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Predictive Analytics in Portfolio Management: A Fusion of AI and Investment Economics for Optimal Risk-Return Trade-offs

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ABSTRACT

Portfolio management has become an essential area of study because of the introduction of artificial intelligence in managing portfolios in a given financial market where risks and returns are dynamic. This study aims to identify the extent of the adoption of AI in portfolio management and investigate the performance of AI models over conventional economic models. The study utilizes both quantitative survey questionnaires and qualitative interviews. The conceptual frameworks refer to the Modern Portfolio Theory, Behavioral Finance, Technology Acceptance Model, and Digital Governance framework. The qualitative results also indicate that portfolio managers understand the importance of using AI to improve portfolio optimization, risk management data, and predictive statistics. However, they also have critical explicit aspects about the data quality, interpretability/understanding of the model, and ethical issues. The quantitative analysis aims to investigate the influence of AI integration, behavioral biases, and perceived ease of use on the effectiveness of AI in portfolio management. AI implementation has a large influence on portfolio performance where the behavioral biases moderate adoption (Coefficients = 0.0075 and direct impact = 0.1235). Digital governance alters the interaction, enhancing the influence of AI (Effect = 0.5215; $P < 0.001$). Overall, AI enhances decision-making and portfolio selection, but concerns remain about data quality and technology application. Digital governance and human input are crucial for optimizing AI use in finance, despite concerns about data quality.

Keywords: Portfolio Management, Risk Return Tradeoffs, Behavioral Bias, Digital Governance
JEL Classifications: Q81, G11, G40, O14, O30

1. INTRODUCTION

Portfolio management is a critical discipline within the field of finance, focusing on the strategic allocation of assets to achieve optimal risk-return trade-offs (Ndikum and Ndikum, 2024). The fundamental principle underlying portfolio management is the risk-return trade-off, which posits that higher potential returns are generally associated with higher levels of risk (Robbetze and Swanepoel, 2022). This relationship necessitates a careful balancing act for portfolio managers, who must navigate a complex landscape of financial instruments, market conditions, and investor preferences. The integration of advanced analytical techniques has become increasingly vital in this context, as traditional methods may fall short in addressing the intricacies of modern financial markets (Zhao et al., 2024). The advent of predictive analytics, particularly through the lens of artificial intelligence (AI), offers the potential to enhance decision-making processes in portfolio management by providing more accurate forecasts and insights into market behavior (Schrettenbrunner, 2023).

AI's role in enhancing predictive analytics is particularly noteworthy. The convergence of machine learning algorithms, big data analytics, and computational power has revolutionized the way financial data is analyzed and interpreted (Chen, 2022, 2024). AI systems can process vast amounts of data at unprecedented speeds, identifying patterns and trends that may

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elude human analysts (Birhane, 2021). This capability is crucial in portfolio management, where timely and informed decisions can significantly impact investment outcomes. Moreover, AI can facilitate the development of sophisticated models that account for a multitude of variables, thereby improving the accuracy of risk assessments and return predictions (Albahri et al., 2023). As such, the integration of AI into portfolio management practices is not merely a trend but a transformative shift that aligns with the broader digitalization of the financial sector.

Further, the United Arab Emirates (UAE) has emerged as a leader in digital governance, showcasing its commitment to leveraging technology to enhance public services and economic performance (Sarker and Rahman, 2023). The UAE's initiatives, particularly those highlighted at the World Government Summit, underscore the importance of digital transformation in driving innovation and efficiency across various sectors, including finance (Al-Hajri et al., 2024). The government's strategic focus on AI and data analytics reflects a recognition of the potential benefits these technologies can bring to investment practices and economic growth. By fostering an environment conducive to technological advancement, the UAE aims to position itself as a global finance and investment hub, attracting domestic and international stakeholders.

In this context, the intersection of AI, predictive analytics, and portfolio management presents a unique opportunity for researchers and practitioners alike. The evolving landscape of financial markets, characterized by increased volatility and complexity, necessitates the adoption of innovative approaches to investment management (Krishna et al., 2023). As portfolio managers seek to optimize their strategies, understanding the implications of AI integration becomes paramount. This study aims to explore portfolio managers' perceptions of the integration of AI into their investment strategies and assess the predictive capabilities of AI models compared to traditional economic models.

Despite the growing interest in AI applications within finance, there remains a significant gap in understanding how portfolio managers perceive and utilize these technologies (Flavián et al., 2022). The integration of AI into investment strategies is not universally accepted, and concerns regarding data quality, algorithmic biases, and the transparency of AI-driven decision-making processes persist. This study seeks to address these issues by investigating portfolio managers' attitudes toward AI integration and examining the effectiveness of AI models in enhancing risk-return optimization.

The primary aim of this research is to explore the integration of AI with investment economics to optimize portfolio management practices. Specifically, the study will investigate how portfolio managers perceive the role of AI in their investment strategies and evaluate the predictive capabilities of AI models in comparison to traditional economic models. By addressing these objectives, the research aims to contribute valuable insights into the evolving landscape of portfolio management.

This study holds significant relevance in contemporary finance, where the integration of AI technologies is reshaping investment practices. By examining the intersection of AI and investment economics, this study provides a comprehensive understanding of how these innovations can enhance portfolio management. Furthermore, the findings will have implications for practitioners, policymakers, and researchers, offering actionable insights into the adoption and implementation of AI-driven strategies in finance. The novelty of this study lies in its focus on the perceptions of portfolio managers. This area has been underexplored in existing literature, filling a critical gap in understanding AI's impact on investment decision-making.

2. LITERATURE REVIEW

2.1. AI in Finance: Overview of Existing Research on AI Applications in Asset Management

Artificial Intelligence (AI) has become an influential innovation in the financial industry, specifically concerning the management of assets, where it increases the efficiency of decision-making, evaluation of risks, and execution of processes. The adoption of artificial intelligence in the management of firms' financial operations has transformed conventional procedures by allowing the aggregation of large amounts of data in a short span. At present, asset management capability is a valuable feature because it enables the development of more effective investment strategies than a human analyst is capable of viewing (Zakaria, 2023; Chen, 2024).

Modern research shows that AI is used not only in trading and portfolio construction but also in risk assessment and identification and prediction of optimal trades. For example, robo-advisors are AI-based instruments applied for individualized investment portfolio recommendations tailored to the customers' risk profiles and financial objectives (Hildebrand and Bergner, 2021). These digital platforms improve customer experience and allow a wide range of populations to secure advanced financial services (Mhlanga, 2020). Also, AI can handle large amounts of real-time data, thus enhancing the authenticity of asset forecasts, which in turn assists asset managers in making efficient decisions within the appropriate time (Dwivedi et al., 2021).

In addition, utilizing AI in asset management is not limited to improving efficiency but also detecting fraud and compliance issues. This study area is helpful for machine learning algorithms as they can detect possible anomalies in transaction patterns, which could flag fraud in the financial institutions' security systems (Farahani and Esfahani, 2022). This proactive approach to risk management is deemed advisable, especially in the current world where financial crimes are evolving to be more advanced. Moreover, AI enhances compliance with required reporting by automatically fulfilling functions related to new/changed financial regulations, thus reducing operational risks (Anagnostopoulos, 2018).

However, like with any emerging technology, there are several drawbacks to the use of AI in the finance industry. Data privacy, algorithmic bias, and the need for transparency in AI decision-making processes remain significant concerns (Nie, 2023; Meske et al., 2020). Thus, it is crucial to solve the specified ethical concerns while using AI technologies in financial institutions to preserve credibility and integrity in the financial system (Bilan et al., 2022).

