Research and Reviews*, 23(2), pp. 708–719. Available at: https://doi.org/10.30574/wjarr.2024.23.2.2394.

Armand, T., Nfor, K.A., Kim, J.-I. and Kim, H.-C. (2024) ‘Applications of Artificial Intelligence, Machine Learning, and Deep Learning in Nutrition: A Systematic Review’, *Nutrients*, 16(7), p. 1073. Available at: https://doi.org/10.3390/nu16071073.

Babashahi, L., Barbosa, C.E., Lima, Y., Lyra, A., Salazar, H., Argôlo, M., Almeida, M.A. de and Souza, J.M. de (2024) ‘AI in the Workplace: a Systematic Review of Skill Transformation in the Industry’, *Administrative Sciences*, 14(6), p. 127. Available at: https://doi.org/10.3390/admsci14060127.

Bălan, C. (2023) ‘Chatbots and Voice Assistants: Digital Transformers of the Company–Customer Interface—A Systematic Review of the Business Research Literature’, *Journal of Theoretical and Applied Electronic Commerce Research*, 18(2), pp. 995–1019. Available at: https://doi.org/10.3390/jtaer18020051.

Bao, Y., Gong, W. and Yang, K. (2023) ‘A Literature Review of Human–AI Synergy in Decision Making: From the Perspective of Affordance Actualisation Theory’, *Systems*, 11(9), p. 442. Available at: https://doi.org/10.3390/systems11090442.

Bell, E., Bryman, A. and Harley, B. (2022) *Business Research Methods*. 6th edn. Oxford: Oxford University Press.

Biswal, A. (2022) *7 Types of Artificial Intelligence That You Should Know in 2020*, *Simplilearn.com*. Available at: https://www.simplilearn.com/tutorials/artificial-intelligence-tutorial/types-of-artificial-intelligence (Accessed: 14 March 2025).

Boamah, F.A., Jin, X., Senaratne, S. and Perera, S. (2025) ‘Transition from Traditional Knowledge Retrieval into AI-Powered Knowledge Retrieval in Infrastructure Projects: A Literature Review’, *Infrastructures*, 10(2), p. 35. Available at: https://doi.org/10.3390/infrastructures10020035.

Bryman, A. (2016) *Social Research Methods*. 5th edn. Oxford: Oxford University Press.

Bunea, O.-I., Corboș, R.-A., Mișu, S.I., Triculescu, M. and Trifu, A. (2024) ‘The Next-Generation Shopper: A Study of Generation-Z Perceptions of AI in Online Shopping’, *Journal of Theoretical and Applied Electronic Commerce Research*, 19(4), pp. 2605–2629. Available at: https://doi.org/10.3390/jtaer19040125.

Burns, T. and Stalker, G.M. (1969) ‘The Management of Innovation.’, *The Economic Journal*, 79(314), pp. 403–405. Available at: https://doi.org/10.2307/2230196.

Bylykbashi, A. and Gavranović, L. (2024) *Mitigating Non-Consumer AI Malfunctions: Response Strategies of Retail Organisations*. Jönköping University. Available at: http://www.diva-portal.org/smash/get/diva2:1870737/FULLTEXT01.pdf (Accessed: 19 March 2025).

Cadarette, S.M., Ban, J.K., Consiglio, G.P., Black, C.D., Dubins, D., Marin, A. and Tadrous, M. (2017) 'Diffusion of Innovations model helps interpret the comparative uptake of two methodological innovations: co-authorship network analysis and recommendations for the integration of novel methods in practice', *Journal of Clinical Epidemiology*, 84, pp. 150–160. Available at: https://doi.org/10.1016/j.jclinepi.2016.12.006.

Caiza, G., Sanguña, V., Tusa, N., Masaquiza, V., Ortiz, A. and Garcia, M.V. (2024) 'Navigating Governmental Choices: A Comprehensive Review of Artificial Intelligence's Impact on Decision-Making', *Informatics*, 11(3), p. 64. Available at: https://doi.org/10.3390/informatics11030064.

Campbell, M. (2018) 'Postmodernism and Educational Research', *Open Journal of Social Sciences*, 6(7), pp. 67–73. Available at: https://doi.org/10.4236/jss.2018.67006.

Campbell, S., Greenwood, M., Prior, S., Shearer, T., Walkem, K., Young, S., Bywaters, D. and Walker, K. (2020) 'Purposive sampling: Complex or simple? Research Case Examples', *Journal of Research in Nursing*, 25(8), pp. 652–661. Available at: https://doi.org/10.1177/1744987120927206.

Chandra, S., Verma, S., Lim, W.M., Kumar, S. and Donthu, N. (2022) 'Personalisation in Personalized marketing: Trends and Ways Forward', *Psychology & Marketing*, 39(8), pp. 1529–1562. Available at: https://doi.org/10.1002/mar.21670.

Chen, W., Men, Y., Fuster, N., Osorio, C. and Juan, A.A. (2024) 'Artificial Intelligence in Logistics Optimisation with Sustainable Criteria: A Review', *Sustainability*, 16(21), p. 9145. Available at: https://doi.org/10.3390/su16219145.

Chen, Z. (2023) 'Ethics and Discrimination in Artificial intelligence-enabled Recruitment Practices', *Humanities and Social Sciences Communications*, 10(1), pp. 1–12. Available at: https://doi.org/10.1057/s41599-023-02079-x.

Chenavaz, R.Y. and Dimitrov, S. (2025) 'Artificial intelligence and dynamic pricing: a systematic literature review', *Journal of Applied Economics*, 28(1). Available at: https://doi.org/10.1080/15140326.2025.2466140.

Cheong, B.C. (2024) 'Transparency and accountability in AI systems: safeguarding wellbeing in the age of algorithmic decision-making', *Frontiers in Human Dynamics*, 6. Available at: https://doi.org/10.3389/fhumd.2024.1421273.

Čirjevskis, A. (2019) 'The Role of Dynamic Capabilities as Drivers of Business Model Innovation in Mergers and Acquisitions of Technology-Advanced Firms', *Journal of Open Innovation: Technology, Market, and Complexity*, 5(1), p. 12. Available at: https://doi.org/10.3390/joitmc5010012.

Creswell, J.W. and Creswell, J.D. (2018) *Research design: Qualitative, quantitative, and Mixed Methods Approaches*. 5th edn. London: SAGE Publications.

Culot, G., Podrecca, M. and Nassimbeni, G. (2024) 'Artificial intelligence in supply chain management: A systematic literature review of empirical studies and research directions', *Computers in Industry,* 162, p. 104132. Available at: https://doi.org/10.1016/j.compind.2024.104132.

Dancausa, G. and Millán, G. (2024) 'An Economic Perspective on the Implementation of Artificial Intelligence in the Restaurant Sector', *Administrative Sciences,* 14(9), p. 214. Available at: https://doi.org/10.3390/admsci14090214.

Darwin, Rusdin, D., Mukminatien, N., Suryati, N., Laksmi, E.D. and Marzuki (2023) 'Critical thinking in the AI era: An exploration of EFL students' perceptions, benefits, and limitations', *Cogent Education,* 11(1). Available at: https://doi.org/10.1080/2331186x.2023.2290342.

Datta, S.D., Islam, M., Rahman Sobuz, M.H., Ahmed, S. and Kar, M. (2024) 'Artificial intelligence and machine learning applications in the project lifecycle of the construction industry: A comprehensive review', *Heliyon,* 10(5). Available at: https://doi.org/10.1016/j.heliyon.2024.e26888.

Davis, F.D. (1989) 'Perceived usefulness, perceived ease of use, and user acceptance of information technology', *MIS Quarterly,* 13(3), pp. 319–340. Available at: http://dx.doi.org/10.2307/249008.

Deliu, D. and Olariu, A. (2024) 'The Role of Artificial Intelligence and Big Data Analytics in Shaping the Future of Professions in Industry 6.0: Perspectives from an Emerging Market', *Electronics,* 13(24), p. 4983. Available at: https://doi.org/10.3390/electronics13244983.

Elegunde, A.F. and Osagie, R. (2020) 'Artificial intelligence adoption and employee performance in the Nigerian banking industry', *International Journal of Management and Administration,* 4(8). Available at: https://doi.org/10.29064/ijma.734734.

Esmeli, R. and Gokce, A. (2025) 'An Analysis of Consumer Purchase Behavior Following Cart Addition in E-Commerce Utilizing Explainable Artificial Intelligence', *Journal of theoretical and applied electronic commerce research,* 20(1), p. 28. Available at: https://doi.org/10.3390/jtaer20010028.

Falatouri, T., Darbanian, F., Brandtner, P. and Udokwu, C. (2022) 'Predictive Analytics for Demand Forecasting – A Comparison of SARIMA and LSTM in Retail SCM', *Procedia Computer Science,* 200(1877-0509), pp. 993–1003. Available at: https://doi.org/10.1016/j.procs.2022.01.298.

Ferrara, E. (2023) 'Fairness and Bias in Artificial Intelligence: A Brief Survey of Sources, Impacts, and Mitigation Strategies', *Sci,* 6(1), p. 3. Available at: https://doi.org/10.3390/sci6010003.

Gandhimani, H. (2025) *Dynamic Pricing in E-commerce: Stay Competitive in 2025*, *Boostmyshop*. Available at: https://www.boostmyshop.com/my-pricing-repricing-tool/dynamic-pricing-ecommerce-2025/ (Accessed: 14 March 2025).

García-Avilés, J.A. (2020) 'Diffusion of Innovation', *The International Encyclopedia of Media Psychology*, pp. 1–8. Available at: https://doi.org/10.1002/9781119011071.iemp0137.

Gerlich, M. (2023) 'The Power of Virtual Influencers: Impact on Consumer Behaviour and Attitudes in the Age of AI', *Administrative Sciences*, 13(8), p. 178. Available at: https://doi.org/10.3390/admsci13080178.

Gligorea, I., Cioca, M., Oancea, R., Gorski, A.-T., Gorski, H. and Tudorache, P. (2023) 'Adaptive Learning Using Artificial Intelligence in e-Learning: A Literature Review', *Education Sciences*, 13(12), p. 1216. Available at: https://doi.org/10.3390/educsci13121216.

González-Arencibia, M., Ordoñez-Erazo, H. and González-Sanabria, J.-S. (2024) 'Explainable Artificial Intelligence as an Ethical Principle', *Ingeniería*, 29(2). Available at: https://doi.org/10.14483/23448393.21583.

Gupta, A. (2016) 'AI and Ethics: Balancing Automation And Human Employment', *SSRN Electronic Journal*, 5(5), pp. 1–9. Available at: https://www.researchgate.net/publication/383278925_AI_and_Ethics_Balancing_Automation_And_Human_Employment.

Gupta, S. (2024) 'Advanced AI-Driven Dynamic Pricing Models in Marketing: Real-World Applications', *SSRN Electronic Journal* [Preprint]. Available at: https://doi.org/10.2139/ssrn.4958529.

Gupta, S., Kushwaha, Pooja.S., Badhera, U., Chatterjee, P. and Gonzalez, E.D.R.S. (2023) 'Identification of benefits, challenges, and Pathways in e-commerce industries: an Integrated two-phase decision-making Model', *Sustainable Operations and Computers*, 4(4), pp. 200–218. Available at: https://doi.org/10.1016/j.susoc.2023.08.005.

Gurukaelaiarasu, T.M. (2024) *Navigating Research Approaches: Advantages and Disadvantages*, *Science of Lives*. Available at: https://scienceoflives.com/navigating-research-approaches-advantages-and-disadvantages (Accessed: 24 March 2025).

Haleem, A., Javaid, M., Qadri, M.A., Singh, R.P. and Suman, R. (2022) 'Artificial Intelligence (AI) Applications for marketing: a literature-based Study', *International Journal of Intelligent Networks*, 3(3), pp. 119–132. Available at: https://doi.org/10.1016/j.ijin.2022.08.005.

Haque, A., Akther, N., Khan, I., Agarwal, K. and Uddin, N. (2024) 'Artificial Intelligence in Retail Marketing: Research Agenda Based on Bibliometric Reflection and Content Analysis (2000–2023)', *Informatics*, 11(4), p. 74. Available at: https://doi.org/10.3390/informatics11040074.

Hashid, A. and Almaqtari, F.A. (2024) 'The Impact of Artificial Intelligence and Industry 4.0 on Transforming Accounting and Auditing Practices', *Journal of Open Innovation: Technology,* *Market, and Complexity*, 10(1), p. 100218. Available at: https://doi.org/10.1016/j.joitmc.2024.100218.

Husband, G. (2020) 'Ethical Data Collection and Recognizing the Impact of Semi-Structured Interviews on Research Respondents', *Education Sciences*, 10(8), p. 206. Available at: https://doi.org/10.3390/educsci10080206.

Islam, M.M.M., Emon, J.I., Ng, K.Y., Asadpour, A., Aziz, M.M.R.A., Baptista, M.L. and Kim, J.-M. (2025) 'Artificial Intelligence in Smart Manufacturing: Emerging Opportunities and Prospects', *Springer Series in Advanced Manufacturing*, pp. 9–36. Available at: https://doi.org/10.1007/978-3-031-80154-9_2.

Izadi, S. and Forouzanfar, M. (2024) 'Error Correction and Adaptation in Conversational AI: A Review of Techniques and Applications in Chatbots', *AI*, 5(2), pp. 803–841. Available at: https://doi.org/10.3390/ai5020041.

Jada, I. and Mayayise, T.O. (2023) 'The impact of artificial intelligence on organisational cyber security: An outcome of a systematic literature review', *Data and Information Management*, 8(2), p. 100063. Available at: https://doi.org/10.1016/j.dim.2023.100063.

Jerab, D.A. and Mabrouk, T. (2023) *The evolving landscape of organisational structures: A contemporary analysis*, *Social Science Research Network*. Rochester, NY. Available at: https://doi.org/10.2139/ssrn.4584643.

Kalogiannidis, S., Kalfas, D., Papaevangelou, O., Giannarakis, G. and Chatzitheodoridis, F. (2024) 'The Role of Artificial Intelligence Technology in Predictive Risk Assessment for Business Continuity: A Case Study of Greece', *Risks*, 12(2), p. 19. Available at: https://doi.org/10.3390/risks12020019.

Kalyvas, V. (2025) *How Netflix, Amazon and TikTok Hack Your Brain with AI (and Keep You Addicted!)*, *Medium*. AI Mind. Available at: https://medium.com/ai-mind-labs/how-netflix-amazon-and-tiktok-hack-your-brain-with-ai-and-keep-you-addicted-6eb4169b0f54 (Accessed: 18 March 2025).

Kassa, B.Y. and Worku, E.K. (2025) 'The Impact of Artificial Intelligence on Organisational Performance: The Mediating Role of Employee Productivity', *Journal of Open Innovation: Technology, Market, and Complexity*, 11(1), p. 100474. Available at: https://doi.org/10.1016/j.joitmc.2025.100474.

Kaushik, V. and Walsh, C.A. (2019) 'Pragmatism as a Research Paradigm and Its Implications for Social Work Research', *Social Sciences*, 8(9), pp. 1–17. Available at: https://doi.org/10.3390/socsci8090255.

Kavakli-Thorne, M. and Dai, Z. (2025) 'AI Algorithms for Positive Change in Digital Futures', *Algorithms*, 18(1), pp. 1–6. Available at: https://doi.org/10.3390/a18010043.

Kessel, A.-L., Sahri, S., Groppe, S., Groppe, J., Khorashadizadeh, H., Pignal, M., Pimparé, E.P. and Vignes-Lebbe, R. (2025) 'Impact of Chatbots on User Experience and Data Quality on Citizen

Science Platforms', *Computers*, 14(1), p. 21. Available at: https://doi.org/10.3390/computers14010021.

Khadragy, S. (2022) 'Artificial Intelligence and the future of employment; a systematic review of the state-of-the-art literature', *International Journal of Mechanical Engineering*, 7(2). Available at: https://kalaharijournals.com/resources/FebV7_I2_367.pdf.

Khan, A.A., Badshah, S., Liang, P., Waseem, M., Khan, B., Ahmad, A., Fahmideh, M., Niazi, M. and Akbar, M.A. (2022) 'Ethics of AI: A Systematic Literature Review of Principles and Challenges', in *The International Conference on Evaluation and Assessment in Software Engineering*. Available at: https://doi.org/10.1145/3530019.3531329.

Khedr, A.M. and Sheeja, R.S. (2024) 'Enhancing Supply Chain Management with Deep Learning and Machine Learning Techniques: A Review', *Journal of Open Innovation Technology Market and Complexity*, 10(4), p. 100379. Available at: https://doi.org/10.1016/j.joitmc.2024.100379.

Khogali, H.O. and Mekid, S. (2024) 'Perception and Ethical Challenges for the Future of AI as Encountered by Surveyed New Engineers', *Societies*, 14(12), p. 271. Available at: https://doi.org/10.3390/soc14120271.

Kokoszka, P. (2018) *Chatbots in retail: nine companies using AI to improve customer experience*, *Retail Insight Network*. Available at: https://www.retail-insight-network.com/features/chatbots-in-retail-ai-experience/?cf-view (Accessed: 18 March 2025).

Kovari, A. (2024) 'AI for Decision Support: Balancing Accuracy, Transparency, and Trust Across Sectors', *Information*, 15(11), p. 725. Available at: https://doi.org/10.3390/info15110725.

Krafft, M., Kumar, V., Harmeling, C., Singh, S., Zhu, T., Chen, J., Duncan, T., Fortin, W. and Rosa, E. (2021) 'Insight is power: Understanding the terms of the consumer-firm data exchange', *Journal of Retailing*, 97(1), pp. 133–149. Available at: https://doi.org/10.1016/j.jretai.2020.11.001.

Krishnamurthy, S., Tirupati, K.K., Ganipaneni, S., Shrivastav, Er.A., Vashishtha, S. and Jain, S. (2024) 'Leveraging AI and Machine Learning to Optimize Retail Operations and Enhance', *Darpan International Research Analysis*, 12(3), pp. 1037–1069. Available at: https://doi.org/10.36676/dira.v12.i3.140.

Kumar, Y., Marchena, J., Awlla, A.H., Li, J.J. and Abdalla, H.B. (2024) 'The AI-Powered Evolution of Big Data', *Applied Sciences*, 14(22), p. 10176. Available at: https://doi.org/10.3390/app142210176.

Lada, S., Chekima, B., Karim, Mohd.R.A., Fabeil, N.F., Ayub, M.S., Amirul, S.M., Ansar, R., Bouteraa, M., Fook, L.M. and Zaki, H.O. (2023) 'Determining factors related to artificial intelligence (AI) adoption among Malaysia's small and medium-sized businesses', *Journal of Open Innovation: Technology, Market, and Complexity*, 9(4). Available at: https://doi.org/10.1016/j.joitmc.2023.100144.

Ledro, C., Nosella, A. and Pozza, I.D. (2023) ‘Integration of AI in CRM: Challenges and guidelines’, *Journal of Open Innovation: Technology, Market, and Complexity*, 9(4), p. 100151. Available at: https://doi.org/10.1016/j.joitmc.2023.100151.

Li, Z. (2024) ‘Review of Application of AI in Amazon Warehouse Management’, *Advances in Economics Management and Political Sciences*, 144(1), pp. 1–8. Available at: https://doi.org/10.54254/2754-1169/2024.ga18980.

Liu-Thompkins, Y., Okazaki, S. and Li, H. (2022) ‘Artificial empathy in marketing interactions: Bridging the human-AI gap in affective and social customer experience’, *Journal of the Academy of Marketing Science*, 50(6). Available at: https://doi.org/10.1007/s11747-022-00892-5.

Madanchian, M. (2024) ‘The Impact of Artificial Intelligence Marketing on E-Commerce Sales’, *Systems*, 12(10), p. 429. Available at: https://doi.org/10.3390/systems12100429.

Mahmud, M., Soetanto, D. and Jack, S. (2021) ‘A contingency theory perspective of environmental management: Empirical evidence from entrepreneurial firms’, *Journal of General Management*, 47(1), pp. 3–17. Available at: https://doi.org/10.1177/0306307021991489.

Malatji, W.R., Eck, R.V. and Zuva, T. (2020) ‘Understanding the usage, Modifications, Limitations and Criticisms of Technology Acceptance Model (TAM)’, *Advances in Science, Technology and Engineering Systems Journal*, 5(6), pp. 113–117. Available at: https://doi.org/10.25046/aj050612.

Marocco, S., Barbieri, B. and Talamo, A. (2024) ‘Exploring Facilitators and Barriers to Managers’ Adoption of AI-Based Systems in Decision Making: A Systematic Review’, *AI*, 5(4), pp. 2538–2567. Available at: https://doi.org/10.3390/ai5040123.

Martins, E. and Galegale, N.V. (2023) ‘Sales forecasting using machine learning algorithms’, *Revista de Gestão e Secretariado (Management and Administrative Professional Review)*, 14(7), pp. 11294–11308. Available at: https://doi.org/10.7769/gesec.v14i7.1670.

Mathew, D.E., Ebem, D.U., Ikegwu, A.C., Ukeoma, P.E. and Dibiaezue, N.F. (2025) ‘Recent Emerging Techniques in Explainable Artificial Intelligence to Enhance the Interpretable and Understanding of AI Models for Human’, *Neural Processing Letters*, 57(1). Available at: https://doi.org/10.1007/s11063-025-11732-2.

McEvoy, P. and Richards, D. (2006) ‘A critical realist rationale for using a combination of quantitative and qualitative methods’, *Journal of Research in Nursing*, 11(1), pp. 66–78. Available at: https://doi.org/10.1177/1744987106060192.

Mer, A., Singhal, K. and Virdi, A.S. (2024) ‘A Review of the Role of Artificial Intelligence in Banking and Stock Market Trading’, *Emerald Publishing Limited eBooks*, pp. 175–198. Available at: https://doi.org/10.1108/978-1-83753-572-920241009.

Mohammed, K. and Shehu, A. (2023) ‘A review of artificial intelligence (AI) challenges and future prospects of explainable AI in major fields: A case study of Nigeria’, *Open Journal of Physical Science*, 4(1), pp. 1–18. Available at: https://doi.org/10.52417/ojps.v4i1.458.

Mondal, S., Das, S. and Vrana, V.G. (2024) 'Exploring the Role of Artificial Intelligence in Achieving a Net Zero Carbon Economy in Emerging Economies: A Combination of PLS-SEM and fsQCA Approaches to Digital Inclusion and Climate Resilience', *Sustainability*, 16(23), p. 10299. Available at: https://doi.org/10.3390/su162310299.

Morić, Z., Dakic, V., Djekic, D. and Regvart, D. (2024) 'Protection of Personal Data in the Context of E-Commerce', *Journal of Cybersecurity and Privacy*, 4(3), pp. 731–761. Available at: https://doi.org/10.3390/jcp4030034.

Murire, O.T. (2024) 'Artificial Intelligence and Its Role in Shaping Organisational Work Practices and Culture', *Administrative Sciences*, 14(12), p. 316. Available at: https://doi.org/10.3390/admsci14120316.

Murugesan, U., Subramanian, P., Srivastava, S. and Dwivedi, A. (2023) 'A Study of Artificial Intelligence Impacts on Human Resource Digitalisation in Industry 4.0', *Decision Analytics Journal*, 7(100249). Available at: https://doi.org/10.1016/j.dajour.2023.100249.

Naz, H. and Kashif, M. (2024) 'Artificial Intelligence and Predictive marketing: an Ethical Framework from Managers' Perspective', *Spanish Journal of Marketing - ESIC*, 29(1). Available at: https://doi.org/10.1108/sjme-06-2023-0154.

Odufisan, O.I., Abhulimen, O.V. and Ogunti, E.O. (2025) 'Harnessing Artificial Intelligence and Machine Learning for Fraud Detection and Prevention in Nigeria.', *Journal of Economic Criminology*, 7, p. 100127. Available at: https://doi.org/10.1016/j.jeconc.2025.100127.

Okeleke, P.A., Ajiga, N.D., Olaoluwa, S. and Ezeigweneme, N.C. (2024) 'Predictive Analytics for Market Trends Using AI: a Study in Consumer Behavior', *International Journal of Engineering Research Updates*, 7(1), pp. 036–049. Available at: https://doi.org/10.53430/ijeru.2024.7.1.0032.

Olaghere, J.A., Inegbedion, H.E. and Osiobe, F.O. (2023) 'The Implications of Digitalisation in Retail Service Delivery on Circular Economy in Nigeria: An Exploratory Case Study', *Sustainability*, 15(17), p. 13192. Available at: https://doi.org/10.3390/su151713192.

Osasona, F., Amoo, O.O., Atadoga, A., Abrahams, O., Farayola, O.A. and Samson, B. (2024) 'Reviewing the ethical implications of AI in decision making processes', *International journal of management & entrepreneurship research*, 6(2), pp. 322–335. Available at: https://doi.org/10.51594/ijmer.v6i2.773.

Osegi, E.N. and Jumbo, E.F. (2021) 'Comparative analysis of credit card fraud detection in Simulated Annealing trained Artificial Neural Network and Hierarchical Temporal Memory', *Machine Learning with Applications*, 6. Available at: https://doi.org/10.1016/j.mlwa.2021.100080.

Ozturk, O. (2024) 'The Impact of AI on International Trade: Opportunities and Challenges', *Economies*, 12(11), p. 298. Available at: https://doi.org/10.3390/economies12110298.

Pacheco-Cubillos, D.B., Boria-Reverter, J. and Gil-Lafuente, J. (2024) ‘Transitioning to Agile Organisational Structures: A Contingency Theory Approach in the Financial Sector’, *Systems*, 12(4), p. 142. Available at: https://doi.org/10.3390/systems12040142.

Pandey, V.K., Srivastava, S., Dash, K.K., Singh, R., Mukarram, S.A., Kovács, B. and Harsányi, E. (2023) ‘Machine Learning Algorithms and Fundamentals as Emerging Safety Tools in Preservation of Fruits and Vegetables: A Review’, *Processes*, 11(6), p. 1720. Available at: https://doi.org/10.3390/pr11061720.

Pattnaik, D., Ray, S. and Raman, R. (2024) ‘Applications of artificial intelligence and machine learning in the financial services industry: A bibliometric review’, *Heliyon*, 10(1), p. e23492. Available at: https://www.sciencedirect.com/science/article/pii/S2405844023107006.

Pennisi, F., Pinto, A., Ricciardi, G.E., Signorelli, C. and Gianfredi, V. (2025) ‘The Role of Artificial Intelligence and Machine Learning Models in Antimicrobial Stewardship in Public Health: A Narrative Review’, *Antibiotics*, 14(2), p. 134. Available at: https://doi.org/10.3390/antibiotics14020134.

Perera, A. (2024) *Postmodernism in Sociology: Characteristics, & Examples*, *Simply Psychology*. Available at: https://www.simplypsychology.org/postmodernism.html (Accessed: 30 March 2025).

Perifanis, N.-A. (2023) ‘Investigating the influence of artificial intelligence on business value in the digital era of strategy: A literature review’, *Information*, 14(2). Available at: https://doi.org/10.3390/info14020085.

Prester, J. (2023) ‘Operating and Dynamic Capabilities and Their Impact on Operating and Business Performance’, *Sustainability*, 15(20), p. 15181. Available at: https://doi.org/10.3390/su152015181.

Qu, C. and Kim, E. (2024) ‘Reviewing the Roles of AI-Integrated Technologies in Sustainable Supply Chain Management: Research Propositions and a Framework for Future Directions’, *Sustainability*, 16(14), p. 6186. Available at: https://doi.org/10.3390/su16146186.

Radanliev, P. (2025) ‘AI Ethics: Integrating Transparency, Fairness, and Privacy in AI Development’, *Applied Artificial Intelligence*, 39(1). Available at: https://doi.org/10.1080/08839514.2025.2463722.

Raman, R., Kowalski, R., Achuthan, K., Iyer, A. and Nedungadi, P. (2025) ‘Navigating artificial general intelligence development: societal, technological, ethical, and brain-inspired pathways’, *Scientific Reports*, 15(1). Available at: https://doi.org/10.1038/s41598-025-92190-7.

Rana, Md.M., Siddiqee, M.S., Sakib, Md.N. and Ahamed, Md.R. (2024) ‘Assessing AI adoption in developing country academia: A trust and privacy-augmented UTAUT framework’, *Heliyon*, 10(18), p. e37569. Available at: https://doi.org/10.1016/j.heliyon.2024.e37569.

Rashid, A.B. and Kausik, A.K. (2024) 'AI Revolutionizing Industries Worldwide: a Comprehensive Overview of Its Diverse Applications', *Hybrid Advances*, 7(100277), p. 100277. Available at: https://doi.org/10.1016/j.hybadv.2024.100277.

Reed, C., Wynn, M. and Bown, R. (2025) 'Artificial Intelligence in Digital Marketing: Towards an Analytical Framework for Revealing and Mitigating Bias', *Big Data and Cognitive Computing*, 9(2), p. 40. Available at: https://doi.org/10.3390/bdcc9020040.

Reyna, V. (2018) 'When Irrational Biases Are Smart: A Fuzzy-Trace Theory of Complex Decision Making', *Journal of Intelligence*, 6(2), p. 29. Available at: https://doi.org/10.3390/jintelligence6020029.

Riad, M., Naimi, M. and Okar, C. (2024) 'Enhancing Supply Chain Resilience Through Artificial Intelligence: Developing a Comprehensive Conceptual Framework for AI Implementation and Supply Chain Optimisation', *Logistics*, 8(4), p. 111. Available at: https://doi.org/10.3390/logistics8040111.

Robertson, J., Botha, E., Oosthuizen, K. and Montecchi, M. (2025) 'Managing change when integrating artificial intelligence (AI) into the retail value chain: The AI implementation compass', *Journal of Business Research*, 189, p. 115198. Available at: https://doi.org/10.1016/j.jbusres.2025.115198.

Sarker, I.H. (2021) 'Machine Learning: Algorithms, Real-World Applications and Research Directions', *SN Computer Science*, 2(3), pp. 1–21. Available at: https://doi.org/10.1007/s42979-021-00592-x.

Saunders, M., Lewis, P. and Thornhill, A. (2019) *Research Methods for Business Students*. 9th edn. Harlow: Pearson.

Scherer, R., Siddiq, F. and Tondeur, J. (2019) 'The technology acceptance model (TAM): a meta-analytic structural equation modeling approach to explaining teachers' adoption of digital technology in education', *Computers & Education*, 128(1), pp. 13–35. Available at: https://doi.org/10.1016/j.compedu.2018.09.009.

SDK.Finance (2021) *Credit Card Fraud Detection. Big Players Experience, SDK.finance - White-Label Digital Core Banking Software*. Available at: https://sdk.finance/credit-card-fraud-detection-big-players-experience/ (Accessed: 18 March 2025).

Shamsuddoha, M., Khan, E.A., Chowdhury, H. and Nasir, T. (2025) 'Revolutionizing Supply Chains: Unleashing the Power of AI-Driven Intelligent Automation and Real-Time Information Flow', *Information*, 16(1), p. 26. Available at: https://doi.org/10.3390/info16010026.

Smith, R.A. and Findeis, J.L. (2013) 'Exploring Audience Segmentation: Investigating Adopter Categories to Diffuse an Innovation to Prevent Famine in Rural Mozambique', *Journal of Health Communication*, 18(1), pp. 6–19. Available at: https://doi.org/10.1080/10810730.2012.688249.

Soori, M., Arezoo, B. and Dastres, R. (2023) ‘Artificial Intelligence, Machine Learning and Deep Learning in Advanced Robotics, A Review’, *Cognitive Robotics*, 3(1), pp. 54–70. Available at: https://doi.org/10.1016/j.cogr.2023.04.001.

Stutchbury, K. (2021) ‘Critical realism: an Explanatory Framework for small-scale Qualitative Studies or an “unhelpful edifice”?’, *International Journal of Research & Method in Education*, 45(2), pp. 1–16. Available at: https://doi.org/10.1080/1743727X.2021.1966623.

Taherdoost, H. (2023) ‘Deep Learning and Neural Networks: Decision-Making Implications’, *Symmetry*, 15(9), p. 1723. Available at: https://www.mdpi.com/2073-8994/15/9/1723.

Taherdoost, H. and Madanchian, M. (2023) ‘AI Advancements: Comparison of Innovative Techniques’, *AI*, 5(1), pp. 38–54. Available at: https://doi.org/10.3390/ai5010003.

Talabi, F.O., Oyewole, J.A., Bello, S.A., Adefemi, V.O., Talabi, J.M., Adesile, T. and Oladele, P.O. (2024) ‘Adoption of Artificial Intelligence in News Gathering and Reporting in Nigerian Mass Media’, *Journal of Ecohumanism*, 3(8). Available at: https://doi.org/10.62754/joe.v3i8.5511.

Tan, L., Liu, S., Gao, J., Liu, X., Chu, L. and Jiang, H. (2024) ‘Enhanced Self-Checkout System for Retail Based on Improved YOLOv10’, *Journal of Imaging*, 10(10), p. 248. Available at: https://doi.org/10.3390/jimaging10100248.

Teece, D.J. (2018) ‘Business models and dynamic capabilities’, *Long Range Planning*, 51(1), pp. 40–49. Available at: https://doi.org/10.1016/j.lrp.2017.06.007.

Teece, D.J., Pisano, G. and Shuen, A. (1997) ‘Dynamic Capabilities and Strategic Management’, *Strategic Management Journal*, 18(7), pp. 509–533. Available at: http://links.jstor.org/sici?sici=0143-2095%28199708%2918%3A7%3C509%3ADCASM%3E2.0.CO%3B2-%23 (Accessed: 20 March 2025).

Tursunbayeva, A. and Gal, H.C.-B. (2024) ‘Adoption of artificial intelligence: A TOP framework-based checklist for digital leaders’, *Business horizons*, 67(4). Available at: https://doi.org/10.1016/j.bushor.2024.04.006.

Uwagaba, J., Omotosho, T.D. and George, G.O. (2023) ‘Exploring the barriers to Artificial Intelligence adoption in sub-Saharan Africa’s Small and Medium Enterprises and the potential for increased productivity.’, *World Wide Journal of Multidisciplinary Research and Development*, 9(6), pp. 4–10. Available at: https://www.researchgate.net/publication/367678657_Exploring_the_barriers_to_Artificial_Intelligence_adoption_in_sub-Saharan_Africa.

Valdivieso, T. and González, O. (2025) ‘Generative AI Tools in Salvadoran Higher Education: Balancing Equity, Ethics, and Knowledge Management in the Global South’, *Education Sciences*, 15(2), p. 214. Available at: https://doi.org/10.3390/educsci15020214.

Wang, C., Ahmad, S.F., Ahmad, A.B., Awwad, E.M., Irshad, M., Ali, Y.A., Al-Razgan, M., Khan, Y. and Han, H. (2023) ‘An empirical evaluation of technology acceptance model for Artificial Intelligence in E-commerce’, *Heliyon*, 9(8), p. e18349. Available at: https://doi.org/10.1016/j.heliyon.2023.e18349.

Wang, F. and Slowik, A. (2024) ‘AI-Empowered Consumer Behavior Analysis for Trustworthy Track Recommendation over Musical Dance Electronic Products’, *Heliyon*, 10(18), p. e37633. Available at: https://doi.org/10.1016/j.heliyon.2024.e37633.

Whyte, S. (2021) ‘Reliable Data Collection: A Tool for Data Integrity in Nigeria’, *Walden Dissertations and Doctoral Studies Collection* [Preprint]. Available at: https://doi.org/10.13140/RG.2.2.23774.20803.

Williams, R. and Yampolskiy, R. (2021) ‘Understanding and Avoiding AI Failures: A Practical Guide’, *Philosophies*, 6(3), p. 53. Available at: https://doi.org/10.3390/philosophies6030053.

Wilson, G., Johnson, O. and Brown, W. (2024) ‘Exploring the Integration of Artificial Intelligence in Retail Operations’, *Preprints.org* [Preprint]. Available at: https://doi.org/10.20944/preprints202408.0012.v1.

Wolniak, R., Stecuła, K. and Aydın, B. (2024) ‘Digital Transformation of Grocery In-Store Shopping-Scanners, Artificial Intelligence, Augmented Reality and Beyond: a Review’, *Foods*, 13(18), p. 2948.

Zirar, A., Ali, S.I. and Islam, N. (2023) ‘Worker and workplace Artificial Intelligence (AI) coexistence: Emerging themes and research agenda’, *Technovation*, 124(124), p. 102747. Available at: https://doi.org/10.1016/j.technovation.2023.102747.

Appendix A: Survey Questionnaire

Introduction:
This questionnaire is designed to explore AI adoption in retail management, its impact on decision-making, associated ethical considerations, and strategies for optimisation. Responses will be kept confidential and used strictly for academic research.

Section A: Demographic Information

1. What is your position in the organisation?

   - ☐ Senior Management
   - ☐ Middle Management
   - ☐ Operational Staff

2. How many employees does your organisation have?

   - ☐ Less than 20
   - ☐ 20-49
   - ☐ 50-99
   - ☐ 100+

3. How long has your organisation been using AI in decision-making?

   - ☐ Less than 1 year
   - ☐ 1 – 3 years
   - ☐ 4-6 years
   - ☐ More than 6 years
   - ☐ My organisation does not use AI in decision-making

4. What industry best describes your company?

   - ☐ Grocery & Supermarket Retail
   - ☐ Fashion & Apparel Retail
   - ☐ Electronics & Appliances
   - ☐ E-commerce
   - ☐ Others (please specify) ___________

Section B: AI Adoption in Management Decision-Making (RQ1)

(5-Point Likert Scale: 1 = Strongly Disagree, 5 = Strongly Agree)

5. My organisation uses AI to analyse customer purchasing patterns.
6. AI plays a role in predicting sales trends and demand forecasting.
7. AI-generated reports influence strategic decision-making in my organisation.
8. My organisation integrates AI into supply chain management for decision-making.
9. AI is used to optimise pricing and promotional strategies in my organisation.

Section C: Benefits and Limitations of AI in Decision-Making *(RQ2)*

(5-Point Likert Scale: 1 = Strongly Disagree, 5 = Strongly Agree)

10. AI improves the accuracy of decision-making in my organisation.
11. AI enhances operational efficiency and reduces costs.
12. AI enables faster decision-making compared to human managers.
13. AI systems occasionally produce errors that impact decision quality.
14. AI decisions sometimes lack the contextual understanding that human managers provide.
15. My organisation faces challenges in integrating AI with existing business processes.

Section D: AI's Impact on the Role of Human Managers *(RQ3)*

(5-Point Likert Scale: 1 = Strongly Disagree, 5 = Strongly Agree)

16. AI has reduced the need for human managers in my organisation.
17. AI has shifted managerial roles towards more strategic and analytical tasks.
18. AI allows managers to focus on high-level decision-making rather than routine tasks.
19. AI increases the pressure on managers to adapt to new technologies.
20. Managers in my organisation feel confident working alongside AI systems.

Section E: Ethical Considerations in AI-Driven Decision-Making *(RQ4)*

(5-Point Likert Scale: 1 = Strongly Disagree, 5 = Strongly Agree)

21. AI decision-making in my organisation is transparent and explainable.
22. My organisation has policies in place to ensure AI-driven decisions are ethical.
23. AI systems in my organisation are free from bias and discrimination.
24. Employees in my organisation trust AI-driven decisions.
25. AI adoption in decision-making has raised concerns about data privacy and security.

Section F: Strategies for Optimising AI Adoption in Management Decision-Making *(RQ5)*

(5-Point Likert Scale: 1 = Strongly Disagree, 5 = Strongly Agree)

26. My organisation provides training to employees on AI adoption.
27. There are clear policies on how AI should be used in decision-making.
28. AI adoption in my organisation is regularly reviewed and updated.

29. Collaboration between AI systems and human decision-makers is actively encouraged.
30. My organisation invests in ethical AI practices to improve decision-making outcomes.

Appendix B: Consent Form

Title of Study: An investigation into the role of Artificial Intelligence (AI) in management decision-making within retail businesses.

Researcher: Ogochukwu Perpetua Ukwuoma

Postgraduate Student

York St John University London campus

Email:

Consent to Participate in Research

Please read the following statements carefully and tick the boxes to confirm your agreement.

Statement	**Yes**	**No**
I have read and understood the Participant Information Sheet for this study.		
I have had the opportunity to ask questions and have received satisfactory answers.		
I understand that my participation is voluntary and that I can withdraw at any time before submitting the questionnaire, without giving a reason and without penalty.		
I understand that my responses will be kept anonymous and confidential, and that any data collected will only be used for academic purposes.		
I understand that the results may be published in academic works, but that I will not be identifiable in any reports or publications.		
I give permission for the researcher to collect and analyse my responses as part of this study.		

Participant Declaration

By signing this form, I confirm that I voluntarily agree to participate in the research project described above.

Signature: ____________________________ Date: _______________

Researcher Declaration

I confirm that I have provided the participant with all necessary information about the study and answered any questions they may have.

Researcher Name: ____

Signature: ____________________________ Date: _______________

Appendix C: Participant Information Sheet

Title of Research: An investigation into the role of Artificial Intelligence (AI) in management decision-making within retail businesses.

1. Introduction

You are being invited to participate in a research study as part of my postgraduate dissertation at York St John University London campus. Please take a moment to read this information carefully before deciding whether or not to take part. Your participation is entirely voluntary.

2. Purpose of the Study

The aim of this research is to examine how artificial intelligence (AI) is being used in retail organisations in Nigeria to support managerial decision-making. It will also explore the benefits, challenges, ethical concerns, and potential strategies for improving AI adoption in the sector.

3. Why Have You Been Chosen?

You have been invited because you are a retail manager or decision-maker with knowledge or experience of AI use in your organisation. Your insights are valuable to understanding real-world applications of AI in retail management.

4. What Will Participation Involve?

If you choose to participate:

You will complete a short questionnaire that takes approximately 10–15 minutes.

All questions are closed-ended (mostly using a 5-point Likert scale).

You do not need to provide your name or any identifying information.

5. Do I Have to Take Part?

No. Participation is completely voluntary. You are free to withdraw at any time before submitting the completed questionnaire, without giving a reason and without penalty.

6. Will My Responses Be Confidential?

Yes. All data collected will remain anonymous and confidential. The data will be stored securely and used only for academic research purposes. The results will be reported in a way that does not identify any individual.

7. Are There Any Risks or Benefits?

There are no anticipated risks in taking part. While you may not receive a direct benefit, your contribution will help develop valuable insights into AI-based decision-making, especially in Nigeria's retail sector.

8. What Will Happen to the Results of the Research?

The results will be analysed for my dissertation and may be published in an academic journal. Again, all information will remain anonymous, and no identifying details will be shared.

9. Contact for Further Information

If you have any questions or concerns, feel free to contact me: ogochukwu.ukwuoma@yorksj.ac.uk

Or contact my academic supervisor: Dr Rana Mohsin Ali at r.mohsinali@yorksj.ac.uk

Thank you very much for considering participation in this study.

Best regards,

Ogochukwu Perpetua Ukwuoma

Postgraduate Student

York St John University London campus

Appendix D: Cross-tabulation and Chi-Square Tests

Position in organisation * AI systems are free from bias and discrimination Crosstabulation

			AI systems are free from bias and discrimination					Total
			Strongly Disagree	Disagree	Undecided	Agree	Strongly Agree	
Position in organisation	Senior Management	Count	5	4	15	6	14	44
		Expected Count	7.5	3.7	13.6	8.9	10.3	44.0
		% within AI systems are free from bias and discrimination	31.2%	50.0%	51.7%	31.6%	63.6%	46.8%
	Middle Management	Count	6	4	9	10	5	34
		Expected Count	5.8	2.9	10.5	6.9	8.0	34.0
		% within AI systems are free from bias and discrimination	37.5%	50.0%	31.0%	52.6%	22.7%	36.2%
	Operational Staff	Count	5	0	5	3	3	16
		Expected Count	2.7	1.4	4.9	3.2	3.7	16.0
		% within AI systems are free from bias and discrimination	31.2%	0.0%	17.2%	15.8%	13.6%	17.0%
Total		Count	16	8	29	19	22	94
		Expected Count	16.0	8.0	29.0	19.0	22.0	94.0
		% within AI systems are free from bias and discrimination	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%

Chi-square test: Position * AI systems are free from bias and discrimination

	Value	Df	Asymp. Sig. (2-sided)
Pearson Chi-Square	9.862[a]	8	.275
Likelihood Ratio	10.904	8	.207
Linear-by-Linear Association	2.079	1	.149
N of Valid Cases	94		

a. 7 cells (46.7%) have expected count less than 5. The minimum expected count is 1.36.

Duration of AI use in decision-making * AI systems are free from bias and discrimination Crosstabulation

			AI systems are free from bias and discrimination					Total
			Strongly Disagree	Disagree	Undecided	Agree	Strongly Agree	
Duration of AI use in decision-making	Less than 1 year	Count	2	2	7	5	3	19
		Expected Count	3.4	1.6	5.8	3.8	4.4	19.0
		% within AI systems are free from bias and discrimination	11.8%	25.0%	24.1%	26.3%	13.6%	20.0%
	1 – 3 years	Count	3	1	6	4	10	24
		Expected Count	4.3	2.0	7.3	4.8	5.6	24.0
		% within AI systems are free from bias and discrimination	17.6%	12.5%	20.7%	21.1%	45.5%	25.3%
	4-6 years	Count	3	0	0	4	2	9
		Expected Count	1.6	.8	2.7	1.8	2.1	9.0
		% within AI systems are free from bias and discrimination	17.6%	0.0%	0.0%	21.1%	9.1%	9.5%
	More than 6 years	Count	0	0	1	0	2	3
		Expected Count	.5	.3	.9	.6	.7	3.0
		% within AI systems are free from bias and discrimination	0.0%	0.0%	3.4%	0.0%	9.1%	3.2%
	My organisation does not use AI in decision-making	Count	9	5	15	6	5	40
		Expected Count	7.2	3.4	12.2	8.0	9.3	40.0
		% within AI systems are free from bias and discrimination	52.9%	62.5%	51.7%	31.6%	22.7%	42.1%
Total		Count	17	8	29	19	22	95
		Expected Count	17.0	8.0	29.0	19.0	22.0	95.0
		% within AI systems are free from bias and discrimination	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%

Chi-square test: Duration * AI systems are free from bias and discrimination

	Value	Df	Asymp. Sig. (2-sided)
Pearson Chi-Square	22.189[a]	16	.137
Likelihood Ratio	25.169	16	.067
Linear-by-Linear Association	3.537	1	.060
N of Valid Cases	95		

a. 18 cells (72.0%) have expected count less than 5. The minimum expected count is .25.

Position in organisation * AI raises data privacy and security concerns Crosstabulation

			AI raises data privacy and security concerns					Total
			Strongly Disagree	Disagree	Undecided	Agree	Strongly Agree	
Position in organisation	Senior Management	Count	1	5	11	13	13	43
		Expected Count	1.8	4.6	11.4	14.6	10.5	43.0
		% within AI raises data privacy and security concerns	25.0%	50.0%	44.0%	40.6%	56.5%	45.7%
	Middle Management	Count	2	3	9	13	8	35
		Expected Count	1.5	3.7	9.3	11.9	8.6	35.0
		% within AI raises data privacy and security concerns	50.0%	30.0%	36.0%	40.6%	34.8%	37.2%
	Operational Staff	Count	1	2	5	6	2	16
		Expected Count	.7	1.7	4.3	5.4	3.9	16.0

	% within AI raises data privacy and security concerns	25.0%	20.0%	20.0%	18.8%	8.7%	17.0%
Total	Count	4	10	25	32	23	94
	Expected Count	4.0	10.0	25.0	32.0	23.0	94.0
	% within AI raises data privacy and security concerns	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%

Chi-square test: Position and "AI raises data privacy and security concerns"

	Value	Df	Asymp. Sig. (2-sided)
Pearson Chi-Square	2.986[a]	8	.935
Likelihood Ratio	3.193	8	.922
Linear-by-Linear Association	1.248	1	.264
N of Valid Cases	94		

a. 8 cells (53.3%) have expected count less than 5. The minimum expected count is .68.

Duration of AI use in decision-making * AI raises data privacy and security concerns Crosstabulation

			AI raises data privacy and security concerns					Total
			Strongly Disagree	Disagree	Undecided	Agree	Strongly Agree	
Duration of AI use in decision-making	Less than 1 year	Count	0	1	4	9	5	19
		Expected Count	1.0	2.0	5.0	6.4	4.6	19.0
		% within Duration of AI use in decision-making	0.0%	5.3%	21.1%	47.4%	26.3%	100.0%
		% within AI raises data privacy and security concerns	0.0%	10.0%	16.0%	28.1%	21.7%	20.0%
		% of Total	0.0%	1.1%	4.2%	9.5%	5.3%	20.0%
	1 – 3 years	Count	1	3	5	10	5	24
		Expected Count	1.3	2.5	6.3	8.1	5.8	24.0
		% within Duration of AI use in decision-making	4.2%	12.5%	20.8%	41.7%	20.8%	100.0%
		% within AI raises data privacy and security concerns	20.0%	30.0%	20.0%	31.2%	21.7%	25.3%
		% of Total	1.1%	3.2%	5.3%	10.5%	5.3%	25.3%
	4-6 years	Count	1	1	2	2	2	8
		Expected Count	.4	.8	2.1	2.7	1.9	8.0
		% within Duration of AI use in decision-making	12.5%	12.5%	25.0%	25.0%	25.0%	100.0%
		% within AI raises data privacy and security concerns	20.0%	10.0%	8.0%	6.2%	8.7%	8.4%
		% of Total	1.1%	1.1%	2.1%	2.1%	2.1%	8.4%
	More than 6 years	Count	0	1	0	0	2	3
		Expected Count	.2	.3	.8	1.0	.7	3.0
		% within Duration of AI use in decision-making	0.0%	33.3%	0.0%	0.0%	66.7%	100.0%
		% within AI raises data privacy and security concerns	0.0%	10.0%	0.0%	0.0%	8.7%	3.2%

		% of Total	0.0%	1.1%	0.0%	0.0%	2.1%	3.2%
	My organisation does not use AI in decision-making	Count	3	4	14	11	9	41
		Expected Count	2.2	4.3	10.8	13.8	9.9	41.0
		% within Duration of AI use in decision-making	7.3%	9.8%	34.1%	26.8%	22.0%	100.0%
		% within AI raises data privacy and security concerns	60.0%	40.0%	56.0%	34.4%	39.1%	43.2%
		% of Total	3.2%	4.2%	14.7%	11.6%	9.5%	43.2%
Total		Count	5	10	25	32	23	95
		Expected Count	5.0	10.0	25.0	32.0	23.0	95.0
		% within Duration of AI use in decision-making	5.3%	10.5%	26.3%	33.7%	24.2%	100.0%
		% within AI raises data privacy and security concerns	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%
		% of Total	5.3%	10.5%	26.3%	33.7%	24.2%	100.0%

Chi-Square Tests-Duration of AI use in decision-making * AI raises data privacy and security concerns

	Value	Df	Asymp. Sig. (2-sided)
Pearson Chi-Square	12.427[a]	16	.714
Likelihood Ratio	13.833	16	.611
Linear-by-Linear Association	1.753	1	.186
N of Valid Cases	95		

a. 17 cells (68.0%) have expected count less than 5. The minimum expected count is .16.

Appendix E: Multiple Regression Analysis Tables

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.751[a]	.564	.550	.74589

a. Predictors: (Constant), ethical considerations, benefits, AI adoption

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	71.134	3	23.711	42.619	.000[b]
	Residual	55.080	99	.556		
	Total	126.214	102			

a. Dependent Variable: strategies to optimise AI

b. Predictors: (Constant), ethical considerations, benefits, AI adoption

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.139	.297		.469	.640
	AI adoption	.206	.081	.232	2.561	.012
	Benefits	.194	.099	.169	1.963	.052
	Ethical considerations	.531	.101	.465	5.275	.000

a. Dependent Variable: strategies to optimise AI

Appendix F: Researcher's Self-Reflection

Completing this research project has been a significant academic and personal journey. At the start, I was intrigued by the increasing use of Artificial Intelligence in retail management but lacked deep understanding of its implications for organisational decision-making. Through this study, I have gained practical and theoretical knowledge about AI tools, their benefits, ethical concerns, and the evolving role of human managers. I developed critical research skills, especially in designing a structured questionnaire, analysing data using SPSS, and interpreting statistical results. Initially, I found quantitative analysis challenging, particularly in understanding regression outputs and ensuring the reliability of data. However, through practice and guidance, I became more confident in using descriptive statistics and inferential tools such as chi-square and regression analysis to answer the research questions.

This dissertation also enhanced my academic writing and time management skills. Balancing between data collection, analysis, literature synthesis, and writing required discipline and careful planning. One key lesson I learned was the importance of data cleaning, as several responses had to be excluded for being incomplete. I also learned to be flexible, adjusting my expectations and approach based on the practical realities of fieldwork and statistical results. If I were to conduct this study again, I would aim for a larger and more diverse sample to improve generalisability. I would also consider using mixed methods to capture deeper insights from qualitative responses. Overall, this research experience has helped me grow as an independent researcher and prepared me for future academic or professional roles that involve data-driven decision-making, ethical considerations, and strategic thinking in digital environments.