Perceptions and Adoption Trends of Artificial Intelligence in Portfolio Construction and Management in the Financial Services Industry of South Africa

By

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Declaration

I, Zeyn Agjee, hereby declare that this research report is my own work except where referenced and acknowledged for the partial fulfilment of the requirements for the degree of Masters of Business Administration in the Faculty of Commerce, Law and Management submitted to the Graduate School of Business at the University of Witwatersrand has not been submitted previously for any degree at this or another university. It is original in design and execution, and all reference material contained therein has been duly acknowledged.

Student Zeyn Agjee **Date** 22 February 2024

Abstract

The adoption of Artificial intelligence (AI) in portfolio construction promises to revolutionise financial services, offering opportunities to enhance efficiency, foster innovation, and drive disruptive change. This qualitative study investigates the perspectives and adoption trends of AI-driven portfolio construction methods among South African financial services organisations. The research uncovers attitudes, challenges, and aspirations surrounding AI adoption through in-depth interviews with nine industry professionals. The study finds that while there is widespread enthusiasm within the industry for AI adoption in portfolio construction and the industry, professionals express reservations about trust, lack of understanding, data challenges, costs and AI's efficacy in navigating the complexities of the South African market.

The study highlights complexities in AI adoption, including transparency, regulatory compliance, accountability, data considerations, overfitting issues, human-machine interactions, lack of agility in companies and potential job displacement concerns. Despite the increasing acceptance of AI in investment management, significant obstacles persist, necessitating concerted efforts to address problems and cultivate trust and openness within the industry. The paper presents valuable insights into the patterns of AI adoption in South Africa, offering practical recommendations for industry practitioners, policymakers, and researchers. It emphasises the importance of trust-building strategies among industry practitioners, highlighting the need for transparent communication and ethical considerations throughout AI adoption. Additionally, the paper underscores the role of policymakers in developing regulatory frameworks that promote responsible AI integration, advocating for guidelines that uphold ethical principles and protect consumer rights.

Further, there is a call for continued support for research and development efforts tailored to the South African market, aiming to address specific challenges and foster innovation in AI technologies. Overall, the findings emphasise the necessity of collaboration between stakeholders to ensure the ethical and widespread practical adoption of AI in South Africa's financial sector.

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Chapter 1: Introduction

1.1 Background of the Study

Innovative technologies continue to disrupt the world economy, bringing uncertainty and opportunity to most industries across all spheres (Ma et al., 2020). Financial services are no exception, primarily where machine learning (ML) and artificial intelligence (AI), which utilise incredible amounts of machine-readable data to come to decisive conclusions, are concerned (Goodell et al., 2021). By comparison, traditional portfolios generally rely on human "gut" feelings, characteristics and qualitative reasoning (Ta et al., 2020). Through these advancements, companies adopting AI are expected to gain sustainable competitive advantages, which should be reflected in the bottom line, creating wealth and value (Lakhchini et al., 2022). Other works, like that of Santos et al. (2022), support this view of gaining an advantage through AI and ML, wherein these tools have allowed the development of techniques to maximise financial rewards for the investor. As a result, this study explores the perceptions and adoption trends of AI and its effectiveness on portfolio construction to maximise performance in the context of the financial services industry in South Africa.

Artificial intelligence is not a new phenomenon; it began in the early 1950s when researchers were looking to develop machines to mimic or perform the tasks of humans in areas of critical thinking and problem-solving (Osterrieder, 2023). Artificial intelligence relates to science that mimics the human aspect of intelligence, critical thinking, and reasoning. This study sought to understand whether AI-adopted portfolio construction is being utilised effectively and implemented broadly in the South African financial services industry, particularly portfolio construction and management. Understanding the effective utilisation and widespread implementation will shed light on the current AI adoption trends in portfolio construction in South Africa's financial services industry. Furthermore, the financial services industry has rapidly adopted breakthrough technologies such as machine learning (ML) and artificial intelligence (AI), particularly in portfolio construction and management (Osterrieder, 2023). These technologies differ from traditional methodologies, which rely primarily on subjective judgement and qualitative reasoning. Instead, AI and ML use massive amounts of machine-readable data to influence decision-making processes, possibly improving performance and establishing long-term competitive advantages for businesses. This transformational movement not only disrupts old processes but also fosters industrial innovation.

Understanding AI usage in portfolio construction allows organisations to position themselves to capitalise on its benefits effectively, make more informed decisions, and better meet client needs while potentially lowering costs. However, these advantages come with obstacles such as ethical considerations, biases, privacy concerns, and the danger of market manipulation, emphasising the significance of responsible adoption and thorough evaluation of associated risks. As a result, monitoring current trends and the effectiveness of AI adoption in portfolio design is critical for driving strategic planning, stimulating innovation, and assuring the long-term success of South Africa's financial services sector.

Such insights are pivotal for several reasons. Firstly, the study offers an understanding of the industry’s embrace of AI technology in portfolio construction, revealing the extent to which AI is revolutionising traditional practices and driving innovation in portfolio construction and management. Secondly, the study allows for assessing the competitive advantages of firms adopting AI in portfolio construction through more informed decisions, better meeting client needs, and driving down costs. Further, the research provides insights into any inhibiting factors of widespread AI adoption and the future of portfolio management.

The study also helps inform strategic planning for financial services and policymakers to foster responsible adoption of AI in the industry. Another critical consideration is that given that AI or ML is not a new phenomenon, there is a need to find out how deeply and widely AI and ML are utilised in portfolio construction versus the traditional portfolio optimisation methods in the financial services sector of South Africa. This qualitative study of professionals' perceptions and adoption trends investigates what circumstances accelerate its use or hamper progress. One must take advantage of the financial revolution in AI or be at a loss (Lakhchini et al., 2022). Investing has become a societal need to create wealth and move humankind forward (Ma et al., 2020).

There has not been a greater need for portfolio optimisation and asset allocation strategies to care for these needs using technologies to make quicker, less costly, and more effective decisions through AI (Santos et al., 2022). The benefits of AI and ML also bring challenges in that there are multiple considerations, including ethical questions, bias, privacy concerns, trust and market manipulation (Osterrieder, 2023).

1.2 Overview of Artificial Intelligence in the Financial Sector

Artificial intelligence and its innumerable uses are currently trending topics in the financial service sector, with endless possibilities if better understood (Golić, 2019). There is the suggestion that the financial sector will struggle to operate without algorithms and technology due to the volume of data fed through the system (Chui, 2017). Studies show their use has outperformed the S&P 500 index regarding higher returns over time (Ta et al., 2020).

Understanding how AI continually transform is critical. The current use of chatbots and AI-generated assistants allows more personalised services in the financial industry, which continues to differentiate service delivery. Quantitative trading allows AI to be helpful in that, by its nature, it can perform better and faster data analytics than humans (Golić, 2019). There is a need to manage this risk. Artificial intelligence can allow multiple scenarios to help predict situations and identify trends and risks to plan more efficiently. Given the financial services sector and its volume of sensitive data, there is a need for ramped-up fraud and cybercrime detection. It is a crucial concern; AI could help provide more security features (Golić, 2019).

In South Africa, the extent of AI adoption in the financial services sector remains relatively unknown. While there are instances where AI technologies are being employed, such as chatbots and AI systems for data analysis, pattern recognition, and portfolio design, complete statistics on their general acceptance and integration across the industry may be lacking. This highlights a gap in current research and underscores the need for further investigation to understand how extensively AI is being utilised within the sector (Services et al., 2016). Challenges like current regulatory alignment are not aligned with the requirements of the digital age to fully leverage the benefits of technological advancements and help reduce transactional costs (Bartram et al., 2020). The authors further mention that AI strategies' “superior” performance may be arbitraged away soon to increase adoption. The authors also highlight data challenges like transforming raw data into appropriate formats for the AI models to function, the sensitivity to data and the historical nature of past data not reflecting future trends. These challenges, cost considerations, and human supervision underscore the complexity that asset managers need to address when adopting AI (Bartram et al., 2020).

While the article does not directly address South Africa, the insights and recommendations remain relevant for understanding the broad challenges of implementing AI in portfolio construction in various regions, including South Africa. A study done closer to home suggests other limiting reasons for limited AI adoption in South Africa's financial services (Matsepe & Van der Lingen, 2022). Limitations include companies expressing doubt about the feasibility of AI due to its complexity, thus reducing confidence in its adoption. There are concerns about job losses coupled with cyber security issues that also suggest hindrances in the adoption of AI (Matsepe & Van der Lingen, 2022). The writers further suggest scepticism and reluctance to adopt AI and ML due to a perception of under-delivery and misunderstanding of these technologies.

Overall, the financial sector in South Africa is gradually embracing AI in various aspects with the perceived benefit of improving efficiency, optimising portfolio performances, increasing profitability, gaining a competitive advantage, enhancing customer experiences and reducing risks; however, there is a lack of mass adoption. The study focuses on the perception and adoption trends of AI in South Africa's financial industry and whether its impact on portfolio construction to optimise performance through asset allocation strategies is working. The study examines whether AI technologies are widely adopted to improve portfolio performance decisions and the perception of AI used by the industry to construct these portfolios in the South African context. The research focuses on adopting AI in portfolio optimisation, comparing its performance with traditional optimisation methods. The study aims to understand the potential benefits and limitations of perception and adoption trends of AI-driven portfolio optimisation. It also seeks to provide insights into the considerations for effective portfolio optimisation and how readily it is being adopted in South Africa in the true sense of the word.

1.3 Research Problem

The integration of Artificial Intelligence (AI) into portfolio construction and management processes holds the promise of enhancing efficiency and optimizing wealth for investors. However, it remains unclear to what extent South African (SA) asset managers are leveraging AI technologies to maximise investor wealth. This uncertainty persists despite the known challenges associated with traditional portfolio construction such as high service costs and delays in real-time info which hinder the consumers' ability to receive optimal advice to grow portfolios (Ma et al., 2020).

Recent studies have shown that advanced algorithms have shown that cutting out the middleman reduces costs to transact and improves the overall financial ecosystem (Ahluwalia et al., 2020). Other scholars like Santos et al. (2022) discuss various AI techniques such as fuzzy techniques, deep learning, and evolutionary algorithms, in portfolio management showing the multitude of techniques advancement in this era.

Despite current trends favouring research on techniques like Reinforcement Learning (RL) and neural networks, particularly in stock-based portfolios, there remains a gap in understanding the qualitative aspects of AI adoption in the financial industry. This includes professionals' perceptions of AI, its actual adoption rates, and whether AI-driven strategies are actively implemented or remain theoretical concepts such as “paper portfolios” (Santos et al., 2022). Overall, scholars are making significant contributions to AI-driven optimisation by exploring all these different models and financial data. However, there are multiple tests of these models quantitatively and comparing which is the best models in which circumstances there is not much research on the qualitative aspect in terms of given all these benefits what is happening in the industry, how professionals perceive it, and is it fully adopted and what will take it forward in terms of the people steeped in the industry to adopt in particular emerging markets like South Africa.

Furthermore, the limited inclusion of non-conventional assets like cryptocurrencies and commodities in AI-driven portfolio optimization raises questions about the broader applicability of AI across diverse asset classes. (Santos et al., 2022). This limitation then begs the question of why there would be widespread adoption in the financial services sector if there are limitations to deriving the best-performing weighted portfolio with the least risk if AI is only associated with stock and not other asset classes. Issues such as defining AI's boundaries, replicating human intelligence, and tailoring AI applications to specific financial domains, as noted by Stahl (2021) and Lackchini et al. (2022), pose additional challenges. By highlighting the importance of these specific domains, the authors emphasise the significance of tailoring AI and ML applications to address the unique challenges and opportunities present in different sectors of the financial industry. With a target focus, one can lead to more impactful implementations of AI and ML in finance, benefiting practitioners and organisations in this sector. Pinpoint accuracy focusing on an emerging market like South Africa can further enhance focus.

Moreover, reliance solely on historically based techniques and data may restrict progress and adaptability, leading to concerns about market shifts, overfitting, and a lack of robustness in AI-driven strategies (Ta et al., 2020). While historical data is critical to building predictive models and understanding trends, relying on it solely can limit progress (Ta et al., 2020). Some limitations are adaptability, especially in market shifts, overfitting, where the machines trained struggle to perform when new data is added and a lack of robustness, as mentioned by the writers. Contrary to the multitude of benefits AI offers, there are challenges and possibilities of instantly unsettling markets due to privacy issues, market manipulation, distrust, and unethical behaviour. These factors are why a transparent, solid regulatory framework may need to be developed in the financial services industry (Njegovanović, 2018).

Addressing these gaps in the literature, this study aims to investigate the perceptions and adoption trends of financial professionals in South Africa regarding AI's role in portfolio construction and management. Specifically, it seeks to assess the current level of AI adoption, factors influencing adoption rates, and perceived benefits and challenges associated with integrating AI technologies into portfolio management practices within the SA financial services sector.

1.4 Statement of Purpose:

Artificial intelligence (AI) is revolutionising the financial industry by transforming portfolio optimization and asset allocation strategies (Golić, 2019; Santos et al., 2022). However, the extent to which AI is adopted, and the factors influencing its adoption in South Africa remain relatively unexplored.

This study aims to investigate the perceptions and adoption trends of AI-driven portfolio construction methods among financial professionals in South Africa. By understanding these perceptions and adoption trends we will hope to uncover valuable insights into the role of AI in portfolio construction and management in the financial services industry of South Africa.

1.5 Research Questions

This study aims to address the following research questions:

RQ1: What is the perception of the impact of AI-adopted portfolio construction on portfolio efficiency compared to traditional portfolio construction methods in the financial services industry in South Africa?

RQ2: What are the key barriers and challenges facing South African financial services companies in adopting AI-driven portfolio construction methods, and how do they impact adoption rates?

RQ3: How do perceived usefulness and ease of use impact the intention to adopt AI-driven portfolio construction methods among South African financial services companies?

RQ4: What are the current perceptions and attitudes of financial professionals in South Africa's financial services industry towards adopting AI-driven portfolio construction and management methods?

1.6 Research Objectives

Objective 1: Assess perception of AI-adopted portfolio construction's impact and adoption trends on portfolio efficiency within the South African financial services industry in contrast to traditional portfolio construction methods.

Objective 2: Identify and analyse South African financial services companies' key barriers and challenges in adopting AI-driven portfolio construction methods and assess their impact on adoption rates.

Objective 3: Investigate the influence of perceived usefulness and ease of use on the intention to adopt AI-driven portfolio construction methods among South African financial services companies.

Objective 4: Examine the current perceptions and attitudes of financial professionals within South Africa's financial services industry towards adopting AI-driven portfolio construction and management methods.

1.7 Justification/Rationale of the Study

The growing importance of AI in the financial industry allows for early adoption since the industry is far more advanced digitally (Golić, 2019). There is a need to understand AI's impact on portfolio optimisation and asset allocation strategies to afford better customer services and lower costs (Golić, 2019). This importance points out that benefits will be gained by utilising AI and ML technologies. The financial industry faces increasing competition, and effective portfolio optimisation strategies are essential to staying ahead. One of the primary considerations and drivers towards the fifth industrial revolution is the so-called AI revolution, which drives customisation and customer services (Golić, 2019). Personalisation and experience will be central to how the consumer reacts and adopts, hence the AI. The study will explore the perceptions and adoption trends of AI in portfolio construction and management in the financial services industry in South Africa.

Therefore, the study provides valuable insights into the adoption trends of AI on portfolio optimisation strategies in South Africa's financial industry and its impact on performance. The findings will help with policy decisions as understanding the risks and benefits through this knowledge can assist policymakers in responsibly guiding regulatory framework. Other benefits to this study for the practitioner are that it will allow insights into AI adoption, help make better-informed decisions, and address concerns in fast-tracking AI adoption and optimisation of portfolio construction. The additional possible contribution to scholarly works can help contribute to the existing literature by firstly just the nature of being qualitative as opposed to the majority of literature around quantitative analysis of AI in financial services, which is a contribution on its own. Secondly, it explicitly examines AI adoption in South Africa, which has challenges and opportunities, especially concerning the scarcity of AI in the emerging market sector.

1.8 Delimitations of the Study

Industry: This study focuses on the financial services industry in South Africa, specifically asset management firms, investment banks, and entities involved in portfolio construction. The decision to focus on this industry is driven by the growing trend of adopting AI-driven methods for portfolio construction within financial institutions globally, including South Africa. The financial services sector plays a pivotal role in the South African economy, making it a pertinent subject for research. By delving into this sector, the study aims to provide a focused analysis tailored to the unique challenges and opportunities in the South African financial landscape. Given the complexities and nuances within different sectors, limiting the study to the financial services industry ensures a focused analysis that can provide actionable insights relevant to this context. The study was limited to the financial services industry that has or is considering adopting AI-driven methods for portfolio construction in South Africa.

Limited scope of analysis: The qualitative analysis of this study primarily explores the perspectives, experiences and insights of a select group of financial services experts or AI-driven professionals who may not consider other stakeholders' views and opinions. While these professionals may possess invaluable insights and expertise, they may not capture the viewpoint of investors, regulators and clients.

Sample size: The study is limited to local SA companies, which could result in a small sample size. The sample may also be homogenous because it will be limited to financial services companies in South Africa that have adopted AI-driven portfolio construction or intend to adopt AI. The relevance of focussing on South African and local entities is that these companies are subject to specific regulatory environments, economic conditions and market dynamics, allowing a more profound understanding of the challenges and opportunities unique to the context. Secondly, there is accessibility to data and resources that are more readily available than international counterparts. Also, this sample helped reduce barriers such as language, time zone, and any other expenses to collecting data within the constraints of the timeline.

1.9 Definitions of Key Terms and Concepts

Artificial Intelligence (AI): AI is a system that exhibits intelligent behaviour by analysing its environment and performing actions with a certain extent of autonomy to accomplish predetermined objectives (Sheikh et al., 2023). The definition of AI is crucial as it is the primary focus of the research. The study aims to explore the impact of AI adoption on portfolio construction in South Africa's financial services industry.

Machine Learning (ML): Machine learning is a dynamic field of computing algorithms that aim to mimic human intelligence by acquiring knowledge from the surrounding environment (El Naqa & Murphy, 2015). ML is a subset of AI designed to enable algorithms to learn data and improve performance over time. The relevance of ML is how it can explore the optimisation of investment decisions by analysing large sets of financial data.

Portfolio Optimisation: Portfolio optimisation determines the best asset combination based on predefined criteria. The aim could include maximising return, minimising risk, or both (Gunjan & Bhattacharyya, 2023). The relevance of the study will be comparing AI-adopted portfolios to traditional ones.

Asset Allocation: determines and maintains a portfolio's relative asset class weights, determining when and how much to invest (SINGLETON, 2013). Asset allocation is relevant because it is crucial to understand how portfolios are managed and constructed, significantly where sophisticated algorithms are used to optimise asset allocation decisions.

Financial Services Industry: Financial services encompass a wide range of activities, such as banking, risk management, capital markets, mutual funds, insurance, venture capital, consumer and corporate finance, as well as the technologies employed in the production, distribution, and regulation of these services (Gunawardane, 2023).

Traditional Portfolio Optimisation Methods: Classical approaches like the Mean-Variance model are utilised in portfolio construction to minimise risk and maximise return on investment without using ML-based techniques. (Gunjan & Bhattacharyya, 2023).

AI-driven optimisation: Using artificial intelligence techniques or “intelligent” approaches, such as machine learning algorithms, neural networks, and reinforcement learning, to optimise portfolio selection and asset allocation strategies decisions (Gunjan & Bhattacharyya, 2023).

1.10 Structure of the Dissertation

This paper is structured to include:

Chapter Two: Literature Review- The discussion will be around the existing research and theories related to the impact of AI and ML on portfolio optimisation and asset allocation strategies in the financial industry.

Chapter 3: Research Methodology- This chapter will explain the research design, data collection methods, and data analysis techniques used in the study.

Chapter 4: Presentation of Research Results - will show the study's findings and discuss the results in detail.

Chapter 5: Discussion of Research Findings - Interpreting the results and drawing conclusions based on the findings.

Chapter 6: Conclusion, Limitations and Recommendations - Summary of the main findings and implications of the study and suggested directions for future research.

Chapter 2 Literature Review

2.1 Introduction

The literature review will systematically provide an empirical view to establish credible evidence by contextualising previous problems. It will further aim to identify gaps in the proposed research and whether they have been sufficiently addressed. This understanding will direct what further research is proposed on AI and its impact on the financial industry relating to portfolio construction. The second part of the review will focus on developing a conceptual framework that these studies highlight to correlate the relevance to this study. The structure of this chapter will show the purpose of AI in portfolio construction and the related benefits and challenges it poses.

Ultimately, the review will provide the framework to answer the question of AI's perceptions and adoption trends in portfolio construction and management in the financial services industry. This systematic literature review aims to establish the lineage and context and critically evaluate how the topic is relevant, highlighting any limitations of the proposed research. The paper will follow a thematic format.

2.1.1 Impact of AI on Portfolio Construction in the Financial Services Industry

Artificial Intelligence and the idea of whether a computer can perform the functions of humans date back to the 1950s when Alan Turing proposed the concept of the "Turing test". This test established whether a computer could think like a human (Gillis, 2023). Years later, through evolution, it is noted that the financial services industry has embraced ML, which is relatively highly adopted (Chui, 2017). Writers also suggest that the financial services industry, which constructs portfolios to deliver on the modern portfolio theory, is prudent (Fabozzi et al., 2008). There is a view that AI can significantly impact portfolio construction in finance, ultimately leading to efficient portfolio optimisation (Ouyang, 2022). The author suggests that in the study, ML methods show promising results in predicting returns and helping investors solve practical issues like timing, selection, and risk (Ouyang, 2022).

Firstly, to understand the impact of AI on portfolio construction, one needs to understand what a portfolio is and the management thereof. An accepted definition of a portfolio is a basket of investment assets (Ta et al., 2020). Portfolio management involves decision-making using strategic tactics to maximise returns for investors (Ta et al., 2020). Artificial intelligence can deliver on this premise because AI can pull information from different sources, albeit images, online posts, and unstructured sources, which humans do not do quickly (Bartram et al., 2020).

This results in less manual intervention or processing, saving time and money (Bartram et al., 2020). This risk-return relationship, or should it be noted, the "efficient relationship", is supported in the works of Santos et al. (2022), where the researchers show a positive correlation that AI plays in reducing risk and maximising returns. Artificial intelligence ultimately improves decision-making and identification of opportunities (Paraphrase from OpenAI's ChatGPT AI language model, personal communication, February 27, 2023).

Literature studies highlight that ML can learn quickly via different acceptable methods (Mammeri, 2019). These include deep learning and reinforcement learning, which comprises supervised, semi-supervised, unsupervised and reinforcement learning (Santos et al., 2022). Osterrieder (2023) also agrees that ML is classified into these categories; however, he argues that its success depends on the integrity of the data and the quality used in training. The adage rings true in "garbage in, garbage out" and how AI can develop filters that mimic human intelligence without biases or limitations. One of the biggest challenges in portfolio construction is optimising an investment portfolio, minimising risk, and creating an optimal investment performance (Koratamaddi et al., 2021). Further limitations are the overfitting aspect, which may lead to instability, the randomness of selection in portfolios and higher risk from the investment (Ouyang, 2022). These limitations suggest that applying AI and ML in portfolio construction presents challenges, especially in noisy and dynamic market environments.

Mentioning portfolio management in the current era would not be complete without the term "robo-advisor"(Njegovanović, 2018). These complex algorithms measure risk profiles and financial targets. The "robo-advisors" allow large amounts of trading to occur daily in real-time, providing better growth opportunities for investors (Njegovanović, 2018). The opportunity these algorithms provide is not without limitations. They allow for abuse since they can only offer real-time trading on the open market. The primary risk associated is societal ill, like market manipulation and compliance challenges available to abusers, since these anomalous behaviours may only be picked up months later (Njegovanović, 2018). These opportunities will continue to play out among the various asset management functions.

The overarching characteristic of AI in portfolio construction is that these models are objective and significant at tasks involving repetition and pattern identification that humans do not fare well with (Bartram et al., 2020). Artificial intelligence in portfolio construction tends to yield better and more accurate outcomes for the investor, according to Bartram et al. (2020). The financial services industry and portfolio constructions are data-driven and complex environments. These studies present a compelling argument for AI's significant impact on portfolio construction in the financial services industry and that it will continue since investors ultimately consider high returns with minimal risk. The assumption is that it does not have restrictive assumptions, allowing easier identification of asset classes to invest in (Bartram et al., 2020). The writers mention that studies have found that the resultant optimisation allows for more asset weighting to those stocks with high alpha and the converse. Osterrieder (2023) confirms that portfolio construction can be optimised by training AI algorithms by deducing the outcomes of various factors like risk aversity, market conditions, and goals. The future is now, and these opportunities presented are exciting for what AI can do in the financial services industry.

Machine learning, a subset of AI, can learn and develop on datasets (Goodell et al., 2021). The article highlights how deep learning addresses or can help address these complex situations, providing suitable options. The writers argue that AI and ML are transforming the finance industry through data analysis, data entry and service automation, and risk management. In its application to finance, Goodell et al. (2021) note that interpretability, data quality and bias may pose significant limitations and ethical and regulatory concerns. Despite these limitations, deep learning algorithms can adapt; hence, optimising portfolio construction through multiple trading strategies is a viable option for using AI (Osterrieder, 2023). Due to its computing capabilities, this deep learning methodology is considered the best way to utilise AI in constructing portfolios (Heaton et al., 2017). Deep learning has its merits; however, it is not the only tool AI can adopt. The following paragraph highlights other methods of commonly used AI practices.

Apart from deep learning, other commonly used AIs in asset management are ANNs and RNNs, LSTM networks, decision trees, LASSO regression SVMs and others (Bartram et al., 2020). Obeidat et al. (2018) suggest that ANNs, RNNs and LSTM networks can produce better and more efficient risk-managed profiles than traditional passive approaches. The paper provides a context of empirical studies showing that diversified equities and bonds outperform standalone equity portfolios. Due to its non-passive nature, AI can assist in improving these risk-adjusted returns in portfolio construction (Obeidat et al., 2018). Machine learning ultimately benefits portfolio construction, according to Snow (2020). The article further highlights that AI is a critical driver of portfolio construction where consideration of asset allocations and weight optimisations can partially replace traditional methods (Snow, 2020).

Goodell et al. 2021 also highlighted that ML is adaptable to analyse extensive data and pattern identification, which can inform decision-making, risk management, and fraud detection. These literary works highlight the need for AI and its associated benefits and limitations in the financial services industry, particularly portfolio construction.

Snow's (2020) words resonate that AI can "partially" replace the traditional approach. The impact of AI on asset allocation in portfolio construction comes with various challenges and benefits. Some common challenges highlighted from the studies of Chui (2017), Heaton et al. (2017), Njegovanović (2018), Golić (2019), Karlíček (2021), Goodell et al. (2021), Ouyang (2022) and Osterrieder (2023) are:

- **Data quality**: AI algorithms rely heavily on high-quality data; however, financial data can be inconsistent, noisy, and open to errors and interpretations. This noise is where AI sees "black boxes" in that they are complicated to interpret.
- **Regulations**: since artificial intelligence in asset management is relatively new, there is limited regulatory guidance.
- **Human biases**: artificial intelligence can perpetuate human bias if the training from the data already has a bias.
- **Implementation costs**: AI requires significant investment in infrastructure, data management and human resources.
- **Lack of interpretability**: Some AI, like deep neural networks, are difficult to interpret, making the decisions challenging to understand as to why they were made, as one cannot possibly explain the rationale behind the decisions made by these models.
- **Model overfitting**: this is where the AI model fits the training data so closely that it cannot generalise to new data.

Therefore, one needs to empirically review the literature to ascertain why and whether AI can and will completely replace the traditional classical approaches, considering the continual evolution of AI.

2.1.2 Benefits and Challenges of AI in the financial services industry

In the twenty-first century, artificial intelligence is viewed as a global disruptor in almost every industry (Bartram et al., 2020). The authors further suggest that AI can improve various aspects of asset management, especially regarding asset allocation, portfolio optimisation and risk management (Bartram et al., 2020). There is much support that it has become and will continue to be a dominant technology in recent years and continue transforming industries (Hilpisch, 2020). With this said, AI is not new, and one must argue, “Why is there a sudden explosion?”. Artificial intelligence and machine learning have arguably been used for decades, yet there is a current obsession with this technology (Osterrieder, 2023). The question is still, why the explosion and why now? Through the literature research, this research paper will help provide insights and possible answers to these questions.

Market-leading companies like Google, Microsoft and Amazon have a fundamental common approach to ensuring competitive advantage; that is, they continue to invest in AI and ML (Lakhchini et al., 2022). The financial services industry is prime for the AI revolution. It is at the forefront of this disruption due to its early adoption of newer computer technologies (Lakhchini et al., 2022). Other works, such as Golic (2019), support the same notion of early adoption in the financial sector. The belief and justification for this opinion are that this sector is generally digitally advanced and supports significant volumes of data. Analytical ML methods are in use, and we understand that AI can provide better performance at a lower cost to serve (Golić, 2019).

The current trend is that many financial service industry companies use AI to trade and manage their platforms to gain an advantage (Bartram et al., 2020). The writers suggest that AI can be helpful in asset allocation and portfolio construction by reducing biases of human analysis and creating more accurate predictions. Bartram et al. (2020) further argue that AI can help asset managers minimise the risk through pattern identification and relationships in big data that may be difficult for humans to detect (Bartram et al., 2020). The caveat that Bartram et al. (2020) warn against is that there needs to be careful consideration of the quality of data, which models are selected, and human oversight to ensure the proper use of AI in asset management. Osterrieder (2023) explains that his drive and surge have resulted from the evolution of "big data" and computer power, making AI far more valuable now. The authors continue to recognise the impact of AI on helping transform the financial industry as the technology matures. Secondly, the volume of data available to help simulate and train AI has increased exponentially since early use decades ago, with algorithms being freely available and easily accessible.

There is a common thread and consensus that AI can help improve returns by applying ML over traditional portfolio management techniques due to its limitations (Bartram et al., 2020). Golic (2019) suggests that AI has the potential to significantly outperform traditional methods, especially since AI can analyse vast data, recognise patterns that may be hidden, and lead to greater accuracy in predictions of outcomes. The author also notes that the traditional approach has a place or role in finance and leans towards a more hybrid approach combining the strengths of AI and traditional methodology for effectiveness. Another study by Jain and Jain (2019) compares ML portfolios with traditional risk-based ones, finding that ML can outperform traditional in certain instances. ML can identify nonlinear patterns that traditional may miss; however, caution that there must be an account for covariance misspecification when using ML approaches (Jain & Jain, 2019). The authors suggest that both ML and traditional approaches have strengths and weaknesses and should be used to improve the performance of portfolios, also agreeing with Golic (2019).

Novick et al. (2019) also highlight the benefits of ML and AI techniques regarding efficiency, risk management, and decision-making compared to traditional approaches; however, they also suggest that human oversight and expertise can never be discounted. Bartram et al. (2020) further suggest that AI can yield higher returns and limit risk versus traditional classic portfolio methods. If this premise holds, one can deduce that at the end of the day, the financial industry and portfolio management exist to deliver superior returns. If AI can deliver, why not utilise it? The limitations and challenges of AI in terms of data quality, interpretability, and overfitting seem contentious (Bartram et al., 2020). AI-based portfolio construction shows promise in outperforming traditional methods where the data shows non-linearity, high dimensional and non-normality; however, there seems to be no clear consensus on whether it can be achieved consistently (Karlíček, 2021). The writer further highlights the effectiveness; however, he mentions that it can work in all market conditions and depends on the quality and quantity of data, which algorithm is used, and the skill of the portfolio manager interpreting this information.

The AI revolution drives the fifth industrial revolution in that customer and consumer satisfaction is at the epicentre with bespoke solutions (Golić, 2019). One would question that these benefits must be aggressively adopted; however, why is it not wholly consuming the industry? Where are the challenges, and what is the real impact? Koratamaddi et al. (2021) throw another dynamic into the mix, suggesting that AI can better incorporate market sentiments, resulting in improved decision-making than traditional methods; however, it also highlights the need for quality data, algorithm design and complexity of the problem. This review of the literature will discuss AI's impact on portfolio construction, particularly in the financial services industry.

2.2 Empirical Review of Literature

Prior literature shows that AI has evolved in efficient construction portfolios, particularly ML. Various AI model applications and uses are identified through the systematic review of over 50 articles. A critical review of whether AI is still in its infancy and what the research on AI on portfolio construction in the financial services industry is. The findings of the empirical review of the literature are discussed in detail below:

2.2.1 AI Trends in Asset Management

There has been an upward trend in articles and publications using AI and ML in portfolio management, particularly over the last eight years (Ahmed et al., 2022). The article shows that AI and ML techniques have increasingly been applied in asset allocation and portfolio construction. Some AI trends in asset management include alternative data usage like social media and satellite imagery to help inform decisions (Goodell et al., 2021). There seems to be an increase in the use of intelligent algorithms to help address the complexities of modern markets and portfolio optimisation (Ouyang, 2022). These trends greatly emphasise ML and AI in portfolio construction and investment-making decisions. These are not without limitations, which also show the instability of the models, performance issues and the overfitting aspect, which may result in unstable, random and biased training results dependent on the Ml method used.

The other noted highlights are the Robo-advisory services used to personalise recommendations based on individual risk and goals. Natural Language Processing (NLP) is also used to analyse news articles, unstructured data sources and sentiment analysis to help investment decision-making processes. The areas found to outperform traditional approaches have been the areas of risk management and optimisation (Ahmed et al., 2022). The use of AI is relatively new and lacks regulations in the financial industry, according to Osterrieder (2023). This finding will impact the rules and regulations of the future. Osterrieder (2023) further highlights the need for transparency, which is crucial for ethical deployment, including data privacy and security.

Novick et al. (2019) believe that AI will remain essential for managing assets since it will potentially mitigate risks, reduce costs, and improve client outcomes. The writers further note a lack of transparency issues, making understanding how AI algorithms make decisions difficult. Lakhchini et al. (2022) acknowledge that AI will be the driving force; however, they argue that AI still needs data and innovative scientists' involvement in evolving. Even with the need to evolve, Novick et al. (2019) suggest that the societal gain from AI will allow better access to information and financial markets to select risk-appropriate portfolios. Novick et al. (2019) suggest that AI can positively revolutionise portfolio construction and decision-making performance. This gain will benefit the investor as well as the investment company. This view is also supported by Ahmed et al. (2022) in that the researchers confirm that ML significantly increases stock prediction compared to traditional approaches. The researchers highlight that traditional models are limited and cannot solve nonlinear problems, making AI an upward-trending technology (Ahmed et al., 2022).

Through the application, deep learning (DL) has shown positive results in the automation of constructing portfolios through training on historic stock performances (Koratamaddi et al., 2021). The writers suggest that AI allocation can be constructed using the Markov Decision Process (MDP). The benefit of using MDP is that it integrates multiple steps into one decision-making process. This integration is in line with a human-like investor that has the potential to overcome traditional challenges (Koratamaddi et al., 2021). The article further highlights the issue with scaling due to the magnitude of data required for most real-life situations, providing complexity and issues with rational thinking. Data integrity and quality are critical to ensure fewer errors and fewer risks for adopting AI (Novick et al., 2019).

To continue developing and innovating AI, the writer suggests that more robust regulatory practices must be established to help limit and prevent market manipulation and data security breaches (Njegovanović, 2018). Machine learning is better suited for analysing more extensive and liquid stocks (Gu et al., 2020). The paper also presented that stock liquidity, risk, and value ratios are significant indicators in portfolio management. This view begs the question of whether AI can consistently outperform traditional methods.

2.2.2 AI techniques to outperform traditional methods in portfolio construction

Quantitative and traditional methods are two standard portfolio management methods (Ta et al., 2020). In the study of Zhang et al. (2017), the researchers cite that hybrid methods in AI allow for better-performing portfolios; however, they suggest that these are not utterly superior to alternative methods. The study uses AI to measure outcomes in portfolio construction, specifically spectral clustering (SC). The conclusion is that AI techniques outperform traditional approaches; however, to what degree is it necessary to make it material? In their study, Bartram et al. (2020) also conclude that AI can improve traditional strategies. The various AI techniques include ANNs, cluster analysis, decision trees, evolutionary algorithms, LASSO regressions, SVMs and NLPs. The writers concluded that AI could better manage risk profiles with greater returns than traditional methods. Other writers like Ouyang (2022) suggest that AI and ML potentially outperform traditional portfolio construction methods, as the writer found that portfolios using support vector regression and neural networks outperform the Dow Jones Index. The writer firmly uses this statement and mentions that it depends on factors like quality data, algorithm choices and the environment in which it operates.

Further, AI can be utilised in portfolio construction to meet yields better than traditional methods (Bartram et al., 2020). Machine learning (ML) performs well and recognises patterns far better than traditional approaches (de Prado, 2020). The writer further argues that the Markowitz efficient frontier or derivatives of this model have been the go-to approach for ages. The limitations highlighted that these solutions succeeded in simple optimal approaches but have performed subpar in out-of-sample environments. In another article, Goodell et al. (2021) agree that the potential of AI and ML can outperform traditional methods as these ML algorithms can analyse big data sets and identify patterns and trends that may not be apparent to humans when analysing the same data. Once again, it is suggested with a caveat depending on proper implementation and ongoing monitoring as the risk of biases and inaccurate results could be the result (Goodell et al., 2021). Historically, these traditional approaches to measuring the market through personal experiences proved to work; however, this is no longer true in this era of the speed of transactions and the explosion of market size (Strader et al., 2020).

Strader et al. (2020), the writers argue a thought-provoking view about AI and the zero-sum game. The writers suggest that if machine learning AI exponentially outperforms traditional predictions, all advisors or investors will use it. This situation will result in no better returns than the other; hence, there is limited information sharing between larger firms and the rest. This viewpoint begs multiple questions. What would be a competitive advantage or unique value proposition if there is total reliance on AI in portfolio construction and everyone successfully relies on it?

2.2.3 AI Identification of complexity in Portfolios to outperform Markowitz model

The Markowitz model, or the Modern Portfolio theory, is a framework for constructing diversified portfolios based on the risk and return trade-off (Bechis, 2020). Another hypothesis is whether AI could benefit the Markowitz (1952) model (Karlíček, 2021). The writer also believed ML could identify complex patterns through prediction and outperform classical portfolio construction approaches. One of the study's drawbacks was that return prediction did not provide enough comfort regarding its accuracy; hence, there could be a drawback regarding how many equity shares should remain in the portfolio. However, the study confirmed that the 1/N approach was great at risk diversification. A gap provided in the study showed that ML techniques were primarily examined separately in the construction of portfolios. Karlicek (2021) highlights the study of group or clustering shares and how this will impact the construction of a diversified portfolio. The findings showed that clustering helps diversify portfolios; however, it failed to show the benefit of ML in mean-variance optimisation (MVO). The researcher offered a possible flaw in that there were errors in return predictions; hence, further research could look at and improve this.

There is an opinion on a standard portfolio construction comprising equities and bonds viz 60% and 40 %, respectively (Zhang et al., 2020). Artificial intelligence can help formulate portfolio management techniques using quantitative data and textual analysis to improve the classically constructed portfolio (Bartram et al., 2020). The argument as to why this is possible relates to multiple factors: Bartram et al. (2020) argue that the advancements in computer processing power currently make AI a feasible option. Secondly, data hygiene and volume have allowed AI to be trained over the last decade. Finally, AI and its uses keep improving without the need for scientists, and they are readily available. The study also points out that the following AI techniques are currently the most utilised, namely ….. "ANNs, cluster analysis, decision trees, evolutionary (genetic) algorithms, LASSO regression, SVMs, and NLP" (Bartram et al., 2020).

Artificial intelligence helps estimate returns and covariances more significantly than the classical, traditional methods (Bartram et al., 2020). The limitations highlighted by Bertram et al. (2020) suggest that AI poses challenges due to poor data quality or complexity for human interpreting, resulting in systemic failures. The solutions suggested incorporating AI to suggest risk-return estimates and use it in traditional models. It also suggests using nonlinear out-of-sample techniques to generate better asset weighting for optimal portfolios (Bartram et al., 2020). Overall, AI potentially outperforms traditional approaches; however, there seem to be many theories, but which is the best? Multiple gaps identified below can allow for greater acceptance of AI in portfolio construction should they be suitably addressed.

2.3 Summary and Gaps in the literature

Firstly, AI still seems theoretical, relying too much on specific conditions to make meaningful assumptions. More innovative thought needs to be developed, which can be theoretical and provide meaningful economic practices (Zhang & Chen, 2017). Njegovanović (2018) does not explicitly list gaps; however, it mentions areas where the studies can focus research on better understanding how AI algorithms make decisions and develop more accurate models to predict financial outcomes. Golić, Z. (2019) highlights a lack of studies evaluating AI's performance in "real world" financial applications. Addressing these gaps is critical for successful integration into the financial sector. The practical approach and finding a purpose to extract economic benefit will lead to investors' and financial advisors' acceptance. The gap in the research shows a realistic economic view of how AI can primarily be utilised to achieve the objective of the modern portfolio theory. Simply put, risk versus reward optimisation moves away from theoretical research.

Secondly, another distinguishable gap relates to the limiting situational analysis in that specific articles look at AI in portfolio management; however, these are done on only smaller sample sets or emerging markets lacking proof of efficiency for comfort (Bartram et al., 2020). The limited sample size generalises findings (Jain & Jain, 2019). The authors argue that existing studies do not count for covariance misspecification, leading to inaccurate portfolio optimisation and suboptimal performances. The writers also suggest that studies do not take the impact of transaction costs in determining the portfolio performances, which can have a material impact on the AI-based portfolio's feasibility in the "real world". There is a need for conclusive evidence and proof that AI will outperform traditional methods categorically, not just on small sample sizes, to generate mass adoption. Other authors like Karlíček, O (2021) also highlight that this limitation of sample sizes leads to the generalisability of findings.

Thirdly, many articles use statistical series analysis to analyse historical techniques, limiting future performances (Ta et al., 2020). Comparing outdated information and not tracking against live current measurements creates a theoretical approach of "if and then" scenarios. Bartram et al. (2020) suggest that there is no doubt that significant AI research in asset management has been done; however, the interpretability of these AI models and their ethics, together with regulatory issues, need to be addressed. The writers also stress that the impact of data quality and quantity and the biases in using AI in asset management are gaps that need addressing. Ouyang Z (2022) also provides the context in that the study considers a limited number of input variables for ML, which may affect results. These assumptions further leave unanswered questions to look to a more comprehensive understanding of the potential of ML algorithms to help predict stock returns.

Fourthly, the deep learning (DL) application is found extensively in articles; however, it is used to predict stocks' potential benefits with little attention to constructing efficient quantitative portfolios (Ta et al., 2020). Karlicek (2021) argues that the proposed model seems practical in the cluster and picking stock; however, errors in return predictions, estimates means, and covariances eroded gains in portfolio optimisation. Santos et al. (2022) highlight that despite the significant number of hybrid models, RL algorithms have little use in conjunction with other techniques. The writers cite that the gap lies in DL combined with RL or other revolutionary AI in portfolio performances. Santos et al. (2022) suggest examining how AI affects conventional asset classes like virtual currency and other commodities. Research papers have been adopting a narrower focus on AI in the field; there seems to be a gap in works comparing different ML capabilities in specific applications (Lakhchini et al., 2022). ***Finally***, AI may require significant investments which may not be accessible to all traders, thereby limiting competition and benefiting huge cash-flush investment companies (Osterrieder, 2023). Studies like that of Manrai et al. (2022) do not directly address setup costs; however, there is a need to consider this a significant consideration for implementing AI technologies. In the works of Goodell et al. (2021), there is also no explicit mention of start-up costs as a prohibitive factor or consequence in AI and Ml; however, there is a discussion on the increasing investments by financial firms to acquire data science and Ml experts. The article also notes the disruptive and transformational nature of AI and ML, which may suggest there will be initial costs; however, these costs may be outweighed by the potential benefits associated with them. The discussion around barriers to adoption due to financial constraints for smaller firms may be contentious, and will it create monopolies?

2.4 Theoretical Framework

The following framework will delineate the theoretical underpinnings that will guide the exploration of the role of the perception and adoption trends in portfolio construction in the financial services industry. The study will be grounded in a dual-theory approach, navigating through established financial theories, the Modern Portfolio Theory (MPT) and the Technology Acceptance Model (TAM). Traditional theories found in the literature include the Modern Portfolio Theory (MPT), the Capital Asset Pricing Model (CAPM), and the Efficient Market Hypothesis (EMH). These older traditional models are possibly the backbone of the prior theoretical frameworks. The AI-based models include Deep Learning (DL), Reinforcement Learning (RL), Natural Language Processing (NLP) and Sentiment Analysis (SA).

The rationale proposed for incorporating MPT lies in its historical significance, aiming to unravel its continued influence on portfolio construction amidst the AI era. Concurrently, TAM provides a lens to examine the acceptance dynamics of AI in portfolio management, centring on perceived usefulness and ease of adoption. This dual framework seeks to dissect the intricate interplay between historical financial paradigms and emergent AI-driven models, offering a nuanced understanding of their combined impact on contemporary portfolio strategies. The Modern Portfolio Theory (MPT), as one of the theoretical frameworks, is used to understand the risk-reward trade-off, which continues to feature in several current literary works. There is a further need to understand how this “age-old” theory still impacts portfolio construction and its relevance in optimising the risk-reward trade-off in the financial industry in the era of AI and first-mover advantages. This research paper will also apply the TAM framework as the second lens to test the theory. The Technology Acceptance Model (TAM) studies how acceptance of "new" technologies, particularly AI in this context, is adopted. The perceived usefulness and the perceived ease of adoption will be the basis of the argument. The rationale is that with the increasing use of AI, there is a need to understand how professionals perceive the usefulness and ease of adoption when constructing portfolios. If there is no ease or adoption, why will users promote its use in portfolio constrictions? This perception may counter AI's advantages in portfolio construction if not readily adopted.

2.4.1 Theoretical Underpinnings: Theory 1 Modern Portfolio Theory (MPT)

One of the most significant drawbacks of managing portfolios is deciding the proportion of asset allocation in optimal portfolios (Obeidat et al., 2018). Does one invest in equity, bonds, or derivatives, and if so, in what weighted allocation? Obeidat et al. (2018) highlight the issue of this conundrum and further suggest that using the theory will help eliminate risks that are not systemic, together with helping construct an optimal allocation distribution between available assets. Ultimately, MPT can be used to examine AI's impact on diversification and identify non-correlated assets to help reduce risk. There is a significant emphasis on the importance of diversification to help reduce risk and highlights an efficient frontier, which is seen as the optimal performance portfolio with the highest expected return and the lowest possible risk for that expected return (Vuković et al., 2020). Markowitz developed the MPT theoretical framework, which proposes and explains how investors should construct portfolios efficiently regarding risk and reward relationships on the efficient frontier (Markowitz, 2010).

The framework, which is well established, will examine an investor's position to construct portfolios that balance risk and reward to maximise returns. Research suggests that portfolio management can quickly become a game of chance if investors use models to predict future returns and do not wholly understand the dependent variables and risk assessment (Jahanian et al., 2022). MPT is steeped in providing theory emphasising the risk as an integral part of returns trade-off. Artificial intelligence has the potential to provide a more accurate, cost-effective, and efficient methodology to select, assess, and identify risks; hence, the focus is on exploring how AI can impact asset allocation in the financial services industry. There are several critical factors of the MPT framework highlighted, namely:

a. Risk – MPT considers the risk of each asset together with the overall risk. This risk is measured by volatility and or price fluctuations. One broad assumption is that investors are risk-averse and want the lowest risk with maximum returns (Paraphrase from OpenAI's ChatGPT AI language model, personal communication, April 27, 2023).
b. Return – where expected future cash flows like dividends and returns measure the asset's return. (Paraphrase from OpenAI's ChatGPT AI language model, personal communication, April 27, 2023).
c. Correlation – measuring how closely returns of assets are related to each other. The premise is that MPT proposes that asset diversification should not be highly correlated to each other. (Paraphrase from OpenAI's ChatGPT AI language model, personal communication, April 27, 2023).
d. Efficient Frontier – MPT uses this concept as the optimal portfolio for a level of risk.
e. Market Portfolio – MPT assumes that this portfolio is the most efficient, where the highest returns are achieved at the level of risk. (Paraphrase from OpenAI's ChatGPT AI language model, personal communication, April 27, 2023).
f. Active management – MPT highlights the need for active management and the ability of fund professionals to gauge and assess the market to pick stocks only where returns generated do not exceed additional costs incurred. (Paraphrase from OpenAI's ChatGPT AI language model, personal communication, April 27, 2023).

Regarding the trade-off between risk and reward, the higher the risk, the better the reward, according to MPT. Diversification of assets is considered to minimise risk across the allocated spread. Efficient portfolios are considered where the expected highest possible return for the corresponding risk is (Markowitz, 2010). Jahanian et al. (2022) further explain portfolio risk management by dividing risk into systemic and unsystematic categories. Systemic market risk impacts the entire market, whereas non-systemic risk is industry-specific. Maqbool and Husnain (2022) found that MPT optimised portfolio performances and minimised risk.

Diversification was found to be important in optimisation and allowed investors to use MPT to diversify portfolios better (Maqbool & Husnain, 2022). Consideration will be given to how MPT and portfolio performances interlink.

2.4.2 Modern Portfolio Theory and Portfolio Performance

The age-old question of how and where to allocate assets to create wealth by asset selection needs to be answered with the lowest risk and where it is considered efficient (Bechis, 2020). Bechis 2020, in the study, combines the portfolio optimisation models of Modern Portfolio Theory (MPT) and Hierarchical Risk Parity (HRP) to try and find a correlation. Modern Portfolio Theory is considered the classic approach focusing on expected returns and covariances to construct efficient portfolios. Bechis 2020 highlights that the issues around the normal distribution of returns are assumptions and that MPT cannot handle linear relationships. In the same study, an out-of-sample test showed much more volatility to random shocks and annualised results.

To address this, the writer proposes the use of HRP theory. Hierarchical Risk Parity is a recent approach that uses clustering algorithms to group assets with similar risk profiles. The critical constructs in this article are portfolio optimisation, risk, expected returns and reinforcement learning. The challenges associated with this include data quality, overfitting, and interpretability. The author finds that the theoretical MPT model has problems such as inconsistency and difficulty estimating potential return and covariances (Bechis, 2020). The author also found in empirical results that HRP was a better approach than Mean-Variance Optimisation (MVO) to obtain a diversified portfolio. The writer further notes that HPR has limitations in that it cannot provide fully diversified portfolios over an extended period. The gaps highlighted are the lack of empirical testing, comparison with other approaches, and the narrowness of one type of portfolio, as the article focuses on US equities and other classes of assets or markets.

More recent works like that of Jang and Seong (2023) propose a novel approach combining MPT and deep reinforcement learning to optimise stock portfolios. This method leverages AI's power and data quality to help improve portfolio performances (Jang & Seong, 2023). This approach suggests it will possibly allow the ability to adapt to dynamic market conditions and allocate assets to market trends, making it an invaluable tool. However, the writers acknowledge that the research stream of model development was followed, no adjustments were made to the reward function, and the nature of reinforcement learning deterministic mean could not be obtained, which could have had errors that may lack data stability.

A common approach to diversification is 60% equity and 40 % lower-risk bonds, often lacking due to a lack of diversification (Bechis, 2020). The Markowitz mean-variance approach is also unreliable and inconsistent as it is challenging to estimate unpredictable returns, hence the need for researchers and economists to push for newer models and theories (Bechis, 2020). This then begs the question, in the current age of AI with Big Data capabilities, how will AI influence the outcome, predict accurately and possibly determine the optimal portfolio using risk-reward trade-offs? This leads one to develop a conceptual model that would consider AI and its relationship to portfolio performance.

2.4.3 Conceptual Framework for Artificial Intelligence and Portfolio Performance

This research project will analyse AI and ML through the theoretical lens of Modern Portfolio Theory (MPT). Modern Portfolio Theory (MPT) is relied on because most models are built on top of what is considered the father of modern-day portfolios, Markowitz. The idea of efficient and optimal portfolio construction using a mathematical approach is interesting. It can provide maximum risk depending on the investor's risk appetite. The ability to measure risk, return, active management, and asset correlation could help determine what asset classes and weights an investor needs to adopt.

The proposed conceptual framework for this study will explore the perceptions and adoption trends of AI in portfolio construction and management in South Africa's financial services industry. The study will also answer whether AI is seen to deliver optimal returns over traditional-based approaches and how widely adopted it is in the sector.

2.5 Theoretical Underpinnings: Theory 2 Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM) is a well-established theoretical framework for understanding technology adoption and use (Manrai & Gupta, 2022). The TAM framework was developed by Fred Davis in 1986 (Lala, 2014). It was used in his PhD thesis to help provide explanations and determine and explain the behaviour of users on computing technology (Lala, 2014). The Technology Acceptance Model (TAM) highlights two primary factors for this study: how AI users adapt based on perceived usefulness and ease of use. This research examines how investors accept and adopt the technology due to its usefulness, ease of use, and accessibility.

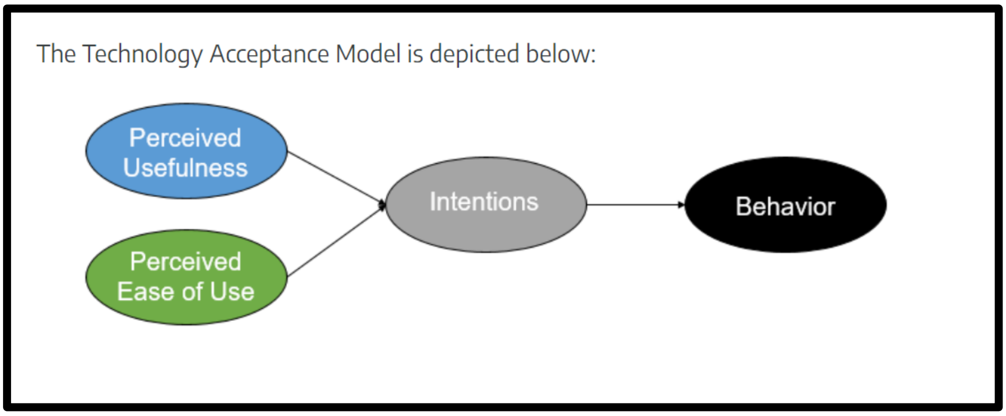

Figure 1 Technology Acceptance Model – Persuasion Theory in Action_ An Open Educational Resource

Financial services are data-rich, controlled and regulated, yet not explosively adopted across all sectors of financial services, in particular portfolio construction and asset allocation. One needs to establish a framework to understand better why it is not exploding and the potential challenges. The TAM framework will be utilised to answer some of these questions. Is it a lack of perceived usefulness? Is there a lack of experience or knowledge of financial consultants? Are there regulatory and ethical considerations that need to be addressed? Alternatively, is its resistance to change and limited resources? This framework will aim to answer these questions.

The TAM framework explains the customer's willingness to adopt technology and is a popular model for information technology adoption (Zhang et al., 2018). Two crucial factors are explored: perceived usefulness and ease of use. Perceived usefulness is the degree to which a user finds technology beneficial; in this perception, they intend to use it more. Perceived ease of use is where the person believes technology will be effortless (Worthington, (n.d.)). Another predictor of TAM includes perceived risk in how exposed a user is if adopting technology (Pavlou, 2003). The limitations of TAM may consist of being criticised for self-reporting data, which may affect the accuracy of model predictions (Lala, 2014). This self-reliance has the potential to introduce biases and inaccuracies. Secondly, Lala (2014) suggested that TAM may be applied for voluntary use, raising generalisation versus where the technology is obligatory.

2.5.1 Technology Acceptance Model and Adoption in the Financial Services Industry

The framework used will explore how financial professionals will adopt and perceive AI's usefulness and ease of adoption when making asset allocation decisions to construct portfolios when still engrained in the traditional model approaches. Further, is AI intuitive enough to users, and what are the barriers and lack of expertise? The role of traditional approaches as a status quo and the hesitancy of diverging from the old technologies. Ultimately, one can ascertain AI integration's potential opportunities and challenges in the financial services industry.

The Technology Acceptance Model (TAM) in literature is probably one widely accepted model that explains technology acceptance (Manrai & Gupta, 2022). The suggested two significant independent variables are perceived usefulness and ease of use (Manrai & Gupta, 2022). Manrai and Gupta (2022) also highlight the links of the psychological theory for acceptance behaviour called the Theory of Reasoned Action (TRA). TAM was initially designed to make up for the lack of the Theory of Reasoned Action (TRA), which highlights the "principle of specificity" (Hu et al., 2019).

Trust is a critical determinant of adopting new technology, according to Manrai and Gupta (2022). The writers highlight two aspects of trust: trust in the service offered and trust in the provider of the services. In their study, Manrai and Gupta (2022) used Robo advisory as a new technology adopting the TAM approach. They concluded that if a customer believes that the provider placed great value on their security and privacy, they are likely to adopt this new technology, which, in turn, will lead to adoption by investors. The study highlighted that there are also potential other positive attitudes that could lead to adopting AI-based investments in Indian clients. Some limitations highlighted by the TAM were biased due to self-reported usages and lack of actual measures in that beliefs and attitudes of users were considered not actual behaviour.

2.5.2 Conceptual Framework for Adoption of Artificial Intelligence in the Financial Services Industry

The proposed conceptual framework will explore how AI capabilities, through the lens of the TAM framework, will assess how swiftly this technology will be adopted in the financial services industry. The conceptual framework will be based on the perceived usefulness of AI methods on portfolio construction compared to traditional MPT methods, the perceived ease of use of AI methods on portfolio construction, the perceived compliance in terms of regulations and ethical considerations in using AI methods of portfolio construction and finally the perceived barriers in adopting AI methods on portfolio construction in terms of lack of expertise, costs, and risks.

The TAM framework helps address the proposed research questions by adding a clear, concise, and systematic way to understand the factors influencing the adoption of AI in portfolio construction in the financial services industry. This framework was chosen as one seeks to investigate the factors that influence the adoption of AI-driven methods in the financial services industry. It is relevant to examine the perception of financial services professionals to get the best return for their investors at the lowest cost and risk. In applying this framework, numerical data can be analysed statistically. TAM's strengths are that it is a well-known model for assessing technology adoption and predicting and explaining behaviour. There are limitations in the framework in that it may not account for all factors that may influence acceptance. The underlying assumption is that decision-makers are rational, which may not be accurate in the real world (Paraphrase from OpenAI's ChatGPT AI language model, personal communication, April 29, 2023).

Chapter 3 Research Methodology

3.1 Introduction

This chapter describes the methodology employed in exploring the perceptions and adoption trends of AI in portfolio construction and management in South Africa's financial services industry. Contrary to the numerous benefits that AI provides to industries such as the financial services industry, there is a need to understand the potential limitations and benefits and whether there is widespread adoption of AI in this industry to construct and manage portfolios in South Africa. This study provides valuable insights into the adoption of AI in portfolio construction in South Africa's financial services industry. The chapter will begin with the research design, followed by the research paradigm, sampling techniques, collection instruments, data analysis, validity, reliability, piloting and ethical considerations.

3.2 Research Design

Adopting AI in portfolio construction is very subjective, with the adoption perceived to be slower in emerging countries like South Africa. AI's nature is emergent, flexible, and quick to respond to change, so the research design will be built around in-depth analysis. There are two methods to consider when collecting data: qualitative and quantitative design methods (Saunders et al., 2007). The mixed method is a combination of both these designs. As opposed to studying cause and effect among a population, qualitative researchers tend to be interested in uncovering the meaning of phenomena (Merriam & Tisdell, 2015). Quantitative research focuses on quantity with philosophical roots in positivism, realism and empiricism (Merriam & Tisdell, 2015). Synonymous with more extensive, random statistical modes of the primary analysis (Merriam & Tisdell, 2015).

Qualitative research, on the other hand, is a humanistic approach to understanding better people's beliefs, attitudes, behavioural nuances, and how one interacts, found in non-numerical data (Pathak et al., 2013). Qualitative research's benefits are that it allows the participants' voices to feed in and share experiences, allowing for an informal setting compared to quantitative research (Pathak et al., 2013). This qualitative method will help unpack perspectives and probe valuable information (Choy, 2014). However, the drawbacks of this approach are that it is time-consuming, particular important info is overlooked or goes unnoticed, and researchers' interpretation is limited (Choy, 2014).

This study employs a qualitative approach to the design. The design caters for an in-depth analysis of any unique factors influencing the adoption process and flexibility in collecting and analysing data through emerging themes and insights. This process helped uncover perspectives contributing to the theories of AI adoption in portfolio construction and its impact on South Africa's financial services industry. The interviews, although limited, were done based on purposive sampling techniques across companies with professional experience in AI-driven optimisation on portfolio construction. This research design was done through interviews to gather insights and provide a more nuanced understanding of the factors that affect adopting AI-driven portfolio construction in financial services in South Africa.

3.3 Research Paradigm

There are three common research philosophies: positivism, interpretivism and critical theory (Ryan, 2018). Positivism is based on the belief that knowledge can be found through observing factual info and empirical evidence. Positivism emphasises objectivity and proving or disproving theories (Ryan, 2018). The theory of positivism tries to establish causal relationships and generalise findings with emphasis on objectivity, quantification and other scientific methods like surveys and experiments. Interpretivism is subjective by nature and aims at understanding and interpreting social phenomena through meaning and experiences. It was born on the premise of valuing subjectivity, which is the opposite of positivism (Ryan, 2018). The focus is on qualitative methods using interview guides and observations to gain a deeper understanding and insights. The critical theory examines power dynamics, social structures, and ideological roles in shaping societal ideals. The critical theory aims to help challenge and change existing structures of power, which originated in the Frankfurt School (Ryan, 2018).

Interpretivism as a philosophy was selected for this area of study because there is a subjective element that acknowledges diverse perspectives of reality and emphasises that this reality shapes an individual's perceptions, experiences, and emotions (Ryan, 2018). Similarly, the perception adoption trends of AI in portfolio construction speak to the experiences, perspectives, and meanings of AI adoption in the financial services industry in South Africa. The chosen philosophy helped the research explore diverse viewpoints and motivations in AI adoption through their subjective experiences. There are also immense complexities in understanding the context of human and social behaviour in the adoption process (Saunders et al., 2007). The authors highlight the importance of interpreting experiences to do meaningful research with subtle gestures like silence and absence. Consulting and interviewing various financial professionals, executives, and decision-makers may help uncover the motives, values and challenges in understanding the decision to adopt AI in the chosen industry. Finally, interpretivism aligns with qualitative studies in that the deep dive interviews, richer understandings, lived experiences, and subjective analysis allow for perspective, narratives and themes to be uncovered (Saunders et al., 2007). As a research paradigm, interpretivism can help gain a deep understanding of subjective experiences and influence social constructs in AI adoption in portfolio construction in South Africa's financial services sector.

3.4 Sampling Technique

Multiple qualitative sampling techniques are commonly used in research: volunteer sampling, random sampling, snowball sampling, and purposive sampling (Gill, 2020). Random sampling is the selection of participants from a population of interests at random, wherein every individual has the same chance of being selected. There is a limitation in this study in that AI adoption in portfolio construction is not too generally found in South Africa, and the techniques require a large heterogeneous sample size; hence, qualitative samples help researchers to identify participants with "direct and personal knowledge" (Sandelowski, 2004). The snowball sampling technique selects a few participants who meet the research criteria and requests further referrals. It can be helpful when the target sample is scarce and there is limited access to potential studies. Purposive sampling entails selecting participants with specific, unique perspectives relevant to the topic. Purposive sampling focuses on understudying groups directly involved or with the expertise to understand AI adoption in their field.

The sampling technique used for this study was purposive sampling, which involved selecting participants based on their specific characteristics and criteria relevant to the research questions. The relevance and expertise through the subject's involvement or exact nature related to AI adoption on portfolio construction are critical. This technique is considered non-probability because participants were selected with predetermined criteria. The chosen sampling technique helped obtain deeper and richer data from participants with specialised knowledge and experience in AI-driven optimisation portfolio construction. The consideration was professionals in the financial services sector in South Africa who have experience with AI-driven portfolio construction methodology. The limitation of the findings can result in the findings not being representative of the entire population group and limited in generalising. The chosen sampling technique has been considered due to the perceived lack of financial services companies adopting AI in portfolio construction.

3.5 Data Collection

3.5.1 Techniques and Instrument

Two broadly used techniques are "survey research methods", including interviews and questionnaires (Morgan & Harmon, 2001). This study used in-depth semi-structured interviews to gain insights into their experiences, perceptions, and attitudes towards AI-driven portfolio optimisation in South Africa's financial services industry. Critical stakeholder engagement included experts, executives, and professional consultants to provide deep insights into their subjective experiences and perspectives through semi-structured interviews. These interviews and questionnaires allowed flexibility, probing deeper and delving into specific topics with open-ended questions to help engage further, which, i.e. mentioned in the works of Morgan and Harmon (2001), where the finding is that qualitative researchers prefer more open-ended with fewer data collection. The interviews were face-to-face, online via video conferences, and in single or group settings to allow for deep discussions.

The instruments adopted were structured and semi-structured interview guides to ensure all critical questions were answered and consistent across participants to analyse the data. The study examined the effects of AI-integrated portfolio construction on portfolio efficiency, the obstacles and difficulties associated with AI-driven portfolio construction, and AI's perceived utility and user-friendliness. It also explored how these factors influence the adoption of AI and the attitudes of professionals in South Africa towards using AI in portfolio construction. These themes were adapted as much of the literature on AI in portfolio construction related to the quantitative aspects of the different ML and AI tools used. These questions aimed to delve deep into what is happening on the ground and how AI has been adopted and effectively utilised in emerging markets like South Africa that are emerging. These interviews were audio recorded with consent from the participants, and notes were taken during the interview to capture both non-verbal and contextual information from the participants.

3.5.2 Data Collection Process

The participants were selected through purposive sampling criteria involving targeted financial services professionals, technology experts, and executives directly involved or with expertise in portfolio construction in the South African financial services sector. A combination of approaches was sought to identify potential participants. These strategies included professional personal networks, industry associations and referrals from crucial participants. The selection process focussed on those in the financial services sector involved in portfolio construction at different experience levels to gauge a total sample size. They were typically aged between 25 and 55 years old and were financial professionals with expertise in portfolio construction. There were nine participants over eight interviews; one interview was done with two participants simultaneously. All the interviews were conducted via Microsoft Teams with no video and were recorded except for one face-to-face interview; however, the recording was still done on Microsoft Teams to ensure record consistency and ease of transcription. The average duration of all interviews was around 448 minutes, with an average of 56 minutes per interview.

3.5.3 Population

The research population is the total set of people or elements who meet the requirements for participation in a study (Boddy, 2016). It depicts the bigger group from which a sample is selected to draw conclusions or generalisations about the population. The research population is the target group that the researcher intends to analyse to draw conclusions based on the data acquired from the sample (Boddy, 2016). In this study, the research population consists of professionals working in South Africa's financial services sector, particularly those actively involved in or with extensive knowledge of portfolio construction and asset allocation procedures. This category included those with job titles of Head: Portfolio Managers, Portfolio Managers, Head : Quantitative Research , Executive directors , Principal Asset Consultants and CIO’s or Deputy CIO’s,.

3.5.4 Sample Size

A sample size, as defined by Boddy (2016), refers to the quantity of data collected or individuals researched to produce insights, understandings, or interpretations of a particular issue within the context of qualitative research. Researchers adopting a qualitative study are rebuked for not justifying sample sizes (Boddy, 2016). The author argues that one single case can be informative across research disciplines. However, notes that according to the concept, data saturation necessitates the analysis of at least two examples, if not more. Boddy (2016) further tries to prove that there is no definitive answer to the correct sample size. The limitation or ambiguity in sample selection will depend on the questions asked and the quality of data provided. Although saturation is functional at conceptual levels, there is little guidance for estimating prior data collection (Guest et al., 2006). The authors found that saturation points become evident at six in-depth interaction interviews and definite saturation at twelve in-depth interviews.

In this study, a sample size of 9 participants was consulted over five different companies to provide detailed, in-depth data and achieve saturation levels. After these participants were interviewed, there was no new information or emergent themes, which indicated that the sample size was sufficient to address the research questions adequately. Boddy (2016) suggests that data saturation occurs when no new information or themes emerge in the data after doing additional interviews. A special note is that qualitative studies prefer developing a depth of understanding versus a breadth of knowledge (Boddy, 2016).

Participant Group	Description	Gender	Age Range	Company
Practioner	Financial professionals with expertise in the field	Male	45-55	Company 1
Decsion Maker	Senior management that offer a wealth of experience and relevant to to decsion making of using AI	Male	45-55	Company 2
Financial Professional	Professionals within the field of study that have expertise by working in sector	Male	35-45	Company 2
Practioner	Financial professionals with expertise in the field	Female	45-55	Company 2
Decsion Maker	Senior management that offer a wealth of experience and relevant to to decsion making of using AI	Male	40-50	Company 3
Practioner	Financial professionals with expertise in the field	Female	25-35	Company 3
Technical Specialist	Technical individuals working in the financial services sector that have contributed to designing and implementing AI-driven optimsation	Male	35-45	Company 3
Financial Professional	Professionals within the field of study that have expertise by working in sector	Male	30-40	Company 4
Technical Specialist	Technical individuals working in the financial services sector that have contributed to designing and implementing AI-driven optimsation	Male	40-50	Company 5

Figure 2 Research Participants Demographics

3.6 Data Analysis

The data analysis for this study involved adopting thematic analysis techniques. Thematic analysis is widely used in qualitative research to identify and interpret the collected data's patterns, themes, and meanings. Although the most used, the thematic analysis is often defined poorly (Lochmiller, 2021). This approach was chosen because it offers a systematic and flexible way to analyse the rich, detailed qualitative data obtained from interviews and document analysis. This step ensured a deep understanding of the content and context of the data. The thematic analysis helped identify persistent gaps of recurring patterns, seeking to evaluate these patterns to help potentially address issues (Lochmiller, 2021). The usefulness of thematic analysis has merits but not without limitations like appearance, that there has been light engagement even after rigorous coding and when a researcher cannot demonstrate how specific connections to the data are made (Lochmiller, 2021).

The next step included coding vis Atlas.ti 2024 software, whereby meaningful data segments were assigned descriptive labels or codes. This process involved breaking the data into smaller units and organizing them into categories or themes. Once the initial coding was completed, the researcher developed themes. Themes represent patterns or recurring concepts that emerge from the coded data. The themes were refined and reviewed through an iterative process, ensuring their accuracy and coherence with the research questions. The researcher also critically examined the relationships and connections between themes to gain a holistic understanding of the data.

Throughout the data analysis process, the researcher maintained a reflective and reflexive stance, acknowledging any potential biases or preconceptions that may influence the interpretation of the data. The qualitative data analysis process was supported using Atlas.ti 2024, which facilitated efficient coding, organisation, and data retrieval. This software assisted in managing the large volume of qualitative data and streamlining the analytical process.

The use of thematic analysis aligns with the research objectives of this study, as it allows for an in-depth exploration of the impact and challenges of AI adoption in portfolio construction. By identifying and interpreting themes within the data, this approach enabled a comprehensive understanding of the experiences, perspectives, and implications of AI adoption in the South African financial services industry."

3.7 Validity and Reliability

In this study, several measures were implemented to enhance the validity and reliability. Participants were selected from various companies in the financial services industry, from large corporations to smaller asset management companies. Detailed descriptions of research methods used to facilitate the transferability of findings of similar contexts exist. Apart from the interviewees, certain participants provided reports used in industry to help reduce the lack of bias or misinterpretation. Consistent data collection protocols regarding questions and recording were followed across all participants to minimise response variability.

Further, to enhance the validity and reliability, Atlas.ti 2024 software was purchased and used to facilitate systematic data organisation, transparent coding and consistency of analysis. Through the Altas.ti 2024 software, qualitative data, including interview scripts, responses, documents, and audio recordings, were systematically organised to ensure efficient retrieval.

3.8 Piloting

Given the time constraints and the period in which the interviews were conducted, a formal pilot study was not feasible for the research.

3.9 Consent and Ethical Standards

Ethical clearance was applied before interviewing participants, and approval was granted by the Wits Business School Ethics Committee on Ethics Clearance Certificate on protocol number WBS/BA2551220/295. Ethical consideration was at the highest standards and consideration throughout the study, with informed consent to all participants and clarification of the purpose of the research together with their rights and explanation of their voluntary involvement in the process. All these measures were taken before they participated in the studies. The interviewees were assured anonymity and confidentiality, explaining how their personal information would be protected. Measures were taken to ensure no unintended consequences like misinterpreting findings that could lead to poor decision-making; however, clear communication in plain language with no jargon helped balance and be easily understood. Using AI in portfolio construction and management also leads to ethical considerations; however, the highest ethical approvals, informed consent, and confidentiality were adhered to.

Chapter 4 Results Presentation

4.1 Overview

This chapter delves into the research problem concerning adopting AI technology in portfolio construction and management within South Africa's financial services industry. Specifically, it investigates perception and adoption trends of whether South African asset managers effectively utilise AI to optimize portfolio processes and maximise investor wealth. The research objectives were established to address this issue, which included evaluating the impact of AI-adopted portfolio construction on portfolio efficiency when compared to traditional methods, identifying the key barriers and challenges to adoption, investigating the influence of perceived usefulness and ease of use on adoption intention, and investigating financial professionals' perceptions and attitudes towards AI adoption.

A qualitative study was conducted using thematic analysis, semi-structured and structured interviews, and purposive sampling techniques to achieve these objectives. This chapter presents the results from the thematic analysis of qualitative interviews via Atlas.ti 2024 software, providing insights into adoption trends, challenges, and perceptions surrounding AI in portfolio management within the South African financial services industry. The layout of the chapter will start with an overview of the identified themes. It is then followed by detailed discussions of each theme or sub-theme supported by relevant quotes from the interviews, offering a comprehensive understanding of the current landscape of AI adoption in South African portfolio management.

4.2 Demographics

The study conducted in-depth interviews with a heterogeneous sample of nine participants representing diverse roles within the South African financial services sector. Gender distribution among the participants consisted of seven males and two females. The age spectrum of respondents spanned from 25 to 55 years, indicating a broad range of demographic representation. Regarding professional tenure, participants reported varying degrees of experience, with some having accumulated over two decades in the industry. Notably, the sample encompassed individuals holding a spectrum of very senior designations and decision-makers, including Head Portfolio Manager, Head of Corporate Portfolio Solutions, Deputy Chief Investment Officer (CIO), Principal Asset Consultant, Co-Founder and Executive Director, Portfolio Manager, Head Quantitative Research, and Head: Research. Of particular note, Interviewee 7 constituted two male and female participants, contributing to the study's richness and diversity of perspectives. Figure 3 provides a summary of the demographic characteristics of the participants:

Interviewee	Gender	Age Range	Years of Experience	Designation
001	Male	35-45	10+	Head: Portfolio Manager
002	Female	45-55	10+	Head: Corporate Portfolio Solutions
003	Male	45-55	10+	Deputy CIO
004	Male	45-55	10+	Principal Asset Consultant
005	Male	40-50	10+	Co-Founder & Executive Director
006	Male	30-40	10+	Portfolio Manager
007A	Male	35-45	10+	Head: Quantitative Research
007B	Female	25-35	10+	Head: Research
008	Male	40-50	10+	Head: Quantitative Research

Figure 3: Demographic Characteristics of Participants

4.3 Relevance and Consistency of Data

Figure 4 below shows the word cloud developed via Atlas.ti 2024 software of the study's relevance across eight interviews, with one interview having two participants in a group totalling nine. The total word count across these interviews comprises 28,081 words. The dominant words were AI, portfolio, construction, machine and use. These prevalent words indicate that AI was the significant focus of the study through the questions and answers of respondents, suggesting that AI adoption was a central theme of the study. Further words like portfolio and construction emerged as dominant words, underscoring the study’s emphasis on AI utilisation in portfolio construction. The word “use” highlights the practical application and utility of AI technologies throughout the process, suggesting theoretical discussions and discussion around the real-world adoption practices and the impact of AI on portfolio construction.

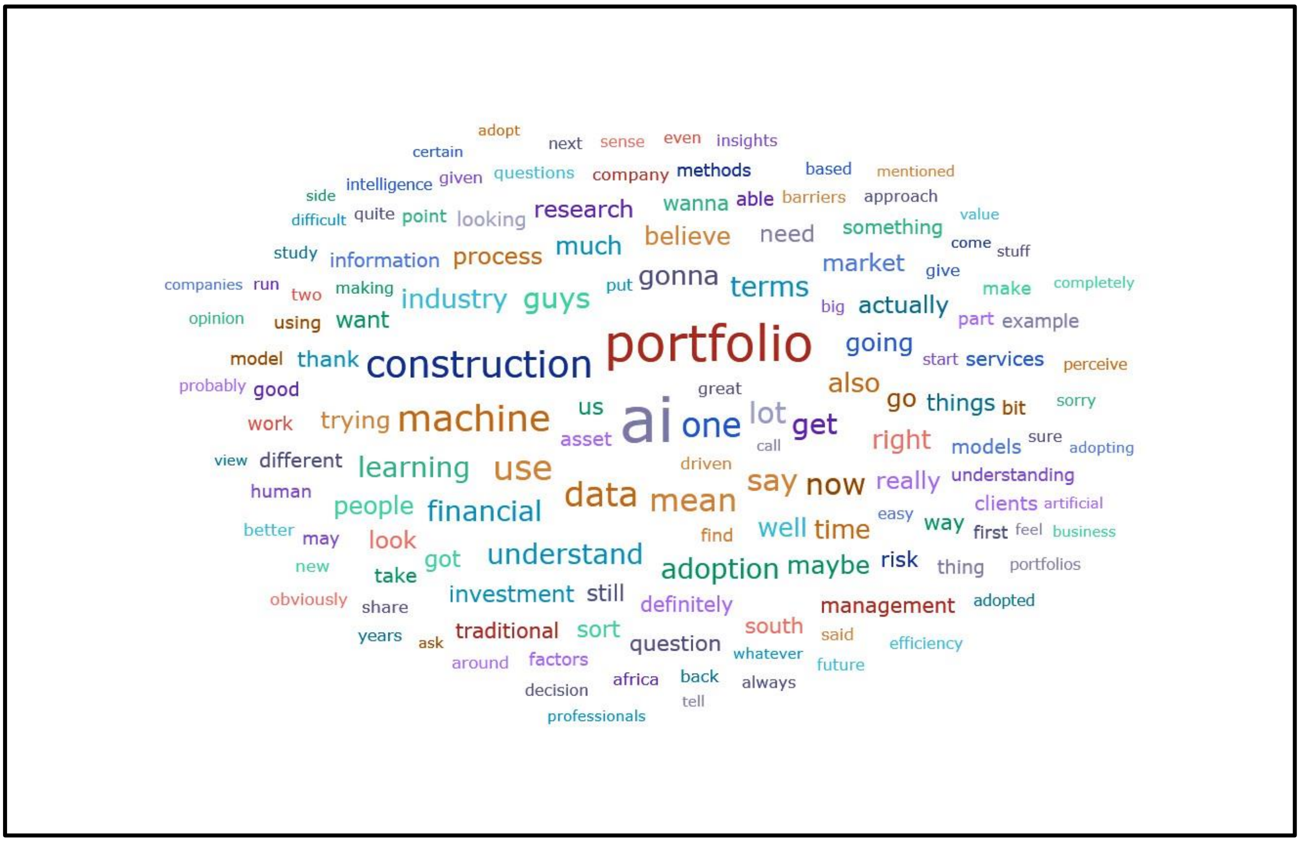

Figure 4 Word Cloud Dominance

4.4 Findings from Empirical Data

Figure 5 displays the thematic analysis results from the collected data, organised by the research questions. Six overarching themes are identified, each with several subthemes elaborated on in later sections. The frequency of codes represents the number of times they are used in the dataset, and it serves as a statistic for estimating the prevalence of matching themes. This numerical representation denotes the recurrence of distinct themes and helps to understand their importance within the dataset.

Theme	**SubThemes**	**Frequency of Theme in Dataset**
○ Theme 1 - Portfolio Construction Methods Used Currently (RQ1)		
	○ Traditional Portfolio Construction	**28**
	○ Machine Learning Usage in Portfolio Construction	**21**
	○ Portfolio Construction Methods: Hybrid	**20**

○ Theme 2 - Impact and Drivers of AI Adoption in Portfolio Construction (RQ1)		
	○ Balancing Speed and Caution in AI Adoption	**86**
	○ Organisational Dynamics and Efficiency Enhancement in AI Adoption	**57**
	○ Abundance of Data both Price and Fundamental Data	**17**
	○ Availability and impact of Computing Power	**16**
	○ Generational Impact & Not new phenomenon	**15**
○ Theme 3 - Barriers to AI Adoption and the Impact in Portfolio Construction (RQ2)		
	○ Psychological Barriers to AI Adoption: Trust, Confidence, and Bias	**49**
	○ Industry First Interest in AI Results	**46**
	○ Lack of understanding of what AI-driven portfolio construction methods is and their complexity	**36**
	○ Data-Related Challenges in AI Adoption: Quality and Traditional Methods	**31**
	○ Bigger Companies lack agility	**5**
○ Theme 4 - Perception and Trust Factors in AI Constructed Portfolios (RQ3)		
	○ Continuous innovation and Evolution	**39**
	○ Cost Structure Analysis	**16**
○ Theme 5 - Perceptions, Attitudes, and Human Factors in AI Adoption (RQ4)		
	○ Professionals' Attitudes and Trust in AI Adoption	**88**
	○ Human-machine dynamics in AI Adoption	**82**
	○ Experimentation and Risk-Taking in AI Adoption	**7**

○ **Theme 6 - Ethical and Regulatory Considerations in AI-driven Portfolio Construction (RQ4)**		
	○ **Fiduciary Duties & accountability & TCF**	**18**
	○ **Job Scarcity Concern of AI Adoption**	**16**

Figure 5 Thematic Analysis: Emergent Themes and Sub-Themes

Figure 5 reflects the thematic analysis of the data collected, organized according to the research questions. Six emergent themes are reflected with multiple subthemes that will be explained in the following sections. The codes' frequency indicates how often this specific code was applied to the data. The number denotes the number of times it was applied and measures how often these, represented by this code, came up in the data collected. It helps understand the prevalence of the themes in the data set.

4.5 Results Analysis Concerning Research Question 1

This section will present the results from the structured and unstructured questions sought to answer research question 1.

RQ1: What is the perception of the impact of AI-adopted portfolio construction on portfolio efficiency compared to traditional portfolio construction methods in the financial services industry in South Africa?

4.5.1 Theme 1: Portfolio Construction Methods Used Currently

Traditional Portfolio Construction

Traditional approaches remain core in portfolio construction methods, as evidenced by the sentiments expressed by various respondents in the South African context. Interviewee 001 said there is a dependence on traditional methods for constructing portfolios, stating, *"So yes, and in the portfolio construction, we use traditional portfolio construction"* (Interviewee 001, 2023:Interview). Interviewee 004 emphasized the simplicity of traditional financial economics models, highlighting the absence of AI in their portfolio construction processes: *"we haven't adopted it "* (Interviewee 004, 2023:Interview).

The dominant sentiment among responders highlights a firm commitment to traditional principles and methodologies. Interviewee 008 explained the reasoning behind traditional portfolio construction, emphasising that striving for the maximum return while considering the associated risk is logical. This principle serves as the foundation for mean-variance optimisation. *"There's always a place for traditional….. So when I say traditional so, from* *portfolio construction perspective, it is absolutely rational and sensical to have a portfolio that has given you an expectation of the highest level of return for a given level of risk. That's the base of mean-variance optimization."*(Interviewee 008, 2023:Interview). Similarly, Interviewee 002 suggested that traditional approaches are likely predominant in portfolio construction practices: *"I would suspect that it's traditional."* (Interviewee 002, 2023: Interview).

Despite emerging advanced technologies, many respondents were reluctant to adopt these innovations in portfolio construction. Interviewee 007AB stated that their organisation still follows a traditional approach to portfolio construction and has not yet incorporated AI, except for operational efficiencies. *"I think at the moment we not using AI for our portfolio construction, we still doing it, we still doing it in the more traditional way."* (Interviewee 007AB 2023:Interview). Interviewee 003 echoed this sentiment, indicating that their portfolio construction process remains rooted in traditional methods: *"I guess our portfolio construction process, I mean, is still very much the traditional approach. "* (Interviewee 003, 2023:Interview).

In summary, while the financial landscape evolves with new technologies, traditional portfolio construction methods remain prevalent among financial practitioners. The enduring appeal of traditional approaches lies in their reliability, simplicity, and adherence to established investment principles despite the growing availability of advanced methodologies.

Machine Learning Usage in Portfolio Construction

When evaluating the incorporation of machine learning into portfolio construction methods, it is clear that traditional methods are still prevalent. However, there is an increasing acknowledgement of the potential advantages of utilising machine learning techniques. During the interview, Interviewee 001 highlighted the significant utilisation of machine learning in selecting stocks and constructing portfolios inside their company: *"we use machine learning quite extensively. Have in both stocks selection as well as in portfolio construction."* (Interviewee 001, 2023:Interview). This respondent was one of only two who have fully fledgedly adopted AI in some parts of the business. Interviewee 003 recognised the advantages of using machines in finance. It emphasised their potential to have a more significant impact in the *future: "machines to play a much bigger role in the finance and investment world going forward. "* (Interviewee 003, 2023:Interview); however, they were still in the infancy of adoption. Interviewee 006 concurred with this perspective, highlighting the supremacy of machines in data analysis; according to Interviewee 006, machines possess the ability to efficiently handle extensive quantities of data, surpassing human capabilities and resulting in more coherent outcomes *“machines can do better than man,…. come out to something that's a lot more cohesive. “* (Interviewee 006, 2023: Interview). Although the advantages of machine learning are recognised, certain respondents nevertheless maintain a cautious stance. Interviewee 004 voiced doubt over the potential of AI in aiding portfolio construction, suggesting a reluctance to adopt machine learning techniques ultimately. *“I'm not quite sure how AI then could assist him,…open to whatever comes along.”* (Interviewee 004, 2023:Interview). Furthermore, Interviewee 007AB emphasised that although they utilise distinct software and neural networks to augment trading judgements, manual intervention is necessary for updates: *“we use it on a supervised basis, right? So we only would use supervised learning “* (Interviewee 007AB, 2023:Interview). Moreover, AI's capacity to improve the decision-making process in portfolio development is acknowledged. Interviewee 005 compared the use of AI to having an additional player on the pitch, emphasising AI's capacity to enhance portfolio resilience: *“that's like having, you know, a 16th player on the rugby field “* (Interviewee 005, 2023:Interview). Interviewee 008 highlighted the application of supervised learning in making tactical asset allocation decisions, demonstrating a strategic method of incorporating machine learning into portfolio management strategies: *“It's like we'd use it for our tactical asset allocation calls. i.e. Which asset classes to move into or away from on a tactical basis? “* (Interviewee 008, 2023:Interview). Generally, although the traditional approaches are still widely used in portfolio development, there is increasing recognition of the potential advantages of incorporating machine learning techniques.

Hybrid Usage in Portfolio Construction

Another subtheme arising from the methods used within the ever-changing realm of portfolio construction methodologies is that a hybrid approach combines the advantages of quantitative research with traditional methods. Interviewees consistently highlighted the mutually beneficial connection between quantitative models and human judgement when creating portfolios.

Interviewees across various financial sectors highlight the significance of this hybrid approach, emphasizing its effectiveness in optimizing investment strategies. Interviewee 002 underlines the necessity for this approach by describing their process as a hybrid model*:” Hybrid, then* *because our process does have a very sort of if you want a quantitative underpin,….. But the implementation is traditional."* (Interviewee 002, 2023:Interview). While quantitative analysis forms the foundation, human expertise guides implementation, ensuring a balanced and comprehensive approach.

Interviewee 003 echoes this sentiment, highlighting the importance of combining quantitative orientation and qualitative understanding in portfolio construction. They emphasize that while quantitative models provide valuable insights, human judgment remains critical in interpreting data and navigating forward-looking market dynamics *" does not purely have to be machine or quantitatively driven; it can be a combination of you know if a fundamental approach versus a view that the machine gives you."* (Interviewee 002, 2023:Interview).

Moreover, Interviewee 006 adds depth to this discussion by emphasizing the need for a collaborative approach between quantitative analysis and human expertise. They advocate for integrating risk metrics adjustment and thorough back-testing, stressing that this hybrid approach leads to more refined investment strategies:*" hybrid where it's just sort of adjusting your risk metrics here or there or to complete portfolio construction and generation to backtesting."* (Interviewee 006, 2023:Interview).

Additionally, Interviewee 008 reinforces the concept of hybrid portfolio construction by illustrating how their methodology combines quantitative optimization techniques with AI-based asset selection. They acknowledge the essential role of AI in asset selection while emphasizing the continued relevance of human judgment in portfolio construction.*" We use AI-based, but for construction purposes. It's definitely a hybrid approach, yes."* (Interviewee 008, 2023:Interview).

In general, the consensus among participants emphasises the practical realisation that constructing a portfolio requires rigorous quantitative analysis and subjective judgment. Investors can efficiently negotiate market difficulties and build robust investment portfolios by adopting this hybrid strategy, which combines the merits of both techniques.

4.5.2 Theme 2: Impact and Drivers of AI Adoption in Portfolio Construction

Adopting Artificial Intelligence (AI) in portfolio construction is multifaceted and interdependent. In this field, it is crucial to comprehend the Adoption Speed and Readiness, which indicates how quickly financial institutions in South Africa are integrating AI into their portfolio management strategies.

Balancing Speed and Caution in AI Adoption

Respondents from several interviews emphasised that adopting AI involves finding a careful equilibrium between the need for quick advancement and cautious consideration. Although there is a strong desire to adopt AI technology quickly and maintain competitiveness, there is also an awareness of the need to approach cautiously to minimise risks and guarantee ethical and responsible deployment.

Interviewee 006 points out the competitive advantage gained by early technology adoption within their industry, emphasizing the importance of staying ahead in tech adoption. "*our business has always been trying to trying to adopt tech and be on the forefront of tech adoption within the industry."* (Interviewee 006, 2023:Interview). This sentiment is further echoed by Interviewee 003, who highlights the opportunity cost of falling behind the curve and stresses the necessity of keeping pace with technological advancements to remain relevant in the market. *"not to be behind the curve relative to other competitors in the market that's perhaps made some progress in that in that space."* (Interviewee 003, 2023:Interview)

However, alongside the eagerness to adopt AI, there is a prevailing sense of caution among respondents. Interviewee 008 points out the relative infancy of AI adoption in finance compared to other sectors, suggesting a need for careful navigation and measured progress in this nascent field. *" the adoption of AI or machine learning to finance is relatively nascent And when compared to other things. So it's new, it's a new thing, and it's taken."* (Interviewee 008, 2023:Interview)

Similarly, Interviewee 004 expresses doubt regarding the true capabilities of AI and emphasizes the importance of understanding its limitations before full-scale integration*." you know, might be a bit of a learning curve, but that's still you're gonna pay some school fees and get there."* (Interviewee 004, 2023:Interview)

This subtheme encapsulates the tension between the imperative to innovate rapidly and the need for prudent decision-making in AI adoption. It emphasises the complex considerations organisations must weigh, including ethical concerns, potential biases, and the need for transparency in AI systems. Achieving a harmonious balance between speed and caution requires a strategic approach acknowledging AI adoption's transformative potential and inherent risks. Organisations must navigate this delicate equilibrium to harness the benefits of AI while ensuring responsible and sustainable implementation.

Organisational Dynamics and Efficiency Enhancement in AI Adoption

The integration of technical capabilities and operational considerations plays a pivotal role in driving the adoption of AI within organisations. Respondents highlight the significance of data availability and technological infrastructure in facilitating AI adoption. Interviewee 001 emphasizes the efficiency gained through AI, illustrating how a small team can achieve comparable output to a larger workforce through automation and advanced algorithms. *"so it's that type of efficiency where two people can do more work than 22 people can."* (Interviewee 001, 2023:Interview). Furthermore, initiatives like developing AI models demonstrate a proactive approach to leveraging existing infrastructure for enhanced performance, as discussed by Interviewee 001: *"we're gonna use the infrastructure and the algorithms developed by Openai for CHATGPT,……… its linguistic ability."* (Interviewee 001, 2023:Interview).

The complexity of integrating AI into existing systems and workflows is also highlighted, with Interviewee 006 describing real-world implementation challenges, including liquidity, trading, and market dynamics, *"implementing that into a real-world portfolio with liquidity, with trading, with costs,…….can be a huge level of complexity"*. (Interviewee 006, 2023: Interview).

The subtheme emphasises the intricate interplay between technical capabilities and operational realities in driving AI adoption. While technological advancements offer transformative potential, organisations must navigate challenges such as workforce implications, regulatory constraints, and technical complexities to realise the full benefits of AI integration.

Among the number of firms implementing AI, there appears to be a clear distinction between teams. Forming distinctive teams and fostering communication among team members introduces subtle complexities that facilitate the acceptance of new technologies, contrasting with those that have not evolved into artificial intelligence. Organisations that used AI maintained conventional business operations. However, they established separate divisions to ensure precise monitoring and differentiation. Developing experts who can recognise and possess the necessary abilities to promote a novel mindset is required. Interviewee 007 emphasises the importance of teamwork and collaboration in achieving success. "*We've got the … next Gen team,…….which is more traditional bottom-up team"*. (Interviewee 007,2023: Interview). Another respondent who has complemented AI in portfolio construction shared a similar stance: *"What we've done is we separated out our company about five or six years ago*. (Interviewee 006,2023: Interview).

Integrating artificial intelligence (AI) into organisational processes has yielded substantial efficiency gains, particularly in data utilization, but not necessarily portfolio construction. Interviewee 005 highlights the pivotal role of AI in enabling organisations to manage large volumes of data effectively. This task was previously daunting due to formatting complexities: *"I think the biggest sort of influence that we've seen is is in the ability for organisations like ourselves to work with large amounts of data."* (Interviewee 005,2023: Interview).

Moreover, the transition from manual to automated systems has significantly enhanced efficiency by enabling automatic data input, thereby reducing the need for human intervention. *"So the efficiency of moving away from, let's say, a manual environment to more kind of automated environment .... I think it's massive."* (Interviewee 005,2023: Interview).

By eliminating manual data entry tasks, AI empowers professionals to focus on higher-order tasks such as interpretation and critical thinking, as noted by *"So I think that that for me is actually you know you don't wanna have A CFA having to run around trying to put data into a system, for example, you want them to do the thinking the interpretation"* (Interviewee 005,2023: Interview). However, challenges remain, as articulated by Interviewee 007AB, who highlights the complexity of data structures: *"I think they are very useful, but I think the challenge is that it does require a lot of….. complex data or also the structure."* (Interviewee 007AB,2023: Interview). Nonetheless, the overarching sentiment is that AI-driven data utilization processes are essential for organisations to harness the full potential of their data and drive performance improvements.

Efficiency gains through AI adoption could translate into significant organisational cost reductions, driving competitiveness and reshaping industry cost structures. Interviewee 001 underscores the transformative impact of AI on cost dynamics, highlighting the disparity between traditional and AI-driven cost structures in the investment management industry: *"it's gonna be tough for those who don't adopt to keep on competing. So, because I mean, the cost structure is just so different. And the investment management industry. In my opinion, has made way too much money"* (Interviewee 001,2023: Interview). Moreover, the minimal capital outlay required at the onset further enhances the cost-effectiveness of AI adoption: "*there isn't massive capital outlay at the beginning. I think it will be six months of the salary of the Chief Investment Officer of Coronation."* (Interviewee 001,2023: Interview).

Interviewee 003 emphasises the cost-saving potential of AI-enabled data processing, which outpaces human capabilities and streamlines operations. Similarly, Interviewee 005 stresses the imperative of cost efficiency in meeting client expectations, underscoring AI's role in delivering more efficient solutions to achieve investment targets: ”*we need to be able to deliver a way more efficient solution to clients that have a higher predictability of achieving certain targets, investment returns or benchmarks”.* (Interviewee 005,2023: Interview). Furthermore, Interviewee 007AB anticipates operational efficiencies resulting from AI adoption, reducing client fees and enhancing overall cost-effectiveness, “*but what will benefit client the most is operational efficiencies, which would which one would expect or hope to see a reduction in fees for clients*” (Interviewee 007AB,2023: Interview).

In essence, the integration of AI not only enhances operational efficiency but also drives down costs, making it a pivotal strategy for organisations seeking to remain competitive and deliver value to clients in a cost-effective manner.

Abundance of Data: Price and Fundamental Data

The widespread availability of data, including financial indicators and unconventional sources like sentiment analysis and social media, is a critical factor in the increasing use of AI in different businesses. Interviewee 001 emphasises the importance of this trend, highlighting the growing accessibility of essential and cost-related information, which was previously difficult to get. *“Fundamental as well as price data, as well as total return series and data availability, has just become so much more freely available in the past, it was really difficult to get especially fundamental data.”* (Interviewee 001,2023: Interview).

Interviewee 006 emphasises the direct relationship between the amount of data and the model's effectiveness, emphasising the necessity for contemporary asset management to utilise AI-powered insights obtained through thorough data analysis: *“ you've got the efficiency, you've got data is everywhere. ……they're looking for the edge they need to outperform.”* (Interviewee 006,2023: Interview).

However, the abundance of data also poses challenges, particularly in data management and processing. Interviewee 005 discusses the historical difficulties of handling large datasets and the transformative impact of AI in streamlining data management processes: *“So I think in the past I think it was very difficult to to work with large amounts of data because it just in the formatting where it where it's set you know it was very difficult to extract it to utilise it to put it into databases”* (Interviewee 005,2023: Interview). Interviewee 007AB further emphasizes the requirement for substantial data volumes to ensure robust testing and decision-making processes in investment management." *for me, it's like it's often requires a lot of data, and we need to have enough data to really thoroughly test.*" (Interviewee 007AB,2023: Interview).

In summary, the subtheme highlights the pivotal role of data abundance in driving AI adoption, enabling organisations to gain a competitive edge through advanced analytics and informed decision-making.

Availability and Impact of Computing Power

The availability and impact of computing power emerge as pivotal factors driving the adoption of artificial intelligence (AI) technologies. Interviewees highlight the transformative role of cloud computing in providing access to robust computational resources, enabling organisations to analyze vast quantities of data swiftly and efficiently. This accessibility to advanced computing capabilities facilitates the development and deployment of AI algorithms with reduced reliance on closed-loop systems, as emphasized by Interviewee 001: *"cloud computing is making it a very easy to analyze vast quantities of data and to force you, you don't have to use closed-loop algorithms anymore."* (Interviewee 001,2023: Interview).

Moreover, the correlation between data processing speed and predictive power points out the significance of computing power in algorithmic development. Interviewee 002 emphasises the importance of processing speed in enhancing predictive capabilities, positioning it as a critical differentiator in strategic asset allocation: *"It's one of our key differentiators. I mean, you can call it AI, I'll call it the quantum vesting "*(Interviewee 002,2023: Interview). This sentiment is echoed by Interviewee 006, who discusses the evolution of machine-driven strategies over time, leveraging extensive historical data to optimize decision-making processes: *"We find that the more data you give it, they generally tend to be better. So in our results, the models that we have on the global scale are a lot more productive they show a lot better results."* (Interviewee 006,2023: Interview).

The exponential growth in computing power enhances predictive modelling and enables organisations to tackle complex analytical tasks at scale. Interviewee 006 highlights the capability of machines to process vast amounts of data, identifying patterns and features that may elude human perception: *"So whereas the human you can go through these and maybe you're picking up one or two flags and features, but with the machines able to do is able to take this data and feed.....able to then come out to something that's a lot more cohesive."* (Interviewee 006,2023: Interview). Furthermore, the availability of robust computing systems facilitates the iterative development and refinement of AI models, contributing to a more streamlined and efficient decision-making process, as articulated by Interviewee 006: *“we run it over the weekend, but a Single Mac book Pro would take it to, it would take it three years to run”* (Interviewee 006,2023: Interview).

In summary, the subtheme underscores the transformative impact of enhanced computing power on AI adoption, facilitating the development of sophisticated algorithms and empowering organisations to extract actionable insights from vast datasets.

Generational Impact & Not a New Phenomenon

The adoption of artificial intelligence (AI) is significantly influenced by generational dynamics, reflecting a shift towards innovation and technological advancement. Younger generations exhibit a greater propensity for embracing novel approaches, as highlighted by Interviewee 003, who emphasizes their inclination towards innovative solutions over traditional methods: *“positive side of things is very much driven from a generational thing where you know younger generations are more prone to try new innovative things.”* (Interviewee 003,2023: Interview). This generational divide extends beyond consumer behaviour to encompass investment practices, with newer generations seeking to apply fresh perspectives to propel the finance and investment sectors forward.

However, while AI adoption may seem revolutionary, it is rooted in longstanding principles and practices. Interviewee 004 stresses the continuity of investment principles developed decades ago, suggesting that AI, in its current form, primarily represents automation rather than genuine consciousness: *“AI, you know, genuine consciousness. I'm not convinced that that has been developed yet, so anything that we do have that is AI is just automation. It's just, you know, coding up and computers doing human work for them.”* (Interviewee 004,2023: Interview). Despite technological advancements, the underlying financial and economic principles remain consistent across generations, indicating continuity in approach despite technological evolution.

Furthermore, the historical precedence of AI initiatives predates contemporary perceptions, as highlighted by Interviewee 007AB. The emergence of AI dates back to the 1980s, indicating that it is not a new phenomenon but a continually evolving field. However, the accessibility of AI technologies, driven by economic factors, is pivotal in driving its widespread adoption, aligning with Interviewee 007AB's observation regarding its leading factor: *“It's not a new phenomenon, but what I'd I believe that is a leading factor driving the adoption of AI is accessibility from a what's IT economic”*. (Interviewee 007,2023: Interview).

The subtheme highlights how generational dynamics and technical advancement interact to influence the adoption of AI. While younger generations support new ideas and technology, the fact that investment principles have stayed the same and AI projects have been around for a long time shows how complicated its uptake is.

4.6 Results Analysis Concerning Research Question 2

RQ2: What are the key barriers and challenges facing South African financial services companies to adopt AI-driven portfolio construction methods and their impact on adoption rates?

4.6.1 Theme 3 Barriers to AI Adoption and the Impact in Portfolio Construction

The subtheme explores the difficulties encountered by the financial sector in implementing artificial intelligence (AI) and machine learning (ML) methods for portfolio development. The industry's cautious attitude is primarily motivated by the necessity to observe concrete outcomes before adopting new approaches.

Industry First Interest in AI Results

This subtheme emphasises the industry's cautious attitude towards adopting AI-driven approaches, motivated by the requirement to observe concrete outcomes before widespread implementation. We investigate the fundamental issues affecting this cautious approach by consulting with experts from many industries. These elements include the need for tangible results, client trust, and the importance of investing time and knowledge. A significant subtheme, "AI Adoption Challenges: Industry's Initial Interest in AI Outcomes," highlights the industry's careful stance, principally motivated by the requirement to observe concrete outcomes before accepting new techniques. Respondents exhibit disbelief towards the deployment of AI, highlighting the industry's inclination towards tangible outcomes rather than theoretical assurances. Numerous interviewees, including Interviewee 001, share this perspective, highlighting the significance of proving actual results. "*I think they they definitely first wanna see some results. Some proper results from the from these methodologies using machine learning and artificial intelligence*." (Interviewee 001,2023: Interview).

Moreover, client confidence and comfort emerge as critical factors influencing AI adoption. Interviewee 002 highlights the necessity of establishing trust and confidence with clients through a proven track record. *"So they're not just gonna sign up for it without seeing a track record".* (Interviewee 002,2023: Interview).   At the same time, Interviewee 007AB emphasizes the importance of tangible evidence and a track record to alleviate client apprehension. *"we need to see evidence of it by means of performance."* (Interviewee 007AB,2023: Interview).

Furthermore, the analysis reveals a significant gap in industry evidence and understanding surrounding AI-driven portfolio construction methodologies. Interviewee 006 discusses the scarcity of evidence in AI fund performance. *"I think guys are looking for opportunities and ways to try and prove the process."* (Interviewee 006,2023: Interview). At the same time, Interviewee 004 expresses doubt regarding the existence of proper artificial general intelligence and the absence of direct applications in the industry. *"I really hope I'm not living under a rock, but it's, you know, I'm looking for and say, well, what I have show me the shred of evidence."* (Interviewee 004,2023: Interview). Overcoming these barriers necessitates a concerted effort to demonstrate the value and efficacy of AI-driven portfolio construction methodologies through verifiable results and a track record of performance.

Furthermore, the report emphasises the need for time and knowledge building to overcome obstacles to AI adoption. Interviewee 003 anticipates that barriers will dissipate as proficiency, expertise, and evidence of AI efficacy accumulate. *"I think those barriers will disappear as we build the proficiencies and expertise and the skills and the evidence to show that it will actually work."* (Interviewee 004,2023: Interview). Interviewee 007AB emphasizes the importance of testing AI models across different economic environments before widespread adoption. *"But I think for them to actually adopt that into their portfolio,…to really test the resilience of that model throughout different economic macro environment."* (Interviewee 007,2023: Interview). Our analysis sheds light on the industry's cautious approach to AI adoption, which is motivated by the need for actual evidence, client trust, and time to develop expertise and track records.

Lack of understanding of what AI-driven portfolio construction methods is and their complexity

The subtheme "AI Adoption Challenges: Lack of Understanding of what AI-driven Portfolio Construction Methods Are and Their Complexity" highlights the industry's difficulty in comprehending AI-driven methodology's fundamental nature and intricacy in portfolio creation.

Interviewee 002 articulates the industry's confusion regarding the distinction between quantitative processes and AI, emphasizing the need for clarity and understanding. *"I'm still trying to understand the, the definition sort of the leap from your quantitative processes, which in, in themselves have got predictive models and that how that differs to AI."* (Interviewee

002,2023: Interview). This sentiment is echoed by Interviewee 004, who expresses uncertainty about AI's definition and practical application in portfolio construction. *"it's the issue of I I'm not really sure what an AI constructed portfolio process would involve."* (Interviewee 004,2023: Interview). The lack of clarity surrounding AI's description and functionality contributes to industry reservations and reluctance to embrace AI-driven methodologies.

Furthermore, Interviewee 003 underlines the current lack of knowledge and research, which impedes the practical deployment of AI in portfolio development. "*the lack of knowledge and and research to apply it in a best possible way to put them in*." (Interviewee 003,2023: Interview). *" I think a lot of people are trying to get their head around what it actually means and how they can create that ease of use."* (Interviewee 003,2023: Interview). This sentiment is compounded by Interviewee 006's observation of the industry's struggle with the complexity of machine learning and deep neural networks. *"for some people, as much as the barriers have come down, this idea of machine learning and the deep neural networks is a complex idea".* (Interviewee 006,2023: Interview). The complexities of AI-driven procedures provide substantial obstacles, necessitating industry professionals' investment of time and effort to grasp and master these strategies.

Furthermore, Interviewee 007AB emphasises the necessity of programming abilities in efficiently exploiting AI in financial services, highlighting the technical challenges that industry experts face. *" those deep learning deep learning models at a very difficult, I think very complex to set up."* (Interviewee 007AB,2023: Interview). The complexity of AI algorithms and models creates a steep learning curve that necessitates a solid understanding of programming languages and computational methodologies.

The subtheme focuses on the industry's struggle with the complex and uncertain nature of AI-powered portfolio construction procedures. Widespread adoption poses significant challenges due to a lack of understanding, technical barriers, and uncertainty.

Psychological Barriers to AI Adoption: Trust, Confidence, and Bias

The subtheme "Trust and Confidence in AI" investigates the complex dynamics behind the industry's fears and uncertainty about implementing AI-driven initiatives. Based on data from interviews with various industry stakeholders, this report explores the critical role of trust and confidence in boosting the use of AI in portfolio management.

Interviewee 002 highlights the indispensable nature of trust and confidence in AI-driven methodologies, emphasizing the fiduciary responsibility towards clients. Their assertion, "And having an element of trust and confidence in it,*" encapsulates the imperative for establishing a robust foundation of trust"* (Interviewee 002, 2023: Interview). Similarly, the significance of a track record in engendering trust is highlighted by Interviewee 002, who stresses the importance of transparency in maintaining client confidence. Their remark, "*We have gotta fiduciary responsibility to clients. I cannot stand up in front of our clients and say to them, oops, sorry. I lost half of your portfolio because my machine learned my inputs and said I must put your money here. It lost half your portfolio,*" showing transparency and accountability's criticality (Interviewee 002, 2023: Interview).

Moreover, Interviewee 003 explains the widespread lack of trust caused by a fundamental misunderstanding of AI models and their operations. Their observation, "*Often there is a misunderstanding or no understanding of what the model is trying to do in the back end, and that creates much uncertainty around, you know, trust for the machine, and people perceive that as a black box,*" emphasises the imperative for transparency and comprehensibility (Interviewee 003, 2023: Interview). Similarly, Interviewee 006 reflects on the prevalent scepticism surrounding AI, highlighting the need to address apprehensions and instil confidence through education and transparency. Their remark, "*There is still this perception that AI is a bit rogue, that you cannot trust it, that it is a machine*," stresses the entrenched doubt (Interviewee 006, 2023: Interview).

Additionally, Interviewee 007AB emphasizes the foundational role of trust in the financial industry, underscoring the necessity of comprehensibility and transparency in AI-driven portfolio management. Their assertion, "*Because ultimately what we do in the fund management industry, asset management industry, what we do is built on trust*," emphasises the symbiotic relationship between trust and efficacy (Interviewee 007AB, 2023: Interview). Additionally, Interviewee 008 elucidates the varying degrees of disbelief in the industry, emphasizing the need for a cautious and measured approach towards AI adoption. Their reflection, "*Some people are a bit more sceptical than others, specifically those that have more on the fundamental-based approach*," points out the nuanced perspectives surrounding AI adoption (Interviewee 008, 2023: Interview).

"Trust and Confidence in AI" highlights the sector's multifaceted challenges when adopting AI-driven initiatives. Establishing trust, fostering transparency, and assuring comprehensibility are critical components in overcoming scepticism and supporting the successful integration of AI into portfolio management. Interviewee 002 currently sees AI as a quantitative tool using just historical data: *"An AI-driven portfolio for me would be one that is, umm, quantitative in nature, which uses historical data. It's got nothing else."* (Interviewee 002, 2023: Interview). Interviewee 003 tends to differ in opinion in that they believe that the returns are forward-looking: *" it's not based on a historical view only, and there are specifics such as eco characteristics on the asset losses that we derive from historical basis, but the returns are very much forward-looking."* (Interviewee 003, 2023: Interview).

Interviewee 004 question about the emergence of artificial general intelligence and reliance on historical returns for portfolio construction underscores another significant barrier—the uncertainty surrounding the capabilities and reliability of AI-driven methods *"either you can look at the historic returns and just simply use your back purely backwards-looking."* (Interviewee 003, 2023: Interview). The historical view of machines adds another layer of complexity to these challenges as firms grapple with reconciling past performance data with the forward-looking nature of AI-driven strategies.

Data-Related Challenges in AI Adoption: Quality and Traditional Methods
Implementing AI in the financial services sector is hampered by significant obstacles that must be overcome, especially related to data concerns and quality. Interviewee 001 highlights the increased data availability in recent years yet emphasizes the persistent obstacle of obtaining proper and high-quality data for building robust models: *"So the biggest obstacle for us has been getting proper data and and and good quality data."* (Interviewee 001, 2023: Interview). Interviewee 002 echoes this sentiment: *"the cleanliness that the data integrity"* (Interviewee 001, 2023: Interview). Interviewee 003 emphasises the importance of data integrity and cleanliness in AI processes, highlighting the risk of "garbage in, garbage out" with machine learning algorithms *"garbage in, garbage out kind of it's kind of an approach."* (Interviewee 003, 2023: Interview). Interviewee 003 further emphasizes the importance of data quality, stressing the impact of unreliable or inadequate data on the outcomes of AI-driven processes." *therefore what data, how you use a data where you get your data from what data gives you certain signals in a in a positive sense or or a negative sense."* (Interviewee 003, 2023: Interview).

Interviewee 006 reflects on the exponential growth of available data, likening it to an iceberg where only a fraction is visible, underscoring the immense challenge of effectively processing vast amounts of data: *"It's like an Iceberg you just see one number, but below it is, is it's kilometres and terabytes worth of data"*. (Interviewee 006, 2023: Interview).

Additionally, the shift from traditional methods to AI-driven approaches has raised the bar for data requirements as noted by Interviewee 006 highlights the transition from Excel-based analysis to deep learning and machine learning techniques due to the sheer abundance of data *"back in the 2000s, where Excel was enough to get you ahead"* (Interviewee 006, 2023: Interview).

Interviewee 007AB adds to this discussion by acknowledging the usefulness of AI but highlighting the significant challenge posed by the complexity and volume of data required for thorough testing and analysis: *"available availability of data."* (Interviewee 007AB, 2023: Interview). The findings highlight the critical necessity of addressing data problems and guaranteeing data quality in AI adoption efforts in the financial services sector since these challenges directly impact the efficacy and dependability of AI-driven processes.

Part of the data-related challenges is also "Paper Portfolios and Overfitting", which explores the many obstacles and nuances associated with implementing AI-driven approaches in portfolio management. These interviews highlight the intricacies linked to overfitting, accessibility, and the black box effect in incorporating AI in portfolio management methods. These factors, identified through interviews with industry leaders, provide substantial obstacles.

Interviewee 002 articulates the concept of paper portfolios, emphasizing their frictionless nature and the allure of automated processes. Their remarks underscore the allure of streamlined methodologies facilitated by AI-driven algorithms yet also raise concerns regarding the transparency and comprehensibility of such approaches (Interviewee 002, 2023: Interview). Moreover, Interviewee 003 highlights the pervasive apprehensions stemming from the perceived black-box nature of AI-driven methodologies. This lack of transparency engenders hesitancy and disbelief among industry professionals, impeding the widespread adoption of AI in portfolio management (Interviewee 003, 2023: Interview).

Additionally, Interviewee 006 delves into AI washing, wherein the indiscriminate application of AI terminology masks substantive deficiencies in portfolio management strategies. Their reflections underscore the need for discernment and scrutiny in evaluating purported AI-driven approaches, emphasizing substantive efficacy rather than superficial labels (Interviewee 006, 2023: Interview). Additionally, Interviewee 007AB elucidates the risks associated with overfitting and data mining, underscoring the importance of robust economic and financial rationale in decision-making processes. Their insights highlight the necessity for rigorous validation and testing protocols to mitigate the pitfalls of overfitting and ensure the generalizability of AI-driven models (Interviewee 007AB, 2023: Interview).

Furthermore, Interviewee 008 explains the difficulties in reducing overfitting and improving model accuracy, highlighting the iterative process of refining and validating the model. The interviewee emphasises AI-driven portfolio management's ever-changing and complex nature, highlighting the need for continuous monitoring and adjustment to address emerging difficulties.

"Paper Portfolios and Overfitting" looks at the numerous challenges and considerations that arise when adopting AI-driven techniques for portfolio management. The high rate of overfitting, the appeal of ease of use, and the lack of transparency in black-box approaches illustrate the inherent difficulties in using AI for portfolio management strategies.

Bigger Companies Lack Agility

The subtheme "Cost and Lack of Agility in Bigger Companies" highlight businesses' significant obstacles, especially larger ones, when implementing artificial intelligence (AI) solutions. These issues stem from cost constraints and organisational resistance to change.

Interviewee 003 discusses the immense financial investment required to integrate AI technology fully into existing operational frameworks. Their remarks highlight the financial burden of adopting AI-driven solutions, posing a substantial barrier for organisations seeking to justify the investment without a clear value proposition: *"That's a big barrier to again almost showcase what the value add is or potential value add is and whether we think we might incorporate that into our portfolios and then clients will buy into that is one of the barriers for us to spend a whole lot of money."* (Interviewee 003, 2023: Interview). Further, the reluctance to allocate substantial resources without assured returns exacerbates the challenge of overcoming the cost barrier inherent in AI adoption.

Interviewee 006 reflects on larger organisations' unique challenges in embracing AI-driven transformations. While acknowledging their financial resources, Interviewee 006 underscores the inherent rigidity and resistance to change prevalent in established enterprises. The bureaucratic hurdles and organisational inertia impede the agility required to adapt swiftly to emerging technologies, prolonging the transition process *"It's not to say the big guys can't do* *it. They've got a huge they've got the, they've got the finance, but sometimes when you're big organisation, it's hard to change completely. "* (Interviewee 006, 2023: Interview).

In contrast, Interviewee 008 contrasts the contrasting responses of more extensive, established, smaller, and more agile firms to AI adoption. They observe that smaller, more agile organisations are better positioned to embrace innovation because of their adaptability and readiness to experiment with new technology. In contrast, larger corporations with entrenched methodologies exhibit more excellent resistance to change, hindering the seamless integration of AI-driven solutions. *"The larger companies that have set methods they are more resistant to change. The nimbler, younger companies that have employed a few more quants are more open to applying these things. "* (Interviewee 008, 2023: Interview).

The subtheme "Lack of Agility in Bigger Companies" emphasises organisations' numerous challenges while deploying AI technologies. Cost restrictions are a vital barrier, while a lack of flexibility and deeply embedded organisational frameworks impede the easy implementation of AI-powered solutions.

4.7 Results Analysis Concerning Research Question 3

RQ3: How do perceived usefulness and ease of use impact the intention to adopt AI-driven portfolio construction methods among South African financial services companies?

4.7.1 Theme 4 Perception and Trust Factors in AI Constructed Portfolios

Perception of AI in PC: Continuous Innovation and Evolution

The industry's perception of artificial intelligence (AI) in portfolio construction revolves around its potential to enhance efficiency, effectiveness, and innovation. Interviewee 001 underscores the efficiency offered by AI-driven sentiment indicators, highlighting the distinction from human-generated sentiment indices: "*They can also create the sentiment index however they want to create it, and they might also use it in their portfolio construction. ....I think that's the key difference and efficiency you get with machine learning and artificial intelligence*." (Interviewee 001, 2023: Interview). This underscores AI's potential to analyze market sentiment objectively, irrespective of human biases.

Similarly, Interviewee 003 reflects on the evolving investment landscape, advocating for a balanced approach that integrates machine-driven insights with human judgment: "*I think the future is not machine living nor with machine-driven investment decision solely.*" (Interviewee 003, 2023: Interview). They caution against solely machine-driven investment strategies.

Interviewee 004 praises the convergence of technology and investment management, emphasising AI's ability to improve operational efficiency and profitability. "*all they would do is tighten up and potentially improve or upraise profitability of a business.*" (Interviewee 004, 2023: Interview). Integrating AI-driven solutions into existing workflows is seen as a means to streamline operations.

Interviewee 005 emphasizes the critical role of predictive analytics in portfolio construction, highlighting AI's ability to improve market trend predictability: "*If you can use the predictive ability of AI and artificial intelligence, can almost allow you to improve your predictability of these things.*" (Interviewee 005, 2023: Interview). This underscores AI's positive impact on decision-making processes.

Furthermore, continuous innovation in AI technologies within portfolio management is crucial, as emphasised by Interviewee 003: "*So I do think that people see the innovation part of it as a positive component, something that should be explored, something that they would want to incorporate ease of use.*" (Interviewee 003, 2023: Interview). This reflects the industry's openness towards exploring AI to enhance operational efficiency.

The iterative nature of model refinement and strategy development is highlighted by Interviewee 006, emphasizing the constant feedback loop between AI teams and portfolio managers: "*And so we have to keep innovating on our data. We have to keep finding new ways to look for market opportunities, strategies and angles, and features for our models.* " (Interviewee 006, 2023: Interview). This iterative process allows for the identification of opportunities and the enhancement of investment outcomes.

Additionally, Interviewee 005 stresses the importance of a stepwise approach to adopting AI technologies, emphasizing ongoing testing and review to refine AI-driven processes: "*I think it is about taking a step, a step approach with regards to adopting AI and to make sure that we that we're testing and reviewing the adoption on an ongoing basis and that's that's pretty much how we've we've approached it is that it's not full-blown.*" (Interviewee 005, 2023: Interview). This incremental approach builds knowledge and confidence in utilizing AI to improve investment outcomes.

Interviewee 007AB discusses the efficiency gains achieved through AI-driven tools for portfolio monitoring and decision-making processes: "*So one way AI can help us is to make the monitoring of the portfolio positions the buy list of stocks or stocks that we put on sell list if we that we can that can help us to better monitoring that help us to do it in a more efficient* *way time-consuming way.*" (Interviewee 007AB, 2023: Interview). Additionally, Interviewee 008 underscores AI's complementary nature as a tool for enhancing portfolio management while maintaining fundamental investment principles: "*It's just like another tool in your toolbox, even though it's a whole other toolbox.*" (Interviewee 008, 2023 Interview).

Collectively, the fundamental principles highlight artificial intelligence's perceived usefulness and efficiency in generating portfolios. Respondents realise the requirement for a well-rounded approach that combines machine-generated insights with human discernment. Experts are excited about the revolutionary capacity of AI to stimulate innovation and increase investment results. Consistent growth in AI technology is critical for continuously improving models and processes, allowing businesses to leverage new technologies and fully enhance long-term investment returns.

Cost Structure Analysis

The subtheme "Perception of AI in Portfolio Construction: Cost Structure Analysis" delves into the industry's view of the costs associated with AI implementation in portfolio management. Interviewee 001 emphasizes the considerable portion of costs allocated to salaries in traditional investment management firms, contrasting it with the relatively lower cost structure associated with AI implementation: *"but I think 70% of their cost base is salaries."* (Interviewee 001, 2023 Interview). This observation highlights the potential cost advantages of employing AI-driven models.

Similarly, Interviewee 003 discusses the balance between research and development costs and the potential returns on investment, cautioning against overinvesting in AI technologies at early stages *"investing too much at at at too early phase….nick you in the butt at the end of the day."* (Interviewee 003, 2023: Interview). This realistic approach acknowledges the importance of cost-effectiveness in AI adoption while ensuring optimal resource utilization.

Interviewee 004 echoes this sentiment by emphasizing the learning curve associated with AI implementation. However, it underscores the long-term benefits of efficiency and cost savings: *"a bit of a learning curve, but that's still you're gonna pay some school fees and get there. "* (Interviewee 004, 2023: Interview).

Finally, the data reflects that AI technology is becoming more widely accepted in investment management, partly due to its ability to streamline processes and reduce costs.

4.8 Results Analysis Concerning Research Question 4

RQ4: What are the current perceptions and attitudes of financial professionals in the financial services industry of South Africa towards the adoption of AI-driven portfolio construction and management methods?

4.8.1 Theme 5 Perceptions, Attitudes, and Human Factors in AI Adoption

Financial professionals exhibit various attitudes towards AI adoption in portfolio construction, ranging from cautious optimism to outright uncertainty. While some professionals recognize the potential of AI to enhance decision-making processes and generate alpha, others express concerns about its reliability, transparency, and ethical implications. The nuanced perspectives reflect the complexity of integrating AI into portfolio management practices. It also further highlights the need for customised solutions tailored to individual clients and market conditions. Furthermore, combining human judgement and machine learning capacities is a significant subject, emphasising the need for human-machine collaboration in efficiently navigating complicated investment environments. Achieving a balanced approach that leverages the strengths of humans and machines is essential for making informed and effective decisions in the evolving landscape of AI adoption within the financial industry.

Perceptions and Attitudes Professionals: Professionals' Attitudes and Trust in AI Adoption

The sub-theme explores professionals' perceptions and attitudes towards AI adoption in portfolio management. Interviewee 001 expresses confidence in machine learning's ability to analyse fundamental data systematically, stating, "*Machine learning is quite helpful to analyze all the fundamental data that we believe actually is important on an unbiased systematic and methodical way and get a probability*" (Interviewee 001, 2023: Interview). Despite this optimism, a cautious tone dominates the conversation.

Interviewee 003 acknowledges the potential benefits of machine learning. However, voices doubt, noting, "*there's very little evidence, especially in the South African market, that it actually can work*" (Interviewee 003, 2023: Interview). Similarly, Interviewee 004 exhibits uncertainty towards AI's transformative impact, stating, "*AI is not gonna make a difference to that*" (Interviewee 004, 2023: Interview).

In contrast, Interviewee 006 presents a forward-thinking perspective, expressing optimism about AI's potential to outperform humans: "*They can run through thousands of thousands of stocks and feed them into their models and come up with something that a man's not able to do so"* (Interviewee 006, 2023: Interview).

Interviewee 005 highlights the perceived difficulty in implementing AI in portfolio construction, stating, "*I think there's definitely a perception that it is, you know, something that's difficult to implement, something that's difficult to do*" (Interviewee 005, 2023: Interview), emphasizing the importance of addressing barriers to adoption. However, Interviewee 007AB discusses the potential of deep learning algorithms to enhance trading decisions. However, it underlines the need for evidence of outperformance compared to traditional strategies, stating, "*I think different neural networks, those deep learning algorithm that can help us to enhance our trading decision*" (Interviewee 007AB, 2023: Interview).

Interviewees are concerned about adopting AI tools for portfolio construction and stock selection. Interviewee 001 characterizes financial professionals' attitudes as "*very apprehensive*" (Interviewee 001, 2023: Interview), a sentiment echoed by Interviewee 002, who expresses disbelief in the possibility of AI disrupting or replacing human expertise: "*I'll be very surprised if, in my lifetime I will see it disrupted or a machine replacing a human*" (Interviewee 002, 2023: Interview).

Moreover, Interviewee 003 highlights hesitancy rooted in the lack of trust towards AI models to guide decision-making consistently (Interviewee 003, 2023: Interview), a sentiment compounded by Interviewee 004's doubt about AI's capacity to replicate human intelligence and consciousness (Interviewee 004, 2023: Interview).

Furthermore, Interviewee 005 underscores the industry's preference for tangible evidence of AI's effectiveness, suggesting a three- to five-year track record is necessary to alleviate apprehensions and instil client confidence (Interviewee 005, 2023: Interview). Interviewee 006 echoes this sentiment, noting the persistent perception of AI as "rogue" and untrustworthy within the industry (Interviewee 006, 2023: Interview).

Interviewee 001 underscores analysts' threat perception towards AI technologies, noting their reluctance to embrace new tools that challenge their expertise and highlight potential shortcomings: "*They are reluctant to embrace the new technology because they are threatened by the technology*" (Interviewee 001, 2023: Interview). This sentiment demonstrates an ego-driven opposition to change, motivated by a fear of being replaced or overshadowed by automated technologies.

Moreover, Interviewee 001 characterizes the industry's tendency to deny or ignore the implications of AI advancements as the "ostrich mentality": "*You wish that you believe that it's not there. So you don't wanna see it because you're scared of it*" (Interviewee 001, 2023:

Interview). This avoidance stems from apprehension towards the unknown and a desire to maintain the status quo.

Interviewee 002 emphasizes the challenge of establishing trust in AI-driven portfolios due to the absence of a proven track record, reflecting a broader industry sentiment reliant on historical performance as a benchmark for adoption: "*I can find you lots of machine portfolios that do that, and that's the challenge because you need a track record*" (Interviewee 002, 2023: Interview).

Furthermore, Interviewee 005 sheds light on the industry's propensity for ignorance and mistrust towards unfamiliar technologies, perpetuating a cycle of scepticism and resistance: "*Yeah, I would say that people are ignorant, you know? So ignorant ignorance is bliss*" (Interviewee 005, 2023: Interview). This sentiment is echoed by Interviewee 008, who emphasizes the industry's aversion to change and comfort with traditional methodologies like discounted cash flow (DCF) analysis: "*Why would we use that? We have our methods, we do DCF*" (Interviewee 008, 2023: Interview).

Moreover, Interviewee 003 raises concerns about AI's inability to craft compelling narratives from a fundamental perspective, potentially leading to apprehension among clients accustomed to human-driven investment strategies: "*Machine cannot necessarily tell me a good fundamental story, and therefore there will be apprehension*" (Interviewee 003, 2023: Interview). This highlights the importance of storytelling and client engagement in investment, where AI may struggle to replicate human intuition and communication skills.

Additionally, the subtheme acknowledges the inherent diversity among investors' financial situations, suggesting that a cookie-cutter approach to portfolio construction may not meet the varied needs of clients: "*The cookie-cutter approach, I don't think that will work*" (Interviewee 003, 2023: Interview). This recognition underscores the complexity of portfolio management and the necessity of tailored solutions that account for individual circumstances.

Interviewee 006 acknowledges the occasional underperformance of AI models, suggesting that no single model is infallible and that fluctuations in performance are inevitable: "*No matter which model we choose, there are small periods where the models underperform*" (Interviewee 006, 2023: Interview). This perspective highlights the importance of managing expectations and recognizing the limitations of AI-driven strategies in achieving consistent outperformance.

Furthermore, Interviewee 005 alludes to the flexibility of AI design, suggesting that the efficacy of AI-driven portfolio construction depends on how the algorithms are crafted and calibrated: "*It's around how you design your AI; I mean, you could also design it to see everything*" (Interviewee 005, 2023: Interview).

Interviewee 001 highlights doubt regarding AI's forecasting capabilities, mainly its ability to capture long-term trends and extreme events that may impact the market: "*Machine learning machines will not be aware of longer-term trends and themes currently influencing the market, or extreme events like a war in Palestine, and will not consider that in their investment methodology*" (Interviewee 001, 2023: Interview).

Similarly, Interviewee 002 underscores the importance of trust and confidence in AI systems, especially concerning client fiduciary responsibilities: "*We've got a fiduciary responsibility to clients*" (Interviewee 002, 2023: Interview).

Interviewee 003 articulates mistrust rooted in a lack of understanding of AI models and their decision-making processes, leading to uncertainty and hesitation in relying on machine-driven recommendations: "*The lack of trust for machines is evident*" (Interviewee 003, 2023: Interview). This sentiment is echoed by Interviewee 004, who expresses doubt about the ability to imbue AI with consciousness and emphasizes the need for a high level of assurance before delegating decision-making to AI: "*I suppose it's level of assurance you would need in the first place. So I can't let the AI go running off and telling my clients what to do unless I'm 150% sure I understand the results*" (Interviewee 004, 2023: Interview).

This sentiment is reinforced by Interviewee 007AB, who emphasizes the foundational role of trust in the asset management industry: "*Because ultimately what we do in the fund management industry is built on trust*" (Interviewee 007AB, 2023: Interview).

The issue of trust and attitudes among financial professionals towards deploying AI in portfolio management is intricate. While specific individuals exhibit faith in the capacity of machine learning to analyse fundamental facts, others harbour doubts regarding its efficacy and transformational influence. Nevertheless, several visionary experts express hope regarding AI's capacity to surpass human talents in processing extensive datasets.

Experimentation and Risk-Taking in AI Adoption

The sub-theme "Experimentation and Risk-Taking in AI Adoption" delves into the cautious approach financial professionals take towards integrating AI into portfolio management, with clients often perceived as guinea pigs for testing new AI technologies and methodologies.

Interviewee 003 expresses concerns about clients being used as guinea pigs to test new AI applications and investment strategies, highlighting potential issues related to treating customers fairly: *"clients are being used as Guinea pigs to test cases or your IP, which again comes can become come to some kind of a TCF issue"* (Interviewee 003, 2023: Interview). This sentiment is echoed by Interviewee 004, who discusses the challenges of coding AI systems to identify individual investment strategies based on risk tolerance accurately: *"But then again, it's the matter of coding that the coding that you know responding to set series of questions and inferring risk tolerance from those answers"* (Interviewee 004, 2023: Interview).

However, Interviewees 006 and 007AB acknowledge the cautious approach of some clients who view AI adoption as more than just a passing trend, recognizing the complexities and uncertainties involved: *"so some more cautious clients, are we saying that AI is not just another fad is this not you're not just sort of chasing the next wave that's ultimately gonna die out and and and we're gonna be left to you know paying the fees for it"* (Interviewee 006, 2023: Interview). Similarly, Interviewee 005 highlights instances where early adopters of AI in portfolio construction failed to achieve expected performance levels, suggesting a need for careful evaluation and consideration: *"So you know, if you look at it, one or two guys that have applied AI pretty early on .....actually didn't seem to generate the levels of performance that they were looking for"* (Interviewee 005, 2023: Interview).

Lastly, Interviewee 008 shares insights into generating alpha through small-scale AI implementations, indicating a measured approach towards integrating AI into portfolio management practices: "*we've actually do have success rates we generating alpha as we speak, you know, but by taking very small bets away from the benchmark"* (Interviewee 008, 2023: Interview).

Overall, this sub-theme underscores the careful navigation of experimentation and risk-taking in AI adoption, with professionals balancing the potential benefits against the need for cautious evaluation and client considerations.

Human-Machine Dynamics in AI Adoption

The sub-theme "Human-Machine Dynamics in AI Adoption" explores the intricate relationship between humans and machines in the context of AI adoption and decision-making.

Interviewee 002 emphasizes the irreplaceable role of human judgment, asserting that while AI can provide insights, it is a human interpretation that ultimately determines their relevance: "*A machine is not gonna be able to yet establish where that makes sense or not….*" (Interviewee 002, 2023: Interview). This sentiment is echoed by Interviewee 003, who emphasizes the importance of translating machine-generated insights into intuitive narratives to build trust: "*If you can translate what the machine is saying to an intuitive story then, then, then it already creates a bit of trust*" (Interviewee 003, 2023: Interview). However, Interviewee 003 also advocates for a balanced approach that integrates human judgment with AI-driven insights.

Interviewee 006 introduces the concept of a 'man-machine strategy,' highlighting the synergistic potential of combining human expertise with AI-driven models. They describe how portfolio managers leverage machine-generated data to inform investment decisions while retaining the final call based on qualitative factors: "we can generate... alpha... giving our portfolio managers... a foundation" (Interviewee 006, 2023: Interview).

Moreover, Interviewee 005 underscores the value of human intuition and diverse perspectives in decision-making, noting that while AI can process vast amounts of data, human intervention adds depth and adaptability to investment strategies: "we're still quite comfortable with the ability of humans to get these calls right" (Interviewee 005, 2023: Interview).

Interviewee 001 highlights the limitations of human analysis, noting biases and emotional attachments that can distort decision-making while emphasizing AI's unbiased approach: "*What's great about the artificial intelligence and the machine learning is that it's unbiased*" (Interviewee 001, 2023: Interview). However, Interviewee 003 raises concerns about AI's limitations in understanding complex human behaviours and nuances, suggesting potential apprehension about solely relying on machine-driven decisions.

Interviewee 006 reiterates the concept of a 'man-machine strategy,' emphasizing the collaborative approach where humans leverage machine-generated insights while providing oversight and guidance: "*We recognize that there's things that a portfolio manager can do better than a machine"*(Interviewee 006, 2023: Interview). This hybrid model acknowledges the strengths of both humans and machines in decision-making processes.

Furthermore, Interviewee 008 highlights AI's superior data processing capabilities compared to humans, acknowledging its potential to absorb vast amounts of information. However, there remains a consensus among experts that human intervention and oversight are essential to complement AI-driven insights and address its limitations.

In conclusion, while AI offers efficiency and objectivity in data analysis, human judgment remains indispensable in interpreting nuanced contexts and providing strategic direction.

4.9.1 Theme 6: Ethical and Regulatory Considerations in AI-driven Portfolio Construction

The analysis of ethical and regulatory factors in AI-driven portfolio design highlights the critical relevance of adhering to fiduciary duty ethical norms and treating clients fairly (TCF) to protect investors' interests and retain trust in the financial services industry. Interviewees express concerns about accountability, transparency, and regulatory compliance in leveraging AI technologies, underscoring the need for rigorous ethical oversight. Simultaneously, examining concerns around job displacement resulting from the acceptance of artificial intelligence reveals the intricate apprehensions surrounding employment loss and the transformation of the work landscape due to technological advancements. Specific individuals express doubt over the immediate occurrence of job loss. However, others emphasise the significance of firms addressing employee concerns and mitigating the hazards of using artificial intelligence. These sub-themes highlight the numerous ethical, legal, and economic considerations that arise when AI is employed in portfolio management. They emphasise the significance of ethical conduct, transparency, and proactive measures to alleviate concerns regarding job stability.

Fiduciary Duties & accountability & TCF

The analysis underscores the importance of upholding fiduciary duties and treating clients fairly (TCF) in integrating AI technologies into portfolio management. Interviewees express concerns about accountability and regulatory compliance, highlighting the need for transparency and ethical conduct. The quotes from various interviewees provide insight into their perspectives on fiduciary responsibilities and the ethical implications of AI adoption.

Interviewee 002 emphasizes the fiduciary responsibility to clients, expressing concern over the potential risk associated with AI-driven decisions and the importance of maintaining accountability for investment outcomes: *"we've gotta fiduciary responsibility to clients... I just lost half of your portfolio because …… my machine learning inputs said I must put your money here, and it lost half your portfolio."* (Interviewee 002, 2023: Interview). This perspective underscores the need for transparency and prudence in leveraging AI technologies to safeguard clients' interests. Moreover, Interviewee 003 raises concerns about treating clients fairly (TCF) and the potential ethical implications of using clients as test cases for AI algorithms: *"clients are being used as Guinea pigs to test cases …… some kind of a TCF issue "* (Interviewee 003, 2023: Interview). This highlights the ethical dilemma of balancing innovation with client welfare and underscores the need for rigorous ethical oversight in AI-driven portfolio management.

Interviewee 004 discusses the liability of owning AI technology and emphasizes accountability in managing clients' assets: *"If I own that, the technology ……..then I'm obviously liable. "* (Interviewee 004, 2023: Interview). This viewpoint underscores the legal and ethical responsibilities of deploying AI-driven solutions in portfolio management.

Additionally, Interviewee 006 highlights the regulatory constraints and reputational risks associated with AI adoption in the highly regulated financial services sector, *"financial services sector which is highly regulated "* (Interviewee 006, 2023: Interview). This emphasizes the importance of compliance with ethical standards and regulatory frameworks to mitigate legal and reputational risks.

Interviewee 005 underscores the ethical principles guiding portfolio management decisions, emphasizing the importance of adhering to regulatory requirements and ethical standards set by professional bodies like the CFA Institute. *"You know, we as a business sign up to the CFA ethics standards"* (Interviewee 005, 2023: Interview). This reinforces the commitment to ethical conduct and regulatory compliance in AI-driven portfolio management practices.

Lastly, Interviewee 007AB emphasizes the fiduciary duty of custodianship and the obligation to explain AI-driven investment outcomes to *clients: "So we have a fiduciary duty as custodians of investors capital"* (Interviewee 007AB, 2023: Interview). This underscores the need for transparency, accountability, and effective client communication to maintain trust and uphold fiduciary obligations.

The analysis emphasises the need for fiduciary responsibility and fairness when incorporating AI technologies into portfolio management methods, addressing concerns about accountability, regulatory compliance, and ethical behaviour. It emphasises transparency, accountability, professional trust and ethical conduct standards.

Job Scarcity Concern of AI Adoption

This thematic exploration explores the apprehensions revolving around job security within the financial sector amidst the integration of AI. A spectrum of concerns emerges, encompassing fears of job scarcity and technological displacement. Interviewee 001 sheds light on prevalent doubt and apprehension regarding job scarcity, remarking: *"Because of the job scarcity or them losing their jobs, or just that they just not believers in it. "* (Interviewee 001, 2023: Interview). This sentiment reflects the multifaceted uncertainties individuals grapple with concerning the repercussions of AI on their professional trajectories.

Correspondingly, Interviewee 003 juxtaposes potential efficiency gains with the looming spectre of job losses, elucidating, *"There is potential efficiency gains they could potentially be pushed back, you know, in terms of job losses, etcetera. "* (Interviewee 003, 2023: Interview). This underscores the ethical dilemma of balancing technological advancement with its socio-economic repercussions.

Interviewee 004 reflects on the prevailing mindset regarding job security in the face of AI adoption: *"And that's sort of sense I get of their mindset, and there's no sense of I'm I'm gonna be done under a job here."* (Interviewee 004, 2023: Interview). The absence of job security concerns may indicate a lack of awareness or acknowledgement of the potential impact of AI on employment.

Conversely, Interviewee 006 illuminates the initial trepidation surrounding AI's potential to replace traditional job roles, asserting: *"people are nervous initially; they don't want it to replace their jobs."* (Interviewee 006, 2023: Interview). Ego and perceived threats to job roles contribute to apprehension regarding AI adoption within the workforce.

Furthermore, Interviewee 005 emphasizes the overarching apprehension about job security as the primary concern surrounding AI adoption: *"So I think the apprehension is the the risk to to jobs into work. I would say that's probably the biggest one,"* (Interviewee 005, 2023: Interview). This underscores the need for organisations to address employee concerns and mitigate fears about technological displacement.

Interviewee 007AB provides a conflicting view in their insights into the industry's perception of job security amid AI integration: *"Industry aren't concerned about losing their jobs. "* (Interviewee 007AB, 2023: Interview). While acknowledging the potential for disruption, there is a recognition of the need for adaptation to technological advancements. Similarly, Interviewee 008 expresses doubt about the immediate threat of job loss due to AI adoption: *"I don't think that that's no one feels that way. Uh, like they're gonna lose their jobs because there's no proof that that unsupervised learning has, "* (Interviewee 008, 2023: Interview). This highlights the importance of evidence-based assessments of AI's impact on employment dynamics.

In conclusion, there are concerns about employment stability in the finance industry due to the inclusion of artificial intelligence. Interviewees question the scarcity of jobs and the displacement induced by technology. Nonetheless, there is widespread agreement that organisations must address employee concerns, reduce the risks of job displacement, and encourage a supportive transition to artificial intelligence. The discussion focuses on ethical considerations and the well-being of employees.

4.10 Concluding Summary

In this concluding summary, the thematic analysis shows a comprehensive grasp of AI attitudes and adoption patterns in South Africa's financial services sector portfolio construction and management. Across six prominent themes and their respective sub-themes, diverse attitudes and challenges among financial professionals towards AI adoption are uncovered. From cautious optimism to scepticism, professionals exhibit varied perspectives, highlighting the complexity of integrating AI into portfolio management practices. Some interviewees express confidence in AI's potential to enhance decision-making processes; others raise concerns about its reliability, transparency, and ethical implications. Moreover, professionals emphasize the importance of ethical oversight and adherence to regulatory frameworks in AI-driven portfolio management.

Furthermore, the analysis illuminates the intricate relationship between humans and machines in decision-making processes, recognizing the complementary nature of human judgment and AI-driven insights. Professionals advocate for a balanced approach that leverages both strengths, emphasizing the significance of ethical conduct, transparency, and accountability in AI adoption. Concerns about potential job displacement underscore the need for organisations to address employee concerns and promote a supportive transition towards AI adoption. These findings provide valuable insights into the multifaceted landscape of AI adoption in South Africa's financial industry, laying the groundwork for further exploration of interpretations and implications in the discussion chapter.

Chapter 5 Discussion Chapter

5.1 Introduction

Integrating Artificial Intelligence (AI) into portfolio construction and management within South Africa's financial services industry presents promise and uncertainty. This study explores how asset managers adopting AI in South Africa can enhance investor value maximisation amidst potential uncertainties. Using a qualitative approach, which involves thematic analysis, semi-structured and structured interviews, and purposeful sampling approaches, this research investigates the perceptions and adoption patterns of AI-driven portfolio design and management approaches among financial services organisations in South Africa. Initially, the chapter scrutinizes the impact of AI-adopted portfolio construction on efficiency compared to traditional methods. Subsequently, it delves into the barriers and challenges hindering AI adoption. Then, it analyses the factors influencing the inclination towards AI-driven approaches. Finally, the chapter provides insights into financial experts' perspectives and attitudes towards implementing artificial intelligence in portfolio construction and management.

5.2 Overview

The study delves into the multifaceted landscape of AI-driven portfolio construction within the South African financial services sector, revealing nuanced perceptions and attitudes among financial professionals. Through thematic analysis, it becomes evident that while optimism regarding AI's potential to enhance efficiency and decision-making exists, concerns regarding reliability, transparency, and ethical implications persist. Additionally, the study highlights the intricate balance between technological advancement and ethical responsibility, emphasising the need for rigorous oversight to uphold fiduciary duties and treat clients fairly. The findings emphasise apprehensions surrounding job security and technological displacement, underscoring organisations' need to address workforce concerns and facilitate a smooth transition towards AI integration.

Further, the study highlights the critical role of ethical conduct, transparency, and regulatory compliance in mitigating risks associated with AI adoption in portfolio management. Financial professionals emphasize the importance of upholding fiduciary responsibilities and ethical standards while navigating the complexities of AI-driven decision-making processes. The findings highlight organisations' need to proactively address employee concerns, promote trust and transparency, and foster a collaborative approach to AI adoption. The study provides valuable insights into the challenges and opportunities presented by AI-driven portfolio construction, advocating for a balanced approach that prioritizes ethical considerations, regulatory compliance, and workforce well-being amidst technological innovation.

5.3 Results Discussion concerning Research Question 1

RQ1: What is the perception of the impact of AI-adopted portfolio construction on portfolio efficiency compared to traditional portfolio construction methods in the financial services industry in South Africa?

5.3.1 Theme 1 Portfolio Construction Methods Used Currently

5.3.1.1 Traditional Portfolio Construction

Our investigation into Research Question 1 (RQ1), which scrutinizes the perception of the impact of AI-adopted portfolio construction on portfolio efficiency compared to traditional methods in South Africa's financial services industry, reveals a pervasive reliance on traditional portfolio construction methods. Interviews with industry professionals highlight a predominant adherence to conventional approaches, with only a minority exploring AI-driven techniques. This resistance towards AI adoption emanates from various factors, including a preference for established principles, the perceived simplicity of traditional models, and a steadfast commitment to client-centric approaches. Golić (2019) suggests that AI's superiority can revolutionise the financial sector by increasing personalised services and offering improved experiences and, significantly, abilities to track market irregularities to help prevent another financial crisis. Additional research, such as de Prado's (2020) findings, implies that traditional asset management strategies may not be appropriate for dealing with complex and dynamic financial markets. This finding supports the superiority of machine learning and artificial intelligence over human and traditional methodologies.

Despite the literature's resounding endorsement of AI's superiority, as evidenced by Golić (2019), de Prado (2020) and Bartram et al. (2020), South Africa's financial sector remains deeply entrenched in traditional methodologies. This incongruity necessitates a deeper exploration of the challenges impeding widespread AI adoption in portfolio construction. Factors contributing to the enduring appeal of traditional methods include their perceived reliability, simplicity, and alignment with established investment principles. It is imperative to delve deeper into the underlying reasons influencing the adoption of AI-driven portfolio construction methods and their potential impact on portfolio efficiency in the South African context.

5.3.1.2 Machine Learning Usage in Portfolio Construction

Our examination of the integration of machine learning into portfolio construction methods unveils a nuanced perspective within the financial services industry. While traditional methods maintain dominance, there is a growing recognition of the potential advantages of leveraging machine learning techniques. Notably, Interviewee 001 emphasized the extensive use of machine learning in stock selection and portfolio construction within their organisation. Moreover, Interviewee 003 expressed optimism regarding the future role of machines in finance. This view is supported by literature like Golić (2019), where the author highlights that Ml is a valuable tool for enhancing portfolio construction in the financial sector. The writer highlights its ability to analyse vast data and help improve decision-making and detect patterns. This optimism is mirrored in de Prado's (2020) assertion that AI can enhance asset management through robust financial data analysis and more accurate portfolio optimization. However, amidst this recognition, some respondents voiced scepticism. Interviewee 004, for instance, expressed reservations regarding AI's potential to assist in portfolio construction.

Additionally, Interviewee 007AB highlighted the need for manual intervention despite utilizing supervised learning techniques. This viewpoint is also backed by de Prado (2020), who emphasises gaps in the literature, one of which is the value of human expertise. While machine learning is a tool, the writer emphasises the importance of human expertise in decision-making, which must be matched with the investment strategy's objectives. Other publications, such as Koratamaddi et al. (2021), imply that AI technologies require continual human intervention and adjustment to account for dynamic market conditions. This cautious yet optimistic stance underscores an awareness of AI's transformative capabilities in portfolio management.

5.3.1.3 Hybrid Usage in Portfolio Construction

Another emerging sub-theme from the interviews is a growing interest in hybrid approaches that combine quantitative research with traditional methods in portfolio construction. Interviewees consistently emphasized the synergistic relationship between quantitative models and human judgment in portfolio creation. This sentiment aligns with Jain and Jain's (2019) recommendations for amalgamating traditional approaches with AI to create hybrid methodologies. The article suggests that combining traditional risk-based methodologies with machine learning techniques in hybrid approaches may enhance portfolio performance more than using each strategy individually (Jain & Jain, 2019). Hybrid strategies may lessen the impact of covariance misspecification while also improving portfolio diversity by combining the capabilities of both approaches. For instance, Interviewee 002 described their organisation's process as a hybrid model, integrating quantitative underpinnings with conventional implementation. This consensus among participants underscores the practical realization that constructing a portfolio necessitates rigorous quantitative analysis and subjective judgment, leading to more robust investment portfolios through hybrid strategies that integrate the strengths of both techniques.

5.3.1.4 Recommendation and Conclusion

The South African financial services industry must embrace a more proactive approach to integrating AI-driven portfolio construction methods. Given the demonstrated potential benefits of AI and hybrid approaches, firms should invest in comprehensive education and training programs to equip professionals with the necessary skills and knowledge. Furthermore, fostering a culture of innovation, experimentation, and strategic partnerships with technology firms can facilitate smoother transitions towards AI adoption. By overcoming existing barriers and embracing emerging methodologies, the industry can enhance portfolio efficiency and risk management, ultimately delivering more excellent value to investors.

In conclusion, while traditional portfolio construction methods continue to dominate, there is a growing recognition of the transformative potential of AI and hybrid approaches. By understanding and addressing the underlying challenges, the South African financial services industry can position itself at the forefront of innovation, driving greater efficiency and effectiveness in portfolio management practices.

5.3.2 Theme 2: Impact and Drivers of AI Adoption in Portfolio Construction

5.3.2.1 Balancing Speed and Caution in AI Adoption

Our exploration into AI adoption in portfolio construction reveals a delicate equilibrium between the desire for rapid progress and the need for careful consideration. Interviewees emphasise the competitive edge gained from early adoption, aligning with Golić (2019) recognition of benefits for the financial services sector. The article suggests that early adoption of AI in the financial sector can provide organisations with a competitive advantage. By embracing AI technologies early on, financial institutions can enhance their operational efficiency, improve customer experiences, and gain insights from data analysis that can lead to better decision-making. For instance, Interviewee 006 highlights their organisation's proactive stance: "Our business has always prioritized tech adoption to stay ahead within the industry" (Interviewee 006, 2023). Similarly, Interviewee 003 stresses the risks of lagging, echoing the imperative of staying abreast of technological advancements (Interviewee 003, 2023).

However, amid this enthusiasm, a sense of caution prevails. Interviewee 008 notes AI's relative infancy in finance, advocating for measured progress. Interviewee 004 expresses scepticism about AI's capabilities, cautioning against premature integration (Interviewee 004, 2023). The article by Golić (2019) emphasises the significance of combining the rapid deployment of AI in the financial sector with caution to reduce potential dangers and obstacles. This tension between rapid innovation and prudent decision-making underscores the complexity of AI adoption. Striking a balance requires acknowledging AI's transformative potential while addressing ethical concerns, biases, and transparency in AI systems.

5.3.2.2 Organisational Dynamics and Efficiency Enhancement in AI Adoption

In examining the organisational dynamics surrounding AI adoption in portfolio construction, our analysis reveals a nuanced interplay between technical capabilities and operational considerations. Interviewee 001 emphasized the efficiency gained through AI, illustrating how "two people can do more work than 22 people can" through automation and advanced algorithms (Interviewee 001, 2023). This view is shared by de Prado (2020), who states that automating asset management can enhance efficiency, speed, scalability, risk management, and compliance. AI and machine learning technology can optimise data analysis, portfolio management, and trade execution, reducing manual work and expenses. However, human oversight and decision-making remain critical for strategic planning and risk assessment.

Moreover, initiatives like the development of AI models demonstrate a proactive approach to leveraging existing infrastructure for enhanced performance, as discussed by Interviewee 001: "*We're gonna use the infrastructure and the algorithms developed by Openai for CHATGPT, the large language models and put it on top of, well basically tell it to forget all of the information other than its linguistic ability*" (Interviewee 001, 2023). From the literature, we note that AI can transform the financial sector by improving operational efficiency, reducing costs, and enhancing risk management (Golić, 2019). The study also highlights the potential of AI to increase financial inclusion and accessibility, particularly in emerging markets. These dynamics and efficiencies relate to enhancement via organisational dynamics and efficiency. Other research agreeing with this sentiment is that AI and machine learning can improve operational efficiency and reduce costs in the asset management industry (Novick et al., 2019).

However, respondents also highlighted the complexity of integrating AI into existing systems and workflows. Interviewee 006 described real-world implementation challenges, including liquidity, trading, and market dynamics, stating that "implementing that into a real-world portfolio with liquidity, with trading, with costs, with market makers with moves, you know, dealing with traders themselves trying to integrate those systems into your trading system alone can be can be a huge level of complexity" (Interviewee 006, 2023). This complexity underscores the need for organisations to navigate challenges such as workforce implications, regulatory constraints, and technical complexities to realise the benefits of AI integration fully. These sentiments are also reflected in the works of Njegovanović, A. (2018), Novick et al. (2019), de Pardo (2020) and Albuquerque et al. (2023), where all attest to the complexity of machine learning models and their interpretation.

Moreover, the transition from manual to automated systems has significantly enhanced efficiency by enabling automatic data input, thereby reducing the need for human intervention. Interviewee 005 highlighted the pivotal role of AI in helping organisations manage large volumes of data effectively, stating that "the biggest sort of influence that we've seen is in the ability for organisations like ourselves to work with large amounts of data" (Interviewee 005, 2023). By eliminating manual data entry tasks, AI empowers professionals to focus on higher-order tasks such as interpretation and critical thinking, as noted by Interviewee 005: "You don't want to have a CFA having to run around trying to put data into a system, for example, you want them to do the thinking, the interpretation" (Interviewee 005, 2023). However, challenges remain, as articulated by Interviewee 007AB, who highlighted the complexity of data structures, stating that "it does require a lot of complex data or also the structure" (Interviewee 007AB, 2023).

Overall, the integration of AI not only enhances operational efficiency but also drives down costs, making it a pivotal strategy for organisations seeking to remain competitive and deliver value to clients in a cost-effective manner.

5.3.2.3 Abundance of Data: Price and Fundamental Data

The widespread availability of data, including financial indicators and unconventional sources like sentiment analysis and social media, is a critical factor in the increasing use of AI across various industries. The financial services section is no exception. This sentiment analysis is found in the works of Koratamaddi et al. (2021), where the writers use deep learning reinforcement for stock allocation using market sentiments from Twitter and natural learning processing. The findings suggest that AI can help investors make better decisions by utilising extensive data and capturing complex relationships through this analysis (Koratamaddi et al., 2021). Karlíček, O. (2021) stresses that data quality and availability are drivers of adoption since ML requires large amounts to be trained effectively and directly impacts the performance if the data quality is lacking.

Furthermore, Goodell et al. (2021) agree on the data quality difficulties; nevertheless, they emphasise that there may be other limitations in AI's ability to manage severe occurrences known as "black swans," which are unusual and unforeseen and can have substantial market consequences. In the research of Ahmed et al. (2022), a highlighted gap the researchers suggest is that more research is needed to investigate the impact of data quality on the effectiveness of AI and ML in portfolio management. The authors note this weakness because they see this gap for further work in that AI and ML require large amounts of high-quality data to be effective and practically used.

Interviewee 001 emphasized the importance of this trend, highlighting the growing accessibility of essential and cost-related information, which was previously difficult to obtain: "Fundamental as well as price data, as well as total return series and data availability, has just become so much more freely available in the past, it was really difficult to get especially fundamental data" (Interviewee 001, 2023). This accessibility of data has necessitated organisations to utilize new technologies such as deep learning and machine learning to efficiently extract value from large datasets, as emphasized by Interviewee 006: "you've got the efficiency, you've got data is everywhere. People are looking for an edge. Uh, financial markets are high. Beating the market is difficult, and not many people do it, so that they're looking for the edge they need to outperform" (Interviewee 006, 2023). Although accurate in terms of the abundance of data in this age, these sentiments need to be qualified as the research highlights the challenge of the quality of data and may cause challenges and systemic failures should the quality be poor (Bartram et al., 2020).

Literature also suggests that the calibre of the data significantly employed influences the precision and dependability of AI models. Inaccurate predictions, biased outcomes, and other difficulties might arise due to low-quality data (Golić, 2019). Large data sets seem to have continued to drive adoption; however, the caveat is the quality, which we will explore later. This sentiment that data is a great driver of adoption is reflected in the works of Heaton et al. (2017), where one of the recommendations suggested driving adoption is to combine ML, which may ensure high data quality inputs to avoid biases and errors (Heaton et al., 2017).

While the abundance of data presents opportunities for innovation and efficiency, it also poses challenges in data management and processing. Interviewee 005 discussed the historical difficulties of handling large datasets and the transformative impact of AI in streamlining data management processes: "So I think in the past I think it was very difficult to work with large amounts of data …… see that value coming through" (Interviewee 005, 2023).

Additionally, Interviewee 007AB emphasized the requirement for substantial data volumes to ensure robust testing and decision-making processes in investment management: "for me, it's often requires a lot of data, and we need to have enough data to really thoroughly test" (Interviewee 007AB, 2023). The works of Jain and Jain (2019) suggest several solutions to help drive adoption, which include improving the quality and quantity of data used in the analysis to reduce the risk of data biases and improve accuracy. Data is a driver of adoption; however, data quality is critical.

In summary, the subtheme underscores the pivotal role of data abundance in driving AI adoption, enabling organisations to gain a competitive edge through advanced analytics and informed decision-making. However, managing and leveraging vast datasets remain essential for successful AI integration and organisational transformation.

5.3.2.4 Availability and Impact of Computing Power

The availability and impact of computing power emerge as pivotal factors driving the adoption of artificial intelligence (AI) technologies. Interviewees highlight the transformative role of cloud computing in providing access to robust computational resources, enabling organisations to analyze vast quantities of data swiftly and efficiently. The literature reaffirms this position: The rapid growth of data and the expansion of computation processing power, storage, the cloud, and data availability have been essential in promoting the growth and implementation of AI and machine learning in different industries, including asset management (Novick et al., 2019). This accessibility to advanced computing capabilities facilitates the development and deployment of AI algorithms with reduced reliance on closed-loop systems, as emphasized by Interviewee 001: "cloud computing is making it very easy to analyze vast quantities of data and to force you, you don't have to use closed-loop algorithms anymore" (Interviewee 001, 2023). The view of technology as a driver of adoption exists in the literature, such as Novick et al. (2019), who argue that when new tools are produced, and computing power becomes more accessible, there will be a more significant push for AI and ML adoption. The view is that technology will be essential in different asset management responsibilities, as it has been for decades. With the development of new tools, the cost of processing power becoming more accessible, and the increasing availability of data, we may expect to see more applications for AI and ML in asset management (Novick et al., 2019).

Moreover, the correlation between data processing speed and predictive power underscores the significance of computing power in algorithmic development. Interviewee 002 emphasizes the importance of processing speed in enhancing predictive capabilities, positioning it as a critical differentiator in strategic asset allocation: “It's one of our key differentiators. I mean, you can call it AI, I'll call it the quantum vesting” (Interviewee 002, 2023). This sentiment is echoed by Interviewee 006, who discusses the evolution of machine-driven strategies over time, leveraging extensive historical data to optimize decision-making processes: “We find that the more data you give it, they generally tend to be better. So in our results, the models that we have on the global scale are a lot more productive they show a lot better results” (Interviewee 006, 2023). Aligning with research, Novick et al. (2019) suggest that improved computing capacity allows computers to analyse massive datasets and detect trends and outliers, ultimately improving decision-making processes and operational workflows in asset management. Furthermore, AI algorithms can scrutinise vast amounts of data to detect patterns and trends, facilitating more precise forecasts of asset values and market fluctuations. (Albuquerque et al., 2023).

The exponential growth in computing power enhances predictive modelling and enables organisations to tackle complex analytical tasks at scale. One of the critical objectives of Ouyang, Z. (2022) was a discussion around the predictive power of algorithms on portfolio performance. The author found that random forest and decision tree methods were unstable and that further studies were needed for ML algorithms to predict stock returns, which may suggest that this could be an inhibiting factor to the adoption process.

Interviewee 006 highlights the capability of machines to process vast amounts of data, identifying patterns and features that may elude human perception: “So whereas the human you can go through these and maybe you're picking up one or two flags and features….something that's a lot more cohesive” (Interviewee 006, 2023). Literature also emphasises the necessity of machine learning in asset management for handling massive data sets that may be difficult for human perception alone (de Prado, 2020). Furthermore, the availability of robust computing systems facilitates the iterative development and refinement of AI models, contributing to a more streamlined and efficient decision-making process, as articulated by Interviewee 006: “we run it over the weekend, but a Single Mac book Pro would take it to, it would take it three years to run” (Interviewee 006, 2023).

In summary, the subtheme underscores the transformative impact of enhanced computing power on AI adoption, facilitating the development of sophisticated algorithms and empowering organisations to extract actionable insights from vast datasets. By democratizing access to advanced computational resources, computing power catalyzes innovation, driving the widespread adoption of AI technologies across diverse industries; however, the limitations proposed in learning methods must be further explored.

5.3.2.5 Generational Impact & Not a New Phenomenon

The adoption of artificial intelligence (AI) is significantly influenced by generational dynamics, reflecting a shift towards innovation and technological advancement. Younger generations exhibit a greater propensity for embracing novel approaches, as highlighted by Interviewee 003, who emphasizes their inclination towards innovative solutions over traditional methods: “positive side of things is very much driven from a generational thing where you know younger generations are more prone to try new innovative things” (Interviewee 003, 2023).

However, while AI adoption may seem revolutionary, it is rooted in longstanding principles and practices. Interviewee 004 underscores the continuity of investment principles developed decades ago, suggesting that AI, in its current form, primarily represents automation rather than genuine consciousness: “AI, you know, genuine consciousness. I'm not convinced that that that has been developed as yet, so anything that we do have that is AI is just automation. It's just, you know, coding up and computers doing human work for them” (Interviewee 004, 2023). Despite technological advancements, the underlying financial and economic principles remain consistent across generations, indicating continuity in approach despite technological evolution.

Furthermore, the historical precedence of AI initiatives predates contemporary perceptions, as highlighted by Interviewee 007AB. The emergence of AI dates back to the 1980s, indicating that it is not a new phenomenon but a continually evolving field. However, the accessibility of AI technologies, driven by economic factors, is pivotal in driving its widespread adoption, aligning with Interviewee 007AB's observation regarding its leading factor: “It's not a new phenomenon, but what I'd I believe that is a leading factor driving the adoption of AI is accessibility from a what's IT economic” (Interviewee 007, 2023). Chui M (2017) states that

AI is relatively new in asset management; however, this was recorded in 2017, and there may have been advancements. Osterrieder (2023) suggests that artificial intelligence and machine learning have been used for decades. (Osterrieder, 2023).

The subtheme underscores the interplay between generational dynamics and technological evolution in shaping AI adoption. While younger generations champion innovation and technological advancement, the continuity of investment principles and the historical precedence of AI initiatives highlight the nuanced nature of its adoption, reflecting a blend of tradition and innovation in the finance and investment sectors.

5.4 Results Discussion concerning Research Question 2

RQ2: What are the key barriers and challenges facing South African financial services companies to adopt AI-driven portfolio construction methods and their impact on adoption rates?

5.4.1Theme 3 Barriers to AI Adoption and the Impact in Portfolio Construction

5.4.1.1 Industry First Interest in AI Results

This subtheme emphasizes the industry's cautious attitude towards adopting AI-driven approaches, motivated by the requirement to observe concrete outcomes before widespread implementation. We investigate the fundamental issues affecting this cautious approach by consulting with experts from many industries. These elements include the need for tangible results, client trust, and the importance of investing time and knowledge.

A significant subtheme, "AI Adoption Challenges: Industry's Initial Interest in AI Outcomes," highlights the industry's careful stance, principally motivated by the requirement to observe concrete outcomes before accepting new techniques. Respondents exhibit disbelief towards the deployment of AI, highlighting the industry's inclination towards tangible outcomes rather than theoretical assurances. This sentiment is echoed by various interviewees, including Interviewee 001, who underscores the importance of demonstrating tangible outcomes: “They are going, I think they they definitely first wanna see some results. Some proper results from the from these methodologies using machine learning and artificial intelligence” (Interviewee 001, 2023). There is also literature where there is an argument that the financial services industry frequently wants to see actual results before completely embracing AI and ML technology (Osterrieder, 2023). This cautious method of seeking results may be essential for risk reduction, industry standing, and competitive edge.

Literature also suggests that there is no degree of certainty that the results are conclusive in outcomes. The results of Obeidat et al. (2018) show promise; however, this study has several limitations. First, the study used historical data, and it is not clear whether these results will be consistent with future data. Second, this study only considers a small number of features for the input data. Incorporating more relevant information could improve the algorithm's performance. Finally, the study only considers a single set of stocks and a single time horizon. This is possibly a factor to consider as to why the market wants results showing benefits. In their research gap, Zhang and Chen (2017) highlight that results need to be more economically meaningful than just theoretical with all the limitations. Interviewee 007AB emphasizes the importance of tangible evidence and a track record to alleviate client apprehension: “we need to see evidence of it by means of performance” (Interviewee 007AB, 2023).

Furthermore, the analysis reveals a significant gap in industry evidence and understanding surrounding AI-driven portfolio construction methodologies. This challenge is also featured in the literature, where it is mentioned that the lack of knowledge of AI and ML technologies among industry personnel can impede their adoption in the financial services business. This lack of knowledge might make it difficult for professionals to explain the decisions and outcomes created by AI and ML algorithms, limiting their general adoption and deployment (Osterrieder, 2023). Interviewee 006 discusses the scarcity of evidence in AI fund performance: “I think guys are looking for opportunities and ways to try and prove the process” (Interviewee 006, 2023). At the same time, Interviewee 004 expresses doubt regarding the existence of proper artificial general intelligence and the absence of direct applications in the industry: “Yeah, little bit pretty much for me, and you know, you know, I really hope I'm not living under a rock but it's, you know, I'm I'm looking for and say well, what I have shown me the shred of evidence” (Interviewee 004, 2023). Overcoming these barriers necessitates a concerted effort to demonstrate the value and efficacy of AI-driven portfolio construction methodologies through tangible results and a track record of performance.

Additionally, the analysis underscores the need for time and expertise building to overcome barriers to AI adoption. Interviewee 003 anticipates that barriers will dissipate as proficiency, expertise, and evidence of AI efficacy accumulate: “I think those barriers will disappear as we build the proficiencies and expertise and the skills and the evidence to show that it that it will actually work” (Interviewee 004, 2023). This sentiment appears in the literature where there is a belief that financial institutions may be more willing to adopt these technologies after observing successful use cases and outcomes, as this provides them with the confidence and proof needed to support the installation of AI and machine learning solutions (Osterrieder, 2023). Interviewee 007AB emphasizes the importance of testing AI models across different economic environments before widespread adoption: “But I think for them to actually adopt that into their portfolio, it will, it will take some time to build that, you know, to really test the resilience of that model throughout different economic macro environment” (Interviewee 007, 2023). Our analysis sheds light on the industry's cautious stance towards AI adoption, driven by the demand for tangible evidence, client confidence, and the need for time to build expertise and track records.

5.4.1.2 Lack of understanding of what AI-driven portfolio construction methods is and their complexity

The subtheme " Lack of Understanding of What AI-driven Portfolio Construction Methods Are and Their Complexity" analysis sheds light on the significant hurdles faced by the South African financial services industry in adopting AI-driven methodologies for portfolio construction. These challenges include a lack of comprehension regarding AI's fundamental nature and complexity, technical barriers, and doubts about its practical application. Asset managers often have a limited understanding of machine learning and its limits, and access to high-quality data is frequently restricted in the asset management industry (de Prado, 2020).

One of the critical implications of this analysis is the urgent need for educational initiatives to enhance industry professionals' understanding of AI-driven portfolio construction methods. Interviewee 002 emphasized that professionals are still grappling with the distinction between quantitative processes and AI: "I'm still trying to understand the definition...how that differs to AI." (Interviewee 002, 2023). This highlights the importance of comprehensive training programs and workshops on AI concepts and machine learning algorithms tailored to the finance sector's needs.

This tendency poses challenges when there is a lack of data accuracy, when the work at hand is too intricate for human monitoring or comprehension, and when a series of AI algorithms reacting to one another could lead to a chain of systemic failures (Bartram et al., 2020). The authors further indicate that asset managers should consider the implications of AI's increasing prevalence and importance. Furthermore, we explore several potential drawbacks of using AI in asset management. AI models frequently exhibit opacity and intricacy, rendering them arduous for managers to oversee and scrutinise. AI models may undergo inadequate training due to using low-quality or insufficient data. Lack of human oversight can result in systematic crashes, an incapacity to detect inference mistakes, and a deficiency in investors' comprehension of investment techniques and performance attribution.

Furthermore, addressing doubts and scepticism surrounding AI adoption requires demonstrating tangible benefits and real-world applications. Interviewee 004 expressed uncertainty about AI's practical application, stating, "I'm not really sure what an AI-constructed portfolio process would involve." Conducting pilot projects and proof-of-concept studies, as suggested by Interviewee 006, could help showcase AI's potential in improving portfolio performance and risk management.

In conclusion, overcoming the barriers to AI adoption in portfolio construction requires a multifaceted approach encompassing education, infrastructure development, and evidence-based advocacy. By addressing these challenges collaboratively, the South African financial services industry can unlock the transformative potential of AI technologies and drive innovation in portfolio management practices.

5.4.1.3 Psychological Barriers to AI Adoption: Trust, Confidence, and Bias

The subtheme "Trust and Confidence in AI" sheds light on the complex obstacles faced by the South African financial services industry in adopting AI-driven approaches. Establishing trust, promoting transparency, and ensuring comprehensibility are crucial factors in addressing doubt and facilitating the successful incorporation of AI in portfolio management.

Interviewee insights underscore the indispensable nature of trust and confidence in AI-driven methodologies, particularly emphasizing the fiduciary responsibility towards clients: "And having an element of trust and confidence in it encapsulates the imperative for establishing a robust foundation of trust" (Interviewee 002, 2023). This highlights the importance of ethical considerations and accountability in AI adoption within the financial sector. Literature like that of Osterrieder, J. (2023) emphasises the importance of trust and confidence in AI adoption in portfolio construction. The writer suggests that trust and confidence are critical elements influencing the adoption of AI and ML technologies, particularly in portfolio construction, where algorithmic decisions directly impact financial results. We find a similar position in de Prado (2020), where the writer emphasises the importance of trust and confidence by stressing the need for human oversight.

Moreover, the interviews reveal a pervasive lack of trust stemming from a fundamental misunderstanding of AI models and their operations: "Often there is a misunderstanding or no understanding of what the model is trying to do in the back end, and that creates much uncertainty around trust for the machine, and people perceive that as a black box" (Interviewee 003, 2023). This underscores the imperative for transparency and comprehensibility to alleviate uncertainties and build stakeholder confidence.

Addressing prevalent scepticism surrounding AI, Interviewee 006 emphasizes the need to assuage apprehensions and instil confidence through education and transparency: "There is still this perception that AI is a bit rogue, that you cannot trust it, that it is a machine" (2023). This highlights the importance of addressing misconceptions and promoting a better understanding of AI-driven methodologies to foster trust and confidence within the industry.

Additionally, Interviewee 007AB underscores the foundational role of trust in the financial industry, stressing the necessity of comprehensibility and transparency in AI-driven portfolio management: "Because ultimately what we do in the fund management industry, asset management industry, what we do is built on trust" (2023). This underscores the symbiotic relationship between trust and efficacy in AI adoption and highlights the critical importance of building trust among industry stakeholders.

Furthermore, the observations from Interviewee 008 highlight the varying degrees of disbelief and scepticism within the industry: "Some people are a bit more sceptical than others, specifically those that have more on the fundamental-based approach" (2023). This indicates the need for a cautious and measured approach towards AI adoption, considering the nuanced perspectives of different stakeholders.

In conclusion, the quotes from industry experts provide valuable insights into the multifaceted obstacles hindering the adoption of AI-driven approaches in portfolio management. Building trust, promoting transparency, and ensuring comprehensibility emerge as critical factors in overcoming doubts and facilitating the successful integration of AI within the South African financial services sector.

5.4.1.4 Data-Related Challenges in AI Adoption: Quality and Traditional Methods

The analysis of data-related challenges in AI adoption within the financial services sector reveals significant impediments rooted in data concerns and quality issues. These challenges, highlighted through industry experts' insights, underscore the importance of addressing data-related hurdles to ensure the efficacy and reliability of AI-driven processes.

Interviewees 001, 002, and 003 collectively emphasize the persistent obstacle of obtaining proper and high-quality data for building robust models. Interviewee 001 highlights increased data availability but notes the challenge of obtaining good-quality data, stating, "So the biggest obstacle for us has been getting proper data and good quality data" (Interviewee 001, 2023: Interview). Interviewee 002 echoes this sentiment, emphasizing the importance of data integrity and cleanliness, stating, "the cleanliness that the data integrity" (Interviewee 001, 2023: Interview). Additionally, Interviewee 003 underscores the risk of "garbage in, garbage out" with machine learning algorithms, stressing the impact of unreliable or inadequate data on AI-driven processes (Interviewee 003, 2023: Interview). The literature expresses the very same sentiments in that high-quality data is required to ensure the correctness and dependability of AI and ML models. In contrast, poor-quality data might negatively impact the performance of these models, potentially leading to incorrect predictions or choices (Osterrieder, 2023).

Moreover, Interviewee 006 vividly illustrates the challenges posed by vast amounts of available data, likening it to an iceberg where only a fraction is visible. They remarked, "It's like an Iceberg; you just see one number, but below it is its kilometres and terabytes worth of data" (Interviewee 006, 2023: Interview). This underscores the complexity of effectively processing and leveraging available data resources. Furthermore, Interviewee 007AB acknowledges the usefulness of AI in portfolio management. However, it highlights the significant challenge posed by the complexity and volume of data required for thorough testing and analysis. They emphasised the "available availability of data" (Interviewee 007AB, 2023: Interview), highlighting the inherent trade-offs involved in AI adoption.

Addressing data concerns and ensuring data quality will be imperative in overcoming the identified challenges. Establishing robust data management strategies, investing in data quality assurance measures, and leveraging advanced data processing techniques will be crucial steps in facilitating successful AI adoption within the financial services sector.

The "Paper Portfolios and Overfitting" analysis delves into the intricate nuances of implementing AI-driven portfolio management approaches. The identified obstacles, including overfitting, the black box effect, and the allure of automated processes, underscore the complexities inherent in utilizing AI for portfolio management strategies.

Interviewees 002 and 003's discussions on paper portfolios emphasize concerns regarding transparency and comprehensibility in AI-driven methodologies. Interviewee 002 articulates the frictionless nature of automated processes facilitated by AI-driven algorithms while highlighting concerns about transparency. Similarly, Interviewee 003's exploration of the black-box nature of AI-driven methodologies emphasizes the need for transparency and understanding to ensure trust and confidence among industry professionals. The view is expressed in the works of de Prado (2020), where the author discusses the concepts of black boxes and paper portfolios in the context of AI adoption for portfolio construction. The article highlights how humans do not easily interpret algorithms' inner workings, emphasising the importance of transparency to help build trust and confidence.

Additionally, Interviewee 006's exploration of AI washing highlights the importance of discernment and scrutiny in evaluating purported AI-driven approaches. They remarked, "There is still this perception that AI is a bit rogue, that you cannot trust it, that it is a machine" (Interviewee 006, 2023: Interview), emphasizing substantive efficacy over superficial labels.

Interviewee 007AB's insights into the risks associated with overfitting and data mining underscore the necessity for rigorous validation and testing protocols. Ensuring the generalizability and reliability of AI-driven models will be essential in mitigating the pitfalls associated with overfitting and data mining.

In conclusion, the collaboration between industry stakeholders, policymakers, and technology providers will be essential in driving the adoption of AI and fostering innovation in portfolio management strategies. Addressing data concerns, ensuring transparency and comprehensibility, and implementing rigorous validation protocols will be crucial in overcoming obstacles and unlocking the transformative potential of AI in portfolio management practices.

5.4.1.5 Bigger Companies Lack Agility

Lack of Agility in Bigger Companies" delves into the significant challenges faced by organisations, particularly larger ones, in adopting AI solutions. These challenges primarily revolve around cost constraints and organisational resistance to change, which pose substantial hurdles to the seamless integration of AI technologies.

Interviewee 003 underscores the financial burden of fully integrating AI technologies into existing operational frameworks. Their remarks shed light on the considerable capital outlays required to justify such investments, emphasizing the challenge of showcasing the potential value added to stakeholders: "That's a big barrier...to spend a whole lot of money due to go to the fully-fledged route of incorporating that into the charities...that's a barrier" (Interviewee 003, 2023: Interview). This highlights the need for organisations to demonstrate clear value propositions to justify the significant investment in AI adoption.

Moreover, Interviewee 006 highlights larger organisations' unique challenges in embracing AI-driven transformations. While acknowledging their financial resources, Interviewee 006 underscores the rigidity and resistance to change prevalent in established enterprises. Bureaucratic hurdles and organisational inertia impede the agility required to adapt to emerging technologies swiftly, prolonging the transition process (Interviewee 006, 2023: Interview).

Interviewee 008 contrasts the responses of larger, more established organisations with smaller, more agile firms regarding AI adoption. They observe that smaller, nimble organisations are better positioned to embrace innovation due to their flexibility and willingness to experiment with new technologies. In contrast, larger corporations with entrenched methodologies exhibit greater resistance to change, hindering the seamless integration of AI-driven solutions (Interviewee 008, 2023: Interview).

The "Lack of Agility in Bigger Companies" discussion underscores organisations' multifaceted obstacles to implementing AI technologies. While cost constraints present a significant barrier, the lack of flexibility and deeply ingrained organisational frameworks pose additional challenges. Addressing these obstacles will require a concerted effort to foster a culture of innovation, agility, and adaptability within larger organisations, enabling them to harness the transformative potential of AI-driven solutions more effectively.

5.5 Results Discussion concerning Research Question 3

RQ3: How do perceived usefulness and ease of use impact the intention to adopt AI-driven portfolio construction methods among South African financial services companies?

5.5.1 Theme 4 - Perception and Trust Factors in AI-Constructed Portfolios

5.5.1.1Continuous Innovation and Evolution

Continuous Innovation and Evolution" provides insights into how the financial industry perceives the role of artificial intelligence (AI) in portfolio management. The discussion centres on AI's potential to enhance efficiency, effectiveness, and innovation in investment strategies.

Interviewees underscore AI's efficiency in generating sentiment indicators and its distinction from human-generated indices. This highlights AI's ability to analyze market sentiment objectively, free from human biases, thereby enhancing decision-making processes (Interviewee 001, 2023: Interview). An opinion expressed in the literature is that AI algorithms can optimise portfolio construction processes, provide data-driven insights, and enhance decision-making by reducing the influence of subjective biases that may impact investment strategies. (de Prado, 2020). The author proposes that leveraging AI and ML asset managers can mitigate the impact of cognitive biases and ultimately make better-informed decisions.

Moreover, the convergence of technology and investment management is praised by industry experts, who recognize AI's potential to improve operational efficiency and profitability. Integrating AI-driven solutions into existing workflows is seen as a means to streamline operations and enhance overall business performance (Interviewees 004, 006, 007AB, 008, 2023: Interview).

Additionally, there is a general openness towards adopting AI technologies within the industry, driven by the desire to improve investment processes and drive innovation (Interviewee 006, 2023: Interview).

The critical role of predictive analytics in portfolio construction is emphasized, highlighting AI's ability to improve market trend predictability and enable more informed decision-making processes (Interviewees 003, 005, 2023: Interview).

Furthermore, continuous innovation in AI technologies within portfolio management is crucial, as emphasized by Interviewee 003. The industry's openness towards exploring AI reflects a commitment to enhancing operational efficiency and staying ahead of market trends (Interviewee 003, 2023: Interview).

The iterative nature of model refinement and strategy development is highlighted, emphasizing the constant feedback loop between AI teams and portfolio managers. This iterative process identifies opportunities and enhances investment outcomes over time (Interviewee 006, 2023: Interview).

Lastly, Interviewee 008 underscores AI's complementary nature as a tool for enhancing portfolio management while maintaining fundamental investment principles. AI is another valuable tool in the investor's toolbox, providing additional insights and analysis to inform investment decisions (Interviewee 008, 2023: Interview).

In conclusion, the discussion highlights the industry's recognition of AI's potential to revolutionize portfolio construction. It acknowledges the necessity of integrating AI-driven insights with human judgment. It emphasizes the importance of continuous innovation in AI technologies. By adopting a culture that values innovation and adaptation, financial firms can effectively leverage AI to enhance investment strategies and improve long-term investment outcomes.

5.5.1.2 Cost Structure Analysis

Cost Structure Analysis" sheds light on the financial industry's viewpoint regarding the cost implications of adopting AI in portfolio management.

Interviewee 001 draws attention to the significant portion of costs allocated to salaries in traditional investment management firms, contrasting it with the potentially lower cost structure associated with AI implementation. This observation underscores the potential cost advantages of employing AI-driven models, which could help alleviate the burden of high labour costs (Interviewee 001, 2023: Interview). Lakhchini et al. (2022) suggest that implementing AI in the financial industry may include initial expenses but could lead to long-term cost reductions by enhancing operations and risk management strategies (Lakhchini et al., 2022). Therefore, understanding the cost implications of AI is crucial to enhancing decision-making, driving innovation and maintaining competitiveness.

Similarly, Interviewee 003 emphasizes the importance of balancing research and development costs and the potential returns on investment in AI technologies. They caution against overinvesting in AI at early stages, highlighting the risk of inefficient resource allocation. This pragmatic approach underscores the significance of cost-effectiveness in AI adoption while ensuring optimal resource utilization (Interviewee 003, 2023: Interview). Echoing this sentiment, Interviewee 004 discusses the learning curve associated with AI implementation. However, it emphasizes the long-term benefits of efficiency and cost savings. They acknowledge the initial challenges as part of the learning process and anticipate eventual cost reductions and operational enhancements (Interviewee 004, 2023: Interview).

Moreover, Interviewee 005 underscores the industry's imperative to become more cost-effective in response to growing pressure on fees and client expectations. They highlight the role of AI in driving operational efficiencies, enabling firms to deliver value to clients more efficiently and effectively (Interviewee 005, 2023: Interview).

In conclusion, the analysis reveals a growing acceptance of AI technology within the investment management sector, driven partly by its potential to streamline operations and reduce costs. While acknowledging initial implementation challenges and learning curves, industry experts recognize AI's significant efficiency and resource optimization advantages. As AI continues to evolve and become more accessible, its integration into portfolio management processes is poised to revolutionize the industry, paving the way for enhanced performance and client satisfaction.

5.5.2 Theme 5 - Perceptions, Attitudes, and Human Factors in AI Adoption

5.5.2.1 Professionals' Attitudes and Trust in AI Adoption

The sub-theme "Perceptions and Attitudes Professionals: Professionals' Attitudes and Trust in AI Adoption" delves into the diverse range of perspectives and attitudes among financial professionals towards adopting AI in portfolio management. The discussion begins with expressions of confidence in AI's potential to enhance investment processes, such as systematic analysis of fundamental data and market sentiment, as highlighted by Interviewee 001. However, cautionary tones emerge, reflecting doubts about AI's effectiveness, particularly in markets like South Africa, as voiced by Interviewee 003, and scepticism regarding its transformative impact, as expressed by Interviewee 004.

In contrast, Interviewee 006 presents a more optimistic view, emphasizing AI's ability to outperform humans in specific tasks, such as processing vast datasets. Despite this optimism, challenges in AI implementation are acknowledged, with Interviewee 005 emphasizing the perceived difficulty and barriers to adoption. Interviewee 007AB adds nuance by recognising the potential of deep learning algorithms to enhance decision-making while stressing the need for evidence of outperformance compared to traditional strategies.

A common thread throughout the discussion is the industry's hesitancy and lack of trust towards AI-driven solutions. Interviewees express apprehension towards AI's ability to consistently guide decision-making and replicate human expertise, underscoring the importance of trust and confidence in AI systems, especially concerning client fiduciary responsibilities, as highlighted by Interviewee 002 and Interviewee 007AB.

The discussion further explores the underlying reasons for this hesitancy, including concerns about the lack of transparency in AI decision-making processes, the industry's reliance on historical performance as a benchmark for adoption, and the perceived inability of AI to craft compelling narratives or predict long-term trends accurately.

Moreover, Interviewees highlight the industry's resistance to change and comfort with traditional methodologies, indicating a preference for tangible evidence of AI's effectiveness and a reluctance to embrace new technologies that challenge established expertise.

Overall, the discussion underscores the complexity of attitudes towards AI adoption in portfolio management, ranging from optimism to scepticism. It highlights the need to address barriers to acceptance, build trust in AI systems, and demonstrate their efficacy through tangible results.

5.5.2.2 Experimentation and Risk-Taking in AI Adoption

The sub-theme "Experimentation and Risk-Taking in AI Adoption" sheds light on financial professionals' cautious approach when integrating AI into portfolio management practices. The discussion begins with concerns expressed by Interviewees 003 and 004 regarding the ethical implications of treating clients as guinea pigs for testing new AI applications and investment strategies. Interviewee 003 particularly highlights the potential risk of unfair treatment of clients, which could lead to regulatory issues.

Despite these concerns, Interviewees 006 and 007AB acknowledge that some clients cautiously approach AI adoption, recognizing the long-term implications and complexities involved. They emphasize the need for careful evaluation and consideration to ensure that AI adoption is not merely a passing trend but a sustainable investment strategy.

Interviewee 005 further contributes to the discussion by highlighting instances where early adopters of AI in portfolio construction failed to achieve expected performance levels. This underscores the importance of thorough evaluation and risk assessment before fully integrating AI-driven solutions into investment practices.

Lastly, Interviewee 008 offers insights into generating alpha through small-scale AI implementations, indicating a measured approach to risk-taking. By taking incremental steps away from the benchmark, professionals can experiment with AI technologies while minimizing potential downsides.

The discussion highlights the delicate balance between experimentation and risk-taking in AI adoption. Financial professionals must weigh the potential benefits of AI against ethical considerations, regulatory compliance, and client interests. Adopting a cautious and measured approach ensures that AI adoption is driven by informed decision-making and a commitment to delivering value to clients while mitigating potential risks.

Human-Machine Dynamics in AI Adoption

The sub-theme "Human-Machine Dynamics in AI Adoption" delves into the complex interplay between humans and machines in the context of adopting AI technologies and decision-making processes. The discussion begins with Interviewees 002 and 003 highlighting the irreplaceable role of human judgment in interpreting machine-generated insights. While AI can provide valuable data, human interpretation determines its relevance. It builds trust by translating complex insights into intuitive narratives.

Interviewee 006 introduces the concept of a 'man-machine strategy,' which emphasizes the synergistic potential of combining human expertise with AI-driven models. This approach allows portfolio managers to leverage machine-generated data while retaining the final decision-making authority based on qualitative factors. The collaborative nature of this strategy acknowledges the complementary strengths of both humans and machines in investment decisions.

Moreover, Interviewees 005 and 001 emphasize the value of human intuition and diverse perspectives in decision-making, highlighting how human intervention adds depth and adaptability to investment strategies. While AI offers unbiased data analysis, human judgment remains crucial in understanding complex human behaviours and nuances that machines may struggle to interpret.

Interviewee 008 further underscores AI's superior data processing capabilities compared to humans but acknowledges the importance of human intervention to complement AI-driven insights and address its limitations. This sentiment reflects a consensus among experts that a balanced approach, leveraging the strengths of both humans and machines, is essential for effective decision-making in the evolving landscape of AI adoption.

In conclusion, while AI brings efficiency and objectivity to data analysis, human judgment remains indispensable in interpreting nuanced contexts and providing strategic direction. Integrating AI technologies into decision-making processes calls for a collaborative and balanced approach that harnesses the strengths of humans and machines to make informed and effective decisions in portfolio management.

5.6 Results Discussion concerning Research Question 4

RQ4:What are the current perceptions and attitudes of financial professionals in the financial services industry of South Africa towards the adoption of AI-driven portfolio construction and management methods?

5.6.1 Theme 6 - Ethical and Regulatory Considerations in AI-driven Portfolio Construction

5.6.1.1 Fiduciary Duties & accountability & TCF

The analysis of "Fiduciary Duties & accountability & TCF" sheds light on the critical considerations surrounding integrating AI technologies into portfolio management, particularly concerning fiduciary responsibilities and the ethical implications of AI adoption. Interviewees express apprehensions regarding accountability, regulatory compliance, and the fair treatment of clients, emphasizing the need for transparency, prudence, and ethical oversight.

Interviewee 002 underscores the fiduciary responsibility to clients and the potential risks associated with AI-driven decisions. This perspective highlights the importance of maintaining transparency and accountability while leveraging AI technologies to safeguard clients' interests. Additionally, Interviewee 003 raises ethical concerns about using clients as test cases for AI algorithms, underscoring the ethical dilemma of balancing innovation with client welfare and advocating for rigorous ethical oversight. The literature emphasises the significance of recognising fiduciary duties and ethics. (Lakhchini et al., 2022). This position is echoed by de Prado (2020), Novick et al. (2023) and Osterrieder (2023).

Furthermore, Interviewee 004 emphasizes the liability of owning AI technology and stresses the accountability in managing clients' assets. This viewpoint underscores the legal and ethical responsibilities of deploying AI-driven solutions in portfolio management. Interviewee 006 highlights the financial services sector's regulatory constraints and reputational risks, emphasizing the importance of compliance with ethical standards and regulatory frameworks to mitigate potential risks.

Moreover, Interviewee 005 emphasizes the ethical principles guiding portfolio management decisions and the commitment to regulatory compliance set by professional bodies like the CFA Institute. This reinforces the importance of adhering to ethical conduct and regulatory requirements in AI-driven portfolio management practices. Lastly, Interviewee 007AB underscores the fiduciary duty of custodianship and the obligation to explain AI-driven investment outcomes to clients, emphasizing transparency, accountability, and effective client communication to maintain trust and uphold fiduciary obligations.

The analysis highlights the importance of fiduciary duties, fairness, and ethical conduct in integrating AI technologies into portfolio management practices. It underscores the need for transparency, accountability, and adherence to professional trust and ethical conduct standards to effectively address concerns about accountability, regulatory compliance, and ethical implications.

5.6.1.2 Job Scarcity Concern of AI Adoption

The "Job Scarcity Concern of AI Adoption" analysis delves into the apprehensions surrounding job security within the financial sector as artificial intelligence (AI) integrates into various processes. Many concerns emerge, including fears of job scarcity and technological displacement.

Interviewee 001 sheds light on prevalent doubts and apprehensions regarding job scarcity, reflecting the multifaceted uncertainties individuals face concerning the repercussions of AI on their professional trajectories. Similarly, Interviewee 003 juxtaposes potential efficiency gains with the looming spectre of job losses, highlighting the ethical dilemma of balancing technological advancement with its socio-economic repercussions.

Interviewee 004 reflects on prevailing mindsets regarding job security in the face of AI adoption, indicating a potential lack of awareness or acknowledgement of the impact of AI on employment. Conversely, Interviewee 006 illuminates initial trepidation surrounding AI's potential to replace traditional job roles, emphasizing ego and perceived threats to job security as contributing factors to workforce apprehension.

Furthermore, Interviewee 005 emphasizes overarching concerns about job security as the primary worry surrounding AI adoption, underscoring the need for organisations to address employee concerns and mitigate fears about technological displacement. Interviewee 007AB provides insights into the industry's perception of job security amid AI integration, recognizing the potential for disruption while emphasizing the need for adaptation to technological advancements.

Lastly, Interviewee 008 expresses doubt about the immediate threat of job loss due to AI adoption, highlighting the importance of evidence-based assessments of AI's impact on employment dynamics.

In summary, there are significant anxieties about job stability within the finance industry due to the incorporation of AI. While concerns about job scarcity and technological displacement are prevalent, there is a unanimous agreement regarding organisations' need to address employee concerns, minimize the risks of job displacement, and promote a supportive transition towards AI adoption. The discussion underscores ethical considerations and the importance of prioritizing the workforce's well-being amidst technological advancements.

Chapter 6 Conclusion

6.1 Opening Overview

The purpose of the study was to investigate the adoption trends and perspectives surrounding AI-driven portfolio creation within the financial services sector in South Africa. Despite the transformative potential of AI in portfolio optimisation and asset allocation, its adoption, impact on portfolio efficiency, and underlying reasons remained largely unexplored in the South African context. Therefore, this research aimed to fill this gap by investigating the barriers, challenges, and drivers influencing the adoption of AI in portfolio construction and management within the South African financial services industry. Additionally, the study sought to identify the key factors influencing the adoption of AI-driven portfolio construction methods, including perceived usefulness, ease of adoption, and ethical considerations.

The study employed a qualitative research approach to investigate the adoption trends and perceptions surrounding AI-driven portfolio construction utilisation in the financial services sector of South Africa through interviews with purposive sampling of 9 financial professionals to gain their insights into the attitudes, challenges and experiences of AI adoption in relation portfolio construction and management.

6.2 Summary of Findings

Key findings demonstrated a general willingness in the financial industry to adopt AI technology in portfolio management, recognising AI's promise to improve efficiency, efficacy, and innovation in investing strategies. However, professionals expressed concerns about AI's effectiveness, trustworthiness, novel understanding and scepticism about its transformational potential, particularly in the South African market. Despite these reservations, the study discovered various factors influencing AI adoption, including perceived usefulness, ease of adoption, and ethical concerns.

RQ1: What is the perception of the impact of AI-adopted portfolio construction on portfolio efficiency compared to traditional portfolio construction methods in the financial services industry in South Africa?

Initially, the research uncovered a prevailing openness within the financial industry towards embracing AI technologies in portfolio management. Professionals recognized AI's capacity to augment efficiency, effectiveness, and innovation in investment strategies. This finding was also evident in papers like Bartram S et al. 2020 where the authors argue that AI can improve investment decision-making and a better ROI for investors but not without limitations. This sentiment was also found amongst the interviewees where concerns and hesitancies regarding AI adoption were notable alongside this optimism. Participants expressed reservations about AI's effectiveness, especially within the nuances of the South African market, and harboured scepticism about its transformative potential. While there is an acknowledgement of AI's potential benefits, there are lingering doubts about its effectiveness and transformative impact on portfolio efficiency compared to traditional methods which was also expressed in the works of de Prado, (2020). The author suggests that traditional approaches are limited and there is a belief that AI in particular ML help overcome these challenges however to fully realise this there is a need for ongoing R&D in this field and one can further extend this to emerging markets, like the South African financial services industry.

RQ2: What are the key barriers and challenges facing South African financial services companies in adopting AI-driven portfolio construction methods, and how do they impact adoption rates?

The analysis underscored the indispensable role of trust and transparency in AI adoption. Stakeholders stressed the importance of cultivating trust in AI systems, particularly concerning client fiduciary responsibilities. Issues regarding the opacity of AI decision-making processes and its perceived inability to replicate human expertise and narratives were highlighted as significant considerations. These findings reveal that trust and transparency are critical barriers and challenges facing South African financial services companies in adopting AI-driven portfolio construction methods, influencing adoption rates and decision-making processes within organisations. A theme also uncovered in the findings of de Prado, M (2020), where the author makes a practical recommendation of focussing on explainability and transparency to build trust relationships with clients and regulators.

RQ3: How do perceived usefulness and ease of use impact the intention to adopt AI-driven portfolio construction methods among South African financial services companies?

Ethical and regulatory dimensions emerged as crucial factors influencing AI adoption. Participants emphasized the necessity of upholding fiduciary duties, ethical conduct, and regulatory compliance when integrating AI technologies into portfolio management practices. Sentiments expressed by Novick et al. (2019) and Chui M (2017) highlight that stakeholders must ensure addressing regulatory and ethical concerns is paramount to moving AI into the financial services industry. Concerns surrounding job scarcity and technological displacement further reflect the industry's anxieties about AI's impact on employment dynamics. This concern highlights the significant role of perceived usefulness and ease of use in influencing the intention to adopt AI-driven portfolio construction methods among South African financial services companies, with ethical considerations and regulatory compliance as crucial determinants in the adoption decision-making process.

RQ4: What are the current perceptions and attitudes of financial professionals in South Africa's financial services industry towards the adoption of AI-driven portfolio construction and management methods?

The research uncovered a prevailing openness within the financial industry towards embracing AI technologies in portfolio management. Professionals recognised AI's capacity to augment efficiency, effectiveness, and innovation in investment strategies. However, concerns and hesitancies regarding AI adoption were notable alongside this optimism. Participants expressed reservations about AI's effectiveness, especially within the nuances of the South African market, and harboured scepticism about its transformative potential. While there is an acknowledgement of AI's potential benefits, there are lingering doubts about its effectiveness and transformative impact on portfolio efficiency compared to traditional methods, particularly in the South African financial services industry.In conclusion, substantial challenges and hesitancies persist despite a growing acceptance of AI technology within the investment management sector. Addressing these concerns and fostering trust and transparency is imperative for promoting responsible and effective AI adoption in portfolio management. The findings of this study offer valuable insights into the intricate landscape of AI adoption trends in South Africa, providing a foundation for future research endeavours and industry initiatives aimed at harnessing AI's potential in portfolio management practices.

Additionally, the implications of these findings extend beyond academia, with a practical impact on industry practitioners, policymakers, and researchers alike. Policymakers can utilise these findings to inform regulatory frameworks that support responsible AI integration while mitigating potential risks. Some policy implications are that policymakers may need to update frameworks to govern the use of AI in portfolio construction, ensuring transparency, accountability and ethical conduct. As this was seen as a dominant theme in the research, it will provide an easy transition if adopted, and stakeholders can quickly adopt it. Some of these policies must emphasise the fiduciary responsibilities of the financial professionals to clients adopting AI to ensure decisions are in the best interests of their clients. Training and education for financial professionals must also be included in policy decisions to ensure the necessary knowledge and skills to implement AI in portfolio construction effectively. There also needs to be a mechanism to monitor and evaluate the impact of AI adoption in portfolio management to offer a reactive strategy addressing any intended consequences.

Industry professionals can leverage these insights to navigate the complexities of AI adoption, implementing strategies that prioritise trust-building and ethical considerations. For researchers, these findings offer fertile ground for further exploration, stimulating inquiry into nuanced aspects of AI adoption and its implications for financial services and beyond.

6.3 Opportunities for Future Research

6.3.1 Expansion of Study Scope

Future studies could consider expanding the scope to include a larger sample size and broader geographical representation to understand better the implications of AI adoption in portfolio construction within South Africa's financial services industry. By having a more diverse range of companies and stakeholders, researchers can comprehensively understand AI adoption trends and perceptions across different segments of the financial services sector. Additionally, exploring the adoption of AI-driven portfolio construction methods in other emerging markets could provide valuable comparative insights.

6.3.2 Quantitative Analysis Integration

While this study focused on qualitative analysis to explore perceptions and adoption trends, future research could complement these findings with quantitative analysis. By integrating quantitative methods, such as data-driven performance metrics and econometric models, researchers can quantitatively measure the impact of AI adoption on portfolio efficiency and risk-adjusted returns. This approach would offer a more comprehensive assessment of the effectiveness of AI-driven portfolio construction methods in South Africa's financial services industry.

6.3.3 Comparative Analysis

Future research could conduct comparative analyses to benchmark AI adoption trends and practices in South Africa against those in other regions or countries. Researchers can identify factors driving or hindering AI adoption in different contexts by comparing AI adoption rates, regulatory frameworks, and market dynamics. This comparative perspective would offer valuable insights for policymakers and industry practitioners seeking to understand global trends in AI-driven portfolio construction.

6.3.4 Ethical and Regulatory Considerations

Given the ethical and regulatory considerations identified in this study, future research could delve deeper into these areas to explore their impact on AI adoption in portfolio management. Researchers could investigate the development of ethical guidelines and regulatory frameworks specific to AI-driven portfolio construction, addressing concerns related to transparency, accountability, bias, and privacy. Understanding the ethical and regulatory landscape is crucial for fostering responsible AI adoption and mitigating potential risks.

6.3.5 Technological Advancements and Innovation

As AI technologies continue to evolve, future research could explore emerging AI-driven portfolio construction techniques and innovations. Researchers could investigate integrating advanced AI algorithms in portfolio optimisation strategies, such as deep learning and reinforcement learning. Additionally, studying the impact of emerging technologies, such as blockchain and quantum computing, on AI-driven portfolio construction could provide insights into future trends and opportunities.

6.3.6 Client Perspectives

Future research could incorporate the views and preferences of clients and investors to complement the perspectives of industry professionals. By conducting surveys or interviews with clients, researchers can explore their perceptions of AI-driven portfolio construction, risk tolerance, and expectations regarding investment outcomes. Understanding client perspectives is essential for aligning AI adoption strategies with investor preferences and building trust in AI-driven investment solutions.

6.3.7 Impact of Economic Conditions

Given the potential influence of external factors on AI adoption in portfolio management, future research could examine the impact of economic conditions and regulatory changes on AI adoption trends. Researchers could conduct scenario analyses to assess how different economic scenarios, such as market downturns or regulatory reforms, affect the pace and direction of AI adoption. Understanding the resilience of AI-driven portfolio construction methods to external shocks is crucial for informing investment strategies and risk management practices.

6.3.8 Limitations

While this study offers valuable insights into the perceptions and adoption trends of AI-driven portfolio construction methods in South African financial services companies, several limitations constrain the scope and robustness of its findings.

Firstly, the sample size of nine participants, while carefully selected to encompass a range of senior-level professionals from various financial firms, may be considered relatively small for drawing broad generalizations. The limited sample size restricts the diversity of perspectives and might not capture the full spectrum of experiences and attitudes towards AI adoption in the industry. Future research should aim for a more extensive and diverse sample to ensure a comprehensive understanding of the subject matter.

Moreover, the predominance of companies in the traditional or hybrid phase of AI adoption poses a challenge in fully exploring the nuances of AI implementation and its impact on portfolio management practices. With most participants representing firms at the early stages of AI integration, the study may not fully capture the challenges and opportunities associated with advanced AI adoption. A more balanced representation across different stages of AI implementation would provide richer insights into the factors influencing adoption trends and perceptions within the industry.

Additionally, while qualitative methods, such as in-depth interviews, offer valuable insights into participants' perspectives and experiences, the absence of quantitative data limits the depth of analysis and the ability to quantify the impact of AI adoption on financial performance metrics. Future research could benefit from incorporating quantitative measures, such as surveys or financial data analysis, to complement the qualitative findings and provide a more comprehensive understanding of the subject matter.

Despite these limitations, this study contributes significantly to the existing knowledge on AI adoption in portfolio management practices. Unlike the majority of research in this area, which is often quantitative, this study provides a qualitative analysis, offering nuanced insights into the perceptions and adoption trends of AI-driven portfolio construction methods. By acknowledging these constraints, researchers can refine their methodologies and address potential biases in future studies, ultimately advancing our understanding of the complex dynamics surrounding AI adoption trends in the financial services sector.

In conclusion, the opportunities for future research outlined above aim to build upon the findings and limitations of this study, contributing to a deeper understanding of AI adoption trends and perceptions in portfolio construction within South Africa's financial services industry. By addressing these research avenues, scholars and practitioners can advance knowledge, inform policymaking, and drive innovation in AI-driven portfolio management practices.

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***Appendices*: (separate attachments)**

i. WBS Ethics Clearance WBS/BA2551220/295
ii. WBS Ethics Title Approval 2551220
iii. Turnitin Report 2551220
iv. ARP Submission Checklist 2551220
v. |Interview Questionnaires 2551220
vi. Supporting Presentations Respondents