To summarize, the influence of AI in asset management is pervasive, providing analytical growth, efficiency improvement, and unique approaches to present as well as future issues in the field of finance. However, with the advancement of the industry, the risks need to be understood, and the ethical issues that follow AI implementation need to be addressed to unlock AI in finance for all stakeholders.

2.2. Risk-Return Trade-Offs: Traditional Economic Models and Their Limitations

The concept of risk and return relationship is probably one of the most well-known and central concepts in the field of finance. Popular models of the conventional macroeconomic framework, such as the CAPM, have been used to explain such relations. However, recent literature over time has presented a host of arguments and findings that have brought into contention the applicability and reliability of these models. For example, with respect to the CAPM model, several studies have come up with negative or nonlinear risk-return trade, especially in developing countries and during economic crises (Abdalla, 2012; Lam, 2001; Lanne and Luoto, 2008; Sehgal and Pandey, 2018).

Another major disadvantage of existing frameworks is that they rely on past market returns to estimate future returns and thus may not capture new market characteristics. It has been argued that the risk/return ratio that defines the optimal level of risk-reward in financial investment depends on market conditions, and thus, static models that do not necessarily reflect real-life conditions are likely to produce inaccurate results (Sehgal and Pandey, 2018; Hongsakulvasu and Liammukda, 2020; Chen and Chiang, 2015). For instance, in the case of returns in the U. S. stock market, a high intercept in the empirical results implies that something other than systematic risk impacts returns (Lanne and Luoto, 2008; Chen and Chiang, 2015). Besides, behavioral finance has risen to show that investor behavior can affect perceptions of risk and expected returns, thus deviating from the theories (Oehler and Wedlich, 2018; Ganzach, 2000; Mukherji et al., 2008).

Possible rebuttals to the criticisms of traditional models usually involve pointing out that they remain the cornerstone of financial theory. Some critics support these models, stating that they offer a strong premise that identifies the fundamentals of risk and return, though having their shortcomings (Lee, 2017; Lorenz and Trück, 2008; León et al., 2007). However, the augment from these models put in place may lead to distortion of investment decisions if the vices are not recognized. For example, the concept that greater risks equal greater returns has been disputed by research that suggests a negative association between risk and return, especially during financial crises (Singh and Singla, 2023; Kumar, 2018; Dimitriou and Simos, 2011).

However, there are still missing links within the literature, including the generalizability of these models across different forms of assets and various markets. It is advisable to use behavioral factors and macroeconomic factors in the risk-return model for better prediction power in subsequent research works (Hosseinpour et al., 2023; Andersen et al., 2007). Also, there is a need to work towards better models that capture the dynamic aspect of risk and return structure, especially in emergent markets, unlike the static models used (Abdalla 2012; Essingone and Diallo 2018).

To sum up, it is essential to critically review the neoclassical economic approaches that explain different aspects of the risk-return relationship based on their theoretical flaw. New-age characteristics with changes in the structure of financial markets and investor nature demand sophisticated techniques that are more capable of capturing various risk and return features.

2.3. Literature Gaps

The existing literature on the integration of AI in portfolio management has several, including the absence of studies on the portfolio managers' attitude toward AI, the relatively low level of discussion of the integration of AI with the economic models, and the insufficient understanding of the effect of AI on the enhancement of risk-return trade-off. The presented literature review in the present study reveals that most of the prior studies have focused on the technicalities of the factors rather than the actual utilization of the factors from the manager's standpoint. This study seeks to fill these gaps by examining portfolio managers' perceptions of AI adoption in investment decision-making, comparing AI-based predictive analytics with conventional economics-based models, and evaluating the opportunities offered by AI in decision-making in portfolio management.

2.4. Conceptual Framework

Drawing from four major theoretical models, this study explores AI integration for portfolio management within the context of MPT, Behavioral Finance, TAM, and the theory of Digital Governance. These constructs form the basis of the hypotheses tested in the present study. For instance, the Modern Portfolio Theory (MPT) holds that diversification results in the optimal risk/return ratio (Wisista and Noveria, 2023). This focuses on the ability of AI to optimize MPT by analyzing the impact of its predictive algorithms on the optimization of asset allocation and risk estimation. Due to its capacity to analyze several data points, AI can be applied to achieve near real-time solutions if the market environment is highly fluid (Ahmad et al., 2021). The hypothesis arising from this construct is:

H_1: AI integration significantly improves portfolio optimization by enhancing risk-return trade-offs.

The second construct is based on the Behavioral Finance concept, which focuses on the effects of psychological filters on investment choices (Valcanover et al., 2020). This focuses on the reception and implementation of AI by portfolio managers and their opinions about it. Horowitz and Kahn (2024) states that there is a possibility that AI adoption can be affected by behavioral considerations such as overconfidence or hostility toward depending on artificial intelligence. Thus, the second hypothesis is:

H_2: Portfolio managers' behavioral biases mediate the relationship between AI integration and its perceived effectiveness in portfolio management.

The third construct, based on the Technology Acceptance Model, posits that perceived usefulness and ease of use are important determinants of technology usage (Wilson et al., 2021). In this context, TAM is employed to assess the roles of these factors in the adoption of AI-based applications in the finance sector. The hypothesis based on TAM is:

H_3: Perceived ease of use and usefulness positively influence the Integration in portfolio management.

The last construct is the Digital Governance Theory, which looks at how the policies of the government, as well as the digital campaigns that are put in place, give an impetus to technology usage (Weymouth, 2023). The analysis of external governance, used for portfolio management, is based on the UAE's approach to digital transformation and AI. The hypothesis derived from this theory is:

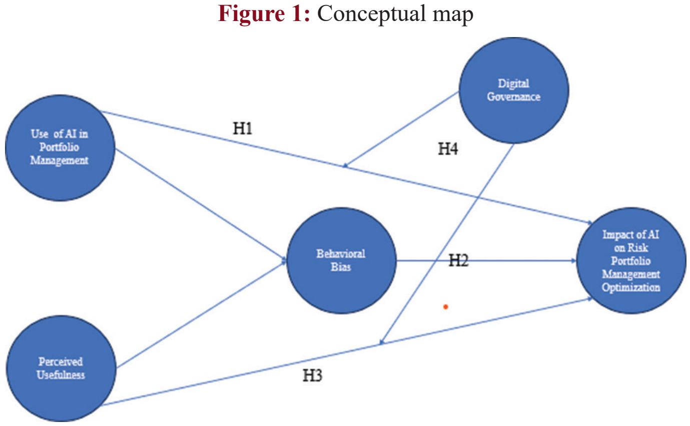
H_4: Digital governance initiatives positively moderate the relationship between AI adoption and portfolio management optimization.

Collectively, these constructs post a theoretical framework that defines relationships that this study aims to explore as illustrated in Figure 1. In this context, the study hypothesizes that improving portfolio optimization is achievable when integrating AI (H1). However, this improvement will be mediated by different factors such as managers' biases (H2), their perceptions of AI considering its ease of use and usefulness (H3), and external support from DGs (H4). These relationships frame hypothesis development for research, which examines how AI can improve portfolio management practices.

3. METHODS AND INSTRUMENTS

This research uses a mixed-method research design, incorporating both qualitative and quantitative approaches to meet the objectives of the research study, which aims to analyze the application of artificial intelligence (AI) in portfolio management. The justification for using mixed methods is that the approach helps capture the context and nature of people's experiences and perceptions while quantifying the identified metrics (Mukumbang, 2023). This two-way approach thus helps the researcher to get a qualitative as well as quantitative view of the extent of AI utilization and the perception of portfolio managers on the extent of success and the hurdles faced when implementing AI tools.

Figure 1: Conceptual map



3.1. Quantitative Phase

The study used a structured questionnaire survey to capture the respondents' understanding of using AI in portfolio management, the extent to which AI has benefited in risk-return optimization, the implementation issues of AI technologies, and awareness of UAE's digital governance. The questionnaire was designed to capture the level of implementation of AI in companies, the perceived impact of AI in addressing bias, and the existing knowledge of governmental policies affecting funding plans.

3.1.1. Sampling and data collection

The survey responses for this study have been received from different portfolio managers, and the stratified random sampling approach was used to include rights firms and experiences. The sample size should include at least 200 respondents in order to yield adequate information. The survey was administered online using Qualtrics, and demographic questions were asked in order to compare responses between groups, including years of experience and firm type.

3.1.2. Data analysis

The collected survey responses were analyzed using basic statistical approaches such as descriptive and regression analyses (Aithal and Aithal, 2020). The analysis sought to capture potential relationships between adopting AI technologies and the perceived efficiency in managing risk-return framework within measurable research questions.

3.2. Qualitative Phase

A semi-structured interview guide was developed and used to elicit detailed responses concerning AI and its use for portfolio management, interfacing it with investment economics, perceived advantages and disadvantages, and the UAE's digital governance efforts. For additional detailed interviews, the sample was narrowed down to 20-30 respondents with variances in experience, employing firm size, and market specialization. The data collection was done in video call format or through in-person sessions.

3.2.1. Data analysis

The interviews were recorded, and the transcripts were generated, which were then subjected to thematic analysis, where the research sought to determine various themes and patterns that emerged from the interviews (Peel, 2020). This qualitative analysis enabled us to investigate further the challenges and possibilities of AI implementation, which a quantitative approach could fail to capture. In addition, it was taken into consideration that the qualitative findings should be connected to the quantitative survey results to enhance the comprehension of the research questions.

3.3. Data Triangulation

The research employed the triangulation methodology in order to compare survey findings with interview findings by determining the similarities and differences between studies. This integrative approach was helpful in the cross-verification of findings derived from the different methodologies and offered richer insight into how AI can improve portfolio management processes (Sridharan, 2021). The study adopts quantitative strength with qualitative insights by employing this mixed methods research design. It embraces the realities of modern portfolio management and state-of-the-art technology such as AI.

4. RESULTS

4.1. Qualitative Insights

4.1.1. Identified themes

The themes used to identify the qualitative phase for the effect of AI adoption on portfolio management are addressed in Table 1. These themes are developed to capture the respondents' understanding of using AI in portfolio management, the extent to which AI has benefited in risk-return optimization, the implementation issues of AI technologies, and awareness of UAE's digital governance.

4.1.2. Theme 1: Integration and adoption of AI in portfolio management

Participants' opinions on AI in portfolio management presented in Table 2, show that the participants are fairly unanimous about addressing the following four aspects with the help of AI: Efficient portfolio, risk, analysis, trading concept, and ESG. Portfolio managers submit that AI tools only complement their efforts in developing well-diversified portfolios reflecting client preferences and market realities. They also indicate that with the help of AI, one can detect some potential risks or patterns in the markets to be in a better position to make informed decisions.

However, participants noted major limitations, especially regarding data quality issues and model interpretability. The trust is negatively affected by uncertainties involving the sources of data used and the 'black box' approach to some of the models. Another important concern is the issue of the privacy of the data and the regulatory concerns associated with it. In general, participants acknowledge the potential of AI in finance and indicate the necessity to consider these threats to reach AI's potential in portfolio management.

Table 1: Identified themes

Theme	Subtheme	Code
Integration and adoption of AI in portfolio management	AI applications	Portfolio optimization Risk management Predictive analytics Trading strategies ESG analysis Impact measurement
	Challenges and limitations	Data quality and reliability Model interpretability Ethical concerns Regulatory compliance Scalability Client education
Benefits and impact of AI	Improved performance	Enhanced decision-making Increased efficiency Reduced costs Enhanced risk management Enhanced portfolio construction Improved impact measurement
	Competitive advantage	Differentiation from competitors Access to new investment opportunities Enhanced client experience
Ethical considerations and governance	Ethical use of AI	Transparency and explainability Bias and fairness Privacy and data security
	Regulatory framework	Government support and initiatives Regulatory compliance Ethical guidelines
Role of human expertise	Complementarity of AI and human judgment	Human oversight Integration of AI and human expertise Addressing limitations of AI
Future trends and opportunities	Emerging AI technologies	Generative AI Natural language processing Reinforcement learning
	Future Applications	Personalized investment advice Enhanced ESG integration New investment strategies

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4.1.3. Theme 2: Benefits and impact of AI

The results presented under Theme 2 in Table 3, shed light on the advantages and effects of AI in the framework of portfolio management, reinforcing themes of enhanced performance and competitive edge. The participants agreed to the effect that AI brings efficiency to the process of arriving at decisions since these decisions are made using available data to result in better investment decisions. Outsourcing of activities that are repetitive in nature not only enhances productivity but also results in less operational expenses, thus enabling firms to deploy their resources optimally. Better solutions in risk management are highlighted, especially when dealing with risks through AI and other tools to protect clients' investments. Moreover, AI aids in constructing diverse portfolios that are consistent with the client's objective and enhances the measurement of social and environmental effects.

In addition, participants also stated that AI gives a competitive advantage by providing value-adding services such as customized investment advice and potential opportunities that are frequently overlooked by conventional approaches. Its implementation in this strategic manner prepares firms for high performance against rivals in a shifting financial environment.

4.1.4. Theme 3: Ethical considerations and governance

The results under Theme 03 depict AI's ethical concerns and management in the portfolio management context, including concerns like the ethical use of AI, ethical compliance, and the necessity of ethical practices as presented in Table 4. Participants felt that there was a lack of interpretability of the AI algorithms, with many deeming the algorithms black boxes. They also stated that improving explainability is one of the significant objectives in engaging with the clients and the regulators. Additionally, the subject of bias and fairness in AI algorithms was discussed and participants followed this up by arguing that AI should be used to eliminate biases and support diversity while avoiding the replication of biases. The areas of privacy and data security were cited as challenges with everyone agreeing that there was the need to address the issues of privacy and security of client data.

It was also evident from the responses that government support is instrumental in creating the right conditions for the ethical use of AI in the finance sector. Participants admitted that government

Table 2: Responses associated with theme 01

Subtheme	Code	Quotes
AI applications	Portfolio optimization	PO1: "We've been using AI primarily for portfolio optimization and risk management." (Private Wealth Manager) PO2: "AI-powered tools have helped us construct diversified portfolios that align with our client's risk tolerance and investment goals." (Private Wealth Manager) PO3: "We use AI to develop more sophisticated portfolio optimization models that can incorporate a wider range of factors, including client preferences, market conditions, and economic indicators." (Robo-Advisor)
	Risk management	RM 01: "AI-powered risk management tools have helped us mitigate downside risk." (Hedge Fund Manager, Private Wealth Manager) RM 02: "AI has allowed us to improve our risk management and identify potential risks that may be overlooked by human analysts." (Institutional Investor) RM 03: "AI-powered risk management tools have helped us protect our client's investments." (Robo-Advisor)
	Predictive analytics	PA 01: "We use AI-driven predictive analytics to identify market trends and anomalies." (Institutional Investor, Private Wealth Manager) PA02: "AI-powered predictive analytics help us identify potential market trends and adjust our investment strategies accordingly." (Robo-Advisor) PA 03: "We use AI-driven predictive analytics to identify potential arbitrage opportunities and construct trading strategies based on statistical models." (Hedge Fund Manager)
	Trading strategies	"We've been using AI extensively in our hedge fund, particularly for high-frequency trading and algorithmic trading strategies." (Hedge Fund Manager) "AI-powered trading algorithms have helped us execute trades more efficiently and reduce transaction costs." (Hedge Fund Manager, Institutional Investor) "AI has allowed us to execute trades at optimal prices and reduce transaction costs." (Institutional Investor)
	ESG analysis	"We've implemented AI-powered tools to analyze ESG data, identify ESG risks and opportunities, and construct portfolios that align with our client's sustainability goals." (ESG-Focused Portfolio Manager) "AI has enabled us to enhance our ESG analysis and identify investment opportunities that are both profitable and sustainable." (ESG-Focused Portfolio Manager) "We use AI to assess the ESG performance of companies more efficiently and accurately, and to engage with companies on ESG issues more effectively." (ESG-Focused Portfolio Manager)
	Impact measurement	"We've implemented AI-powered tools to assess the impact of our investments and engage with investee companies." (Impact Investing Portfolio Manager) "AI has allowed us to enhance our impact measurement and reporting." (Impact Investing Portfolio Manager) "AI has enabled us to track the social and environmental outcomes of our investments more effectively and to communicate our impact story to our clients." (Impact Investing Portfolio Manager)
Challenges and Limitations	Data quality and reliability	"One of the main challenges we've faced is ensuring the quality and reliability of the data used to train AI models." (Hedge Fund Manager) "There can be inconsistencies and biases in ESG ratings, which can impact our investment decisions." (ESG-Focused Portfolio Manager) "Ensuring the quality and reliability of data is crucial for accurate and effective AI applications." (Institutional Investor)
	Model interpretability	"The black-box nature of some AI algorithms can make it difficult to understand and explain their decision-making processes." (Hedge Fund Manager, Private Wealth Manager) "Explainability is essential for building trust with clients and regulators." (Robo-Advisor) "We need to develop more transparent and interpretable AI models to enhance our understanding of their decision-making processes." (Institutional Investor)
	Ethical concerns	"We've had to address concerns related to data privacy and security, as well as the ethical implications of using AI in investment decision-making." (Institutional Investor) "Ensuring ethical use of AI is crucial for maintaining trust in the financial industry." (Private Wealth Manager) "We need to develop ethical guidelines and frameworks to ensure that AI is used responsibly and equitably." (Hedge Fund Manager)
	Regulatory compliance	"Government support has also provided a framework for ensuring responsible and ethical use of AI, which is crucial for maintaining trust in the financial sector." (Hedge Fund Manager, Private Wealth Manager) "Staying compliant with relevant regulations and standards is essential for using AI in portfolio management." (Institutional Investor)

(Contd...)

Table 2: ***(Continued)***

Subtheme	Code	Quotes
		"The regulatory landscape for AI is evolving rapidly, and we need to stay informed about new regulations and best practices." (Robo-Advisor)
	Scalability	"We've had to address concerns related to the scalability of our AI systems to handle large datasets and complex models." (Institutional Investor)
		"Ensuring that our AI systems can handle the increasing volume and complexity of data is a key challenge." (Private Wealth Manager)
		"We need to invest in infrastructure and technology to ensure that our AI systems can scale to meet our growing needs." (Hedge Fund Manager)
	Client education	"One of the main challenges we've faced is ensuring that our clients understand the benefits and limitations of AI-driven investment strategies." (Private Wealth Manager)
		"Educating clients about AI can be challenging, but it's essential for building trust and transparency." (Robo-Advisor)
		"We need to develop effective communication strategies to educate clients about the benefits and risks of AI-driven investment solutions." (Institutional Investor)

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Table 3: Responses associated with benefits and impact of artificial intelligence

Subtheme	Code	Quotes
Improved performance	Enhanced decision-making	"AI has empowered us to make faster and more data-driven decisions." (Hedge Fund Manager, Institutional Investor)
		"AI has allowed us to make more informed and timely investment decisions." (Private Wealth Manager, ESG-Focused Portfolio Manager)
	Increased efficiency	"AI can automate routine tasks, freeing up time for more strategic analysis." (Hedge Fund Manager, Private Wealth Manager, Institutional Investor)
		"AI has allowed us to provide affordable and accessible investment advice to a wide range of clients." (Robo-Advisor)
	Reduced costs	"AI-powered trading algorithms have helped us execute trades more efficiently and reduce transaction costs." (Hedge Fund Manager, Institutional Investor)
		"AI can automate many routine tasks, reducing costs and improving efficiency." (Robo-Advisor)
	Enhanced risk management	"AI-powered risk management tools have helped us mitigate downside risk." (Hedge Fund Manager, Private Wealth Manager)
		"AI has allowed us to improve our risk management and identify potential risks that may be overlooked by human analysts." (Institutional Investor)
		"AI-powered risk management tools have helped us protect our clients' investments." (Robo-Advisor)
	Enhanced portfolio construction	"AI has enabled us to construct diversified portfolios that align with our clients' risk tolerance and investment goals." (Private Wealth Manager)
		"AI has allowed us to identify undervalued assets and construct diversified portfolios." (Institutional Investor)
		"AI has enabled us to develop more sophisticated asset allocation models that can incorporate a wider range of factors." (ESG-Focused Portfolio Manager)
	Improved impact measurement	"AI has allowed us to enhance our impact measurement and reporting." (Impact Investing Portfolio Manager)
		"AI has enabled us to track the social and environmental outcomes of our investments more effectively." (Impact Investing Portfolio Manager)
		"AI has enabled us to assess the ESG implications of our investment choices and to engage with companies on ESG issues more effectively." (ESG-Focused Portfolio Manager)
Competitive advantage	Differentiation from competitors	"AI has allowed us to provide more personalized and tailored investment advice to our clients." (Private Wealth Manager)
		"AI has allowed us to achieve significant alpha generation and outperformance." (Hedge Fund Manager)
		"AI can provide a competitive advantage by enabling us to identify investment opportunities that may be missed by human analysts." (Institutional Investor)
	Access to new investment opportunities	"AI has enabled us to identify undervalued assets that may not be easily detectable using traditional methods." (ESG-Focused Portfolio Manager)
		"AI can help us discover new investment opportunities by analyzing alternative data sources and identifying hidden patterns." (Hedge Fund Manager)
	Enhanced client experience	"AI has allowed us to provide a more personalized and tailored investment experience to our clients." (Private Wealth Manager)
		"AI can improve the client experience by providing faster and more efficient service." (Robo-Advisor)
		"AI can help us build stronger relationships with our clients by providing them with valuable insights and recommendations." (Institutional Investor)

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Table 4: Interview responses on ethical considerations and governance

Subtheme	Code	Quotes
Ethical use of AI	Transparency and explainability	"The black-box nature of some AI algorithms can make it difficult to understand and explain their decision-making processes." (Hedge Fund Manager, Private Wealth Manager) "Explainability is essential for building trust with clients and regulators." (Robo-Advisor) "We need to develop more transparent and interpretable AI models to enhance our understanding of their decision-making processes." (Institutional Investor)
	Bias and fairness	"Ensuring that AI algorithms are unbiased and fair is crucial for ethical decision-making." (ESG-Focused Portfolio Manager) "We need to be aware of the potential for bias in AI algorithms and take steps to mitigate it." (Hedge Fund Manager) "AI should be used in a way that promotes diversity and inclusion." (Private Wealth Manager)
	Privacy and data security	"We've had to address concerns related to data privacy and security, as well as the ethical implications of using AI in investment decision-making." (Institutional Investor) "Protecting client data is a top priority, and we must ensure that AI is used in a way that complies with data privacy regulations." (Robo-Advisor) "We need to implement robust data security measures to protect sensitive client information." (Hedge Fund Manager)
Regulatory Framework	Government support and initiatives	"The UAE government's support for digital innovation has been instrumental in fostering a favorable environment for the adoption of AI in the financial sector." (Hedge Fund Manager, Private Wealth Manager) "Government initiatives have provided a framework for ensuring responsible and ethical use of AI." (ESG-Focused Portfolio Manager) "Government support has also provided a framework for ensuring responsible and ethical use of AI, which is crucial for maintaining trust in the financial sector." (Hedge Fund Manager, Private Wealth Manager)
	Regulatory compliance	"Staying compliant with relevant regulations and standards is essential for using AI in portfolio management." (Institutional Investor) "The regulatory landscape for AI is evolving rapidly, and we need to stay informed about new regulations and best practices." (Robo-Advisor) "We need to ensure that our AI systems comply with all relevant data privacy and security regulations." (Private Wealth Manager)
	Ethical guidelines	"We need to develop ethical guidelines and frameworks to ensure that AI is used responsibly and equitably." (Hedge Fund Manager) "Ethical guidelines can help to promote transparency, accountability, and fairness in the use of AI." (ESG-Focused Portfolio Manager) "We need to establish clear ethical principles for the use of AI in investment management." (Institutional Investor)

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initiatives are crucial for defining the guidelines for the proper usage of AI. There is an agreement that compliance with the regulatory requirements is vital, as the audience emphasizes the dynamic development of AI regulations and the need to update the information as often as possible. Further, the need to establish proper ethical frameworks to promote proper and fair utilization of AI is voiced, as well as the need for non-hiding practice within financial institutions. In general, these results indicate awareness of ethical issues and readiness to meet them while using AI's opportunities in portfolio management.

4.1.5. Theme 4: Role of human expertise

The best practices highlighted under Theme 4 as shown in Table 5, stress the importance of using people's knowledge in synergy with technology when working with portfolios. The use of AI was also deemed important when highlighting that, while AI can provide value, human supervision is crucial to the right application of the technology. It will help eliminate biases within the AI algorithms that are in place. Furthermore, there is the evidence that AI improves people's skills through relieving them from mundane tasks and supporting decision-making; it thus becomes clear that AI is complementary to human beings. But the participants also identified artificial intelligence's drawbacks, including the fact it is a 'black box' and overemphasise the importance of data. It is vital to highlight the human intervention necessary in mitigating these limitations and guiding AI usage. In general, it is evident that practical comprehensiveness of both human know-how and artificial intelligence to decision-making mechanisms in portfolio management should be viewed as a proper blend that needs to be implemented efficiently.

4.1.6. Theme 5: Future trends and opportunities

The observations under Theme 4 also underscore the need to involve human skills and knowledge in combination with AI in management portfolios. Table 6, illustrated that the respondents appreciated that AI needs to be supervised since its implementation can be beneficial yet may lead to adverse outcomes if used inappropriately. This integration helps in the selection and the eradication of prejudice in AI algorithms.

Table 5: Interview responses on role of human expertise

Subtheme	Code	Quotes
Complementarity of AI and Human Judgment	Human oversight	"Human oversight is essential to ensure that AI is used effectively and ethically." (Hedge Fund Manager) "While AI can provide valuable insights, human judgment is still necessary to make informed decisions." (Private Wealth Manager) "Human oversight can help to identify and address potential biases in AI algorithms." (ESG-Focused Portfolio Manager)
	Integration of AI and human expertise	"AI can complement human expertise by providing data-driven insights and automating routine tasks." (Institutional Investor) "A successful AI implementation requires a collaborative approach that combines the strengths of both humans and machines." (Robo-Advisor) "Human judgment is essential for interpreting AI-generated insights and making informed decisions." (ESG-Focused Portfolio Manager)
	Addressing the limitations of AI	"Human judgment can help to address the limitations of AI, such as the black-box problem and the risk of overreliance on data-driven decisions." (Hedge Fund Manager) "We need to develop strategies for addressing the limitations of AI and ensuring that it is used responsibly and ethically." (Institutional Investor) "Human expertise can help to identify and mitigate the risks associated with AI-driven decision-making." (Private Wealth Manager)

AI: Artificial intelligence

Table 6: Interview responses on future trends and opportunities

Subtheme	Code	Quotes
Complementarity of AI and Human Judgment	Human oversight	"Human oversight is essential to ensure that AI is used effectively and ethically." (Hedge Fund Manager) "While AI can provide valuable insights, human judgment is still necessary to make informed decisions." (Private Wealth Manager) "Human oversight can help to identify and address potential biases in AI algorithms." (ESG-Focused Portfolio Manager)
	Integration of AI and human expertise	"AI can complement human expertise by providing data-driven insights and automating routine tasks." (Institutional Investor) "A successful AI implementation requires a collaborative approach that combines the strengths of both humans and machines." (Robo-Advisor) "Human judgment is essential for interpreting AI-generated insights and making informed decisions." (ESG-Focused Portfolio Manager)
	Addressing limitations of AI	"Human judgment can help to address the limitations of AI, such as the black-box problem and the risk of overreliance on data-driven decisions." (Hedge Fund Manager) "We need to develop strategies for addressing the limitations of AI and ensuring that it is used responsibly and ethically." (Institutional Investor) "Human expertise can help to identify and mitigate the risks associated with AI-driven decision-making." (Private Wealth Manager)

AI: Artificial intelligence

Furthermore, the responses reveal that AI complements human skills by offloading tedious work and delivering evidence-based analysis to combine human and artificial intelligence teamwork. However, the participants also noted that AI has its drawbacks it is a 'black box,' and it is easy to get rid of reliance on data. These limitations should be handled through human input, which plays a crucial role in using artificial intelligence. The results generally qualify the claims of introducing cognitive and expert system support to the decision-making context within portfolio management strategies and 'best practices'.

4.2. Quantitative Findings

4.2.1. Demographics

The demographic data collected from the survey provides valuable information regarding the professional portfolio management environment. A majority of 60% of the participants hold the portfolio manager title, signifying this title is overrepresented within the sample. Financial Analysts make up 35% of the respondents' collective, which implies a strong backbone instrumental to decision-making. Finally, 5% of respondents fall under the "Other" category, implying that people's roles within this industry are very varied. Regarding experience, most participants (63%) have worked in portfolio management for 1-5 years, which indicates that this area has a young workforce. Only 12.5% said they have <1 year's supply, and 18.5% of professionals have 6-10 years of experience, and 6% have more than 10 years of experience, indicating that the industry is attracting young talent. Concerning the firm type, 53% of the respondents are employed in hedge funds, followed by mutual funds at 29% and private equity at 17%, which reveals a preference for hedge fund techniques in the survey sample.

4.2.2. Interaction with AI tools

The survey responses regarding the interaction of the participants with AI previously for portfolio management show that there is vast adoption of AI technologies, with 90% of the firms saying they are deploying the technologies in portfolio management. Algorithmic trading is applied in 30.5%, robo-advisor in 26.5%, and predictive analytics at 24%. Firms applying portfolio management have a relatively low 10% of not using AI as part of the processes. These findings indicate that AI prevails in the investment management industry, where firms use it to improve trading, investment advice, and forecasting. Such high adoption is attributed to the perceived usefulness of AI in an array of tasks, including portfolio enhancement and risk mitigation.

4.2.3. Integration of AI on portfolio management practices

The descriptive statistics presented in Table 7, suggest that the respondents had a positive attitude toward using AI in managing portfolios. The mean scores for statements concerning A.I

Table 7: Future trends and opportunities items descriptives

Descriptive statistics	Statistic						Skewness	
	n	Minimum	Maximum	Mean	SD	Variance	Statistic	SE
The integration of AI technologies significantly enhances the optimization of portfolio management	200	2.00	5.00	4.0350	0.71155	0.506	−0.558	0.172
AI-driven predictive analytics improve the accuracy of risk assessments in my portfolio management practices	200	2.00	5.00	4.1450	0.70460	0.496	−0.647	0.172
Utilizing AI tools allows for better asset allocation decisions compared to traditional methods	200	3.00	5.00	4.1750	0.73284	0.537	−0.286	0.172
AI technologies help mitigate behavioral biases in my investment decisions	200	2.00	5.00	3.9650	0.64487	0.416	−0.876	0.172
Valid N (listwise)	200							

SD: Standard deviation, SE: Standard error, AI: Artificial intelligence

Table 8: Impact of artificial intelligence on portfolio optimization descriptives

Descriptive statistics	Statistic						Skewness	
	n	Minimum	Maximum	Mean	SD	Variance	Statistic	SE
AI technologies significantly enhance the optimization of portfolio management	200	3.00	5.00	4.1950	0.64736	0.419	−0.211	0.172
The integration of AI improves the accuracy of risk assessments in portfolio management	200	3.00	5.00	4.0600	0.43282	0.187	0.328	0.172
AI-driven predictive analytics provide better insights into market behavior compared to traditional methods	200	3.00	5.00	4.1950	0.64736	0.419	−0.211	0.172
Using AI tools has led to improved investment decision-making in my firm	200	3.00	5.00	4.3000	0.62607	0.392	−0.323	0.172
Valid n (listwise)	200							

AI: Artificial intelligence, SD: Standard deviation, SE: Standard error

Table 9: Behavioral biases items descriptives

Descriptive statistics	Statistic						Skewness	
	n	Minimum	Maximum	Mean	SD	Variance	Statistic	SD
My confidence in AI recommendations is influenced by my previous experiences with technology	200	1.00	5.00	3.3800	0.92731	0.860	−0.484	0.172
I tend to rely more on traditional methods than on AI due to skepticism about its effectiveness	200	1.00	4.00	1.3700	0.75893	0.576	2.190	0.172
I believe that behavioral biases can negatively impact the adoption of AI in my firm	200	1.00	5.00	3.3700	1.12670	1.269	−0.981	0.172
Overconfidence in my own judgment affects my willingness to trust AI tools	200	1.00	5.00	3.3000	1.16912	1.367	−0.509	0.172
Valid n (listwise)	200							

AI: Artificial intelligence, SD: Standard deviation, SE: Standard error

Table 10: Perceived usefulness and ease of use items responses

Descriptive statistics	Statistic						Skewness	
	n	Minimum	Maximum	Mean	SD	Variance	Statistic	SE
I find AI-based applications easy to use in my daily work tasks	200	1.00	5.00	3.7250	1.01713	1.035	−0.989	0.172
The usefulness of AI applications positively influences my decision to use them in portfolio management	200	1.00	5.00	3.5450	0.92317	0.852	−1.140	0.172
I believe that using AI tools enhances my productivity as a portfolio manager	200	1.00	5.00	3.7750	0.93205	0.869	−0.890	0.172
I am likely to recommend the use of AI applications to my colleagues based on their effectiveness	200	1.00	5.00	3.7750	0.93205	0.869	−0.890	0.172
Valid N (listwise)	200							

AI: Artificial intelligence, SD: Standard deviation, SE: Standard error integration ranges from 3.965 to 4.175, indicating consensus that AI does boost the portfolio optimization process, increases risk analysis, and helps in far superior asset allocation. The standard deviations differed from 0.645 to 0.733, which, in turn, suggests moderate variability in the responses, the skewness values ranging from −0.286 to −0.876 shows that most respondents reported a higher agreement, probably due to possessing a favourable view towards AI technologies in investment practices.

4.2.4. Impact of AI on portfolio optimization

The descriptive statistics presented in Table 8, show that the overall impression of AI's impact on portfolio management based on the respondents' reactions is relatively positive. The mean scores are between 4.060 and 4.300, indicating a very high level of agreement that the application of artificial intelligence technologies in delivering optimization, better risk assessment, and value addition in investment decisions. The standard deviations represent moderate response variability between 0.433 and 0.647. The skewness values are primarily negative, which means that more participants assessed the agreement on the higher side of the scale and held a positive attitude toward the AI applications.

4.2.5. Behavioral biases

The descriptive analysis provides a window into behavioral biases influencing the use of AI in investment decision-making, as shown in Table 9. The participants' mean score about the perceived social support was 3.380 for the confidence level in AI recommendations

Table 11: Digital governance policies items responses

Descriptive statistics	Statistic						Skewness	
	n	Minimum	Maximum	Mean	SD	Variance	Statistic	SE
The UAE's digital governance initiatives positively influence my firms use of AI technologies	200	1.00	5.00	3.3550	1.12486	1.265	−0.607	0.172
Government policies encourage the adoption of AI technologies in the finance sector	200	1.00	5.00	3.5900	1.08526	1.178	−0.985	0.172
Digital governance initiatives provide necessary support for integrating AI into portfolio management practices	200	1.00	5.00	3.6150	1.04990	1.102	−0.729	0.172
Awareness of digital governance initiatives has increased my confidence in using AI technologies for investment decisions	200	1.00	5.00	3.5900	1.08526	1.178	−0.985	0.172
Valid N (listwise)	200							

AI: Artificial intelligence, SD: Standard deviation, SE: Standard error

Table 12: Correlation matrix

Correlations	AIinPM	BB	TAM	DIGIGOR	AIUSE
AIinPM					
Pearson correlation	-				
n	200				
BB					
Pearson correlation	0.911**	-			
Significant (two-tailed)	0.000				
n	200	200			
TAM					
Pearson correlation	0.875**	0.929**	-		
Significant (two-tailed)	0.000	0.000			
n	200	200	200		
DIGIGOR					
Pearson correlation	0.883**	0.954**	0.969**	-	
Significant (two-tailed)	0.000	0.000	0.000		
n	200	200	200	200	
AIUSE					
Pearson correlation	0.951**	0.929**	0.920**	0.926**	-
Significant (two-tailed)	0.000	0.000	0.000	0.000	
n	200	200	200	200	200

**Correlation is significant at the 0.01 level (two-tailed). BB: Behavioral biases, DIGIGOR: Digital governance initiatives

Table 13: Model summary for mediator and moderator

Model information	Analysis 1	Analysis 2
Dependent variable (Y)	AIinPM (impact of AI adoption on portfolio management optimization)	AIinPM (impact of AI adoption on portfolio management optimization)
Independent variable (X)	Usefulness and Ease of Use of AI in portfolio management	Adoption of AI in portfolio management
Mediator (M)	BB	BB
Moderator (W)	DIGIGOR	DIGIGOR
Sample size	200	200

BB: Behavioral bias, DIGIGOR: Digital governance initiatives, AI: Artificial intelligence due to prior technology experiences, which reveals a moderate degree of agreement. A different trend can be observed with regard to the AI, and its mean has been registered at 1.370, which indicates high conventional texture density. The pre-conceived notions resulting in a negative behavioral influence on AI scored 3.370, while overconfidence that impacts the trust given to AI tools had a mean of 3.300, which may suggest a considerable impact of personal judgment on the acceptance of technology.

4.2.6. Perceived usefulness and ease of use

The descriptive statistics presented in Table 10, suggest that respondents have a relatively positive attitude toward the usability and utility of AI applications. The mean ease of use score is 3.725, which implies that participants do not find it difficult to incorporate AI-based applications in their activities. Exploitation of applications that involve artificial intelligence was estimated with a mean of 3.545, which explains that they have positive impacts on decision-making relating to the portfolios. Moreover, the high means of 3.775 on both the improvement of productivity and the probability of recommending AI tools to improve working processes can be considered a high level of agreement with AI tools' efficiency.

4.2.7. Digital governance policies

The descriptive statistics presented in Table 11, suggest that participants have a positive attitude towards the UAE's digital governance, with an average mean of 3.355, regarding the impact of these factors on the extent of AI usage in firms. This sets off from the slightly higher mean of 3.590 recorded for policies that support the usage of AI by the governments, which shows compliance with the use of technology in finance. The mean score for the structural support's digital governance proffer as requisite to support AI integration was 3.615; as to the awareness of such initiatives, it also improved confidence towards the use of AI technologies, having scored 3.590 showing the relevance of governance on the enhancement of AI setup.

4.2.8. Correlation analysis

The correlation analysis presented in Table 12 shows that there are positive coefficients that show that AIinPM has a significant relationship with the factors being analyzed. The highest correlation is detected between AIinPM and TAM, with the Pearson correlation coefficient value equal to 0.875. This suggests that adopting AI applications in portfolio management is likely to occur in cases where portfolio managers consider the application valuable and easy to use.

Behavioral biases (BB) also have a positive correlation with the AI impact on Portfolio optimization (r = 0.911), suggesting that managers' psychological tendencies can impact their views and use of AI. Digital governance initiatives (DIGIGOR) are also highly positively linked with AIinPM with a correlation coefficient of 0.883, implying that government support for the regulation of AI applications can go a long way in enhancing AI integration in portfolio management.

Lastly, the AIUSE is highly significant with all other variables, and the coefficients range from 0.920 to 0.951. This implies that the effectiveness of AI is equally determined by perceived usefulness, behavioral biases, and the proliferation of digital governance policies.

4.2.9. Hayes process macro (direct and indirect effect of model presented in Figure 1)

The Hayes Process Macro technique is used to examine the direct and indirect effects of the model presented in Figure 1. The results of this technique are presented in Tables 13-18. The estimations of the basics of mediation analysis, based on Hayes Process Macro, are reported in Table 13. The mediation analysis relies on the inclusion of a single (continuous) mediator to the model which enables the mediator to act like a covariate in the model, and thereby showing the causal relationship between the target variables. We first identity the model summary for the moderator (W) and mediator (M) effect in our model as in analysis 1 and analysis 2.

Second, we address the results of whether the mediator (behavioral bias (BB)) can impact the use of AI technologies on the performance of portfolio investment, an in Table 14. The results in Table 14 support H1 in which integrating AI leads to improved portfolio optimization. When BB as mediating factor is included in the estimation, the effects of the adoption of AI and the usefulness and ease of use of AI (as measured by perceptions of managers toward the use of AI) on portfolio optimization are strongly observed, confirming H2 and H3. This suggests that managers' biasness strengthens the impact of the AI adoption and managers' perceptions toward the use of AI on enhancing the performance of portfolio investment.

Another issue on our analysis is test for the conditional effects of independent variables (usefulness and ease of use of AI in portfolio management (Analysis1) and the adoption of AI in portfolio management (Analysis 2) on the mediator (BB) with respect to the moderating factor (external support from digital governance

Table 14: Model summary for mediator

Model summary	Analysis 1	Analysis 2
R	0.9648	0.9698
R2	0.9308	0.9405
F	879.36	1033.29
P	<0.001	<0.001
df1-df2	3-196	3-196

Table 15: Conditional effects of independent variables on mediator

Moderator (DIGIGOR)	Effect (TAM→BB)	SE	P	LLCI	ULCI	Effect (AIUSE→BB)	SE	P	LLCI	ULCI
2.75	0.1649	0.0749	0.0288	0.0172	0.3125	0.3215	0.0657	<0.001	0.192	0.451
4	0.3012	0.0795	<0.001	0.1444	0.4581	0.4882	0.0641	<0.001	0.3617	0.6146
4.25	0.3285	0.0809	<0.001	0.1689	0.4881	0.5215	0.0647	<0.001	0.3938	0.6492

SE: Standard deviation, BB: Behavioral biases

(DGs)). We find that there a conditional effect of the adoption of AI and the usefulness and ease of use of AI represented by the TAM and AIUSE theories with respect to DGs on improving portfolio management practices, confirming hypothesis H4. Table 15 reveals that the effectiveness of AI adoption is not the only factor that is useful for improving portfolio management practices, but other factors such as perceived usefulness, behavioral biases, and the proliferation of digital governance policies can also play a pivotal role on improving the performance of portfolio investment.

Table 16 shows the model summary of the effect of AI adoption on portfolio performance with respect to the mediator (BB). It shows that there is a strong correlation between the proxies for independent variable and the enhancement of portfolio investment s can be seen in both analyses.

Following the findings of Table 16, Table 17 presents the direct and indirect effects of the independent variable (X: AI adoption and the perceptions of AI adoption) on the dependent variable (Y: portfolio investment optimisation) with respect to the effect of TAM on AIinPM and AIUSE on AIinPM. Analysis 1 and 1, show that there is a significant and strong direct effect from the independent variable (both measures) to dependent variable. This suggest that there is a strong direct causal effect coming from X toward Y, suggesting that AI adoption directly affect the performance of portfolio investments. In addition, it is found that there is also strong indirect causal effect when the mediating factor is considered in the analysis with respect to digital governance. This indirect effect is coming from X to M to Y. This means AI adoption enables BB to make changes in portfolio investment optimisation when government support for the regulation of AI applications is better.

Table 16: Model summary for independent variable (impact of artificial intelligence on portfolio management optimisation)

Model summary	Analysis 1	Analysis 2
R	0.914	0.9536
R2	0.8354	0.9094
F	499.82	988.94
P	<0.001	<0.001
df1-df2	2-197	2-197

Table 18 shows the results of the index of moderation (DGs). This moderator has a positive correlation with the AI impact on portfolio optimization, suggesting that digital governance initiatives (DIGIGOR) are highly positively linked with AI adoption, implying that government support for the regulation of AI applications can enhance AI integration in portfolio management.

5. DISCUSSION

This study explores portfolio management with an emphasis on using Artificial Intelligence (AI) for prediction and the economic costs of portfolio selection. It measures how portfolio managers assess AI efficiency and its forecast accuracy in portfolio composition, risk management, and investment choices. This research adopts a conceptual framework comprised of predictive analytics, artificial intelligence models, and the investment economics of portfolios to assess managerial practices in portfolio management. This has the implication that AI can improve decision-making, forecast markets, and construct portfolios more efficiently, as well as imply that human tendencies and AI are symbiotic counterparts.

The study findings reveal the benefits of integrating AI in the management of portfolios to enhance decision-making, risk analysis, and performance. It can process extensive data, understand market directions, and adjust investment portfolios so that decisions can be made promptly and accurately. In parallel with these findings, Bartram et al. (2019) and evidence that AI improves portfolio management, trading, and risk management regarding efficiency, accuracy, and compliance and generates new risks.

However, the interview findings also reveal that AI models face challenges in the Interpretability and quality of data with concerns about whether some models are ‘black boxes.’ Sensitivity and explainability are paramount in regulated domains, while data integrity and credibility are important. Building on this, Rudin and Radin (2019) devised a fully interpretable model for the Explainable Machine Learning Challenge, arguing against the black-box approach to AI. Similarly, Guidotti et al. (2019) have proposed a technique to enhance the transparency and trust in

Table 17: Direct and indirect effects

Effect	Analysis 1 (TAM→AIinPM)	SE	P	LLCI	ULCI	Analysis 2 (AIUSE→AIinPM)	SE	P	LLCI	ULCI
Direct effect (X→Y)	0.1235	0.0458	0.0075	0.0333	0.2138	0.6341	0.048	<0.001	0.5394	0.7288
Indirect effect (X→M → Y)										
DIGIGOR=2.75	0.071	0.0269		0.0105	0.117	0.0393	0.0121		0.0177	0.0654
DIGIGOR=4.00	0.1297	0.0288		0.0682	0.1816	0.0596	0.0176		0.0275	0.0972
DIGIGOR=4.25	0.1415	0.0295		0.0784	0.1947	0.0637	0.0188		0.0295	0.1035

SE: Standard error, DIGIGOR: Digital governance initiatives

Table 18: Index of moderation

Moderator (DIGIGOR)	Index	Boot SE	Boot LLCI	Boot ULCI	Analysis
2.75	0.047	0.0069	0.034	0.0607	Analysis 1
4	0.0163	0.0051	0.0071	0.0268	Analysis 2

SE: Standard error, DIGIGOR: Digital governance initiatives

AI applications through data mining knowledge into the SVM models.

Further, there is a similar emphasis on ethical concerns and regulatory factors in interviews as significant factors that define AI application in the finance sector. It stresses the need for a strong regulatory mechanism to govern the functioning of AI systems so that they can adhere to ethical standards, be fair to the clients, and safeguard their information. It also raises the synergism where AI works hand in hand with human knowledge to reduce problems with excessive dependence on the algorithms as the judgment instruments. For example, Gao et al. (2023) and Steyvers and Kumar (2023) have underscored the need to train complementary policy in a human-AI team to optimize decision rewards while at the same time avoiding risks inherent in many situations.

Furthermore, survey responses highlight that the majority of the firms in UAE have adopted 90% of the usage of AI technologies in portfolio management, involving algorithm trading, robo advisors, and predictive analysis. This underlines the growing role of artificial intelligence as a tool that can help investment companies enhance trade execution and minimize expenditures. However, 10% of firms are not using it yet, which implies that companies still have a long way to go when integrating AI into their operations. The study shows that overconfidence or reliance on traditional methods, as part of behavioral bias, has a positive impact on the efficiency of AI in portfolio management optimization as part of the impact of AI in enhancing portfolio management optimization accurately and with a statistical significance of 0.1297 (indirect effect). The indirect effects imply that managers' bias plays a critical role in the performance of AI tools in portfolio management. Digital governance also has a substantial moderation effect; the higher the digital governance, the stronger the relationship between the use of AI and portfolio optimization (Effect = 0.5215, $P < 0.001$).

As a result of the above, the significant moderation effect of digital governance on the relationship between AI use and portfolio optimization becomes particularly apparent. These results suggest that with higher levels of digital governance, AI tools better facilitate portfolio management improvement, as evidenced by the large effect size reported (Effect = 0.5215, $P < 0.001$). This is further substantiated by those who argue that regulation and governance enhance the possibility of applying AI in different sectors such as the finance sector (Goldfarb and Trefler, 2018). The theme of governance as a crucial element of technology adoption and utilization is also reflected in the literature, which presents the importance of governance structures for enhancing the utilization of AI technologies (Wagner, 2020).

As one of the specific findings of the study, the study conclusion can also point to the potential of artificial intelligence to become a competitive advantage for those who can offer and use individual investment solutions or find opportunities for them. The integration of artificial intelligence tools in the ESG approach is helpful in the process of sustainable investment management. However, there is concern voiced about the potential of large-scale AI systems because the value of AI is directly proportional to data processing; that is, AI will require constant development. The findings of this research have important theoretical and practical implications for academia and industry.

Overall, the present study has significant implications, which suggest that deploying AI technologies in the portfolio management context can bring improved risk management of funds, cost reduction, and competitive advantage. However, the study also points to the importance of being ethical in how AI is used, and for this, there should be transparency, interpretability, and regulations. From the perspective of future research, this study provides implications for further research on AI in finance in the four areas, which include the quality of data, human-AI relationships, and interactions. In conclusion, AI application in portfolio management can be quite possible when integrated and regulated properly.

6. CONCLUSION

In conclusion, this study aimed to examine the impact of AI tools in enhancing portfolio management optimization, supporting the link between the predictions of the TAM and the modern portfolio investment. The study results empirically corroborate the effectiveness of AI in improving decision-making, forecasting, and portfolio management. While helping portfolio managers to process large quantities of data and present sophisticated analyses in real-time, AI enhances the calibration and effectiveness of portfolios and the overall administration of risks within the investment. However, there are also some downsides of overreliance on AI, such as data quality and its ethical questions, and interpretation of the results of the AI models. The study also considers the requirement of the structures of electronic decision-making, as well as the combination of Artificial Intelligence and human-controlled endeavour. In general, proper usage of Advanced Intelligent Initiative provide such competitive tab advantage and higher degree of efficiency in portfolio management.

The paper discusses carries out important policy implications for public authorities, practitioners, policymakers, shareholders, and researchers. First, portfolio managers can benefit from the findings of our study by maximizing their investment strategies, reshaping their investment practices, and optimizing asset allocation. Our findings also allow portfolio managers to understand the importance of using AI to improve portfolio return optimization, risk management strategies, and predictive statistics. The integration of AI into investment strategies can help assess the predictive power of AI models in reaching the optimal risk-return profile of any portfolio compared to traditional economic models. Shareholders may also appreciate the implementation of our study's results in their mentoring mechanisms on managerial actions. If shareholders realize managerial usage of AI techniques, they will be able to reduce agency costs, information asymmetry, moral hazard, adverse selection, and managerial opportunism. They could analyse the behavioural biases within different groups of investors in the market, thus having more future control over the overuse of AI techniques in portfolio performance. Given our findings, public authorities can enhance their regulatory framework to govern the unrestricted use of AI in managing portfolio investments, thereby eliminating future catastrophic corporate losses. Overall, our findings on using AI in portfolio investment can enhance the decision-making and portfolio selection processes, thereby increasing the benefit of AI usage in all financial aspects. This paper offers actionable insights and clear guidance into implementing AI techniques into portfolio investment.

The study has some limitations. One of the limitations relates to the target community used in the study, where the UAE is considered a target research community. The UAE market might not entirely reflect the effect of AI on portfolio investment since the financial market is still inefficient and suffers from premature use of AI in the investment field, given the unique investment culture followed by investors in this country. The behaviours of investors, including portfolio managers, in the UAE might differ from those in developed countries. Applying this study to different global communities might provide different results than our findings. Furthermore, the measures of the perceptions of AI used in the study might be insufficient, given the presence of many measures for AI perception. Different measures for the AI perception on portfolio management, such as generating indices through Google Trends or the social media, might offer more meaningful results. These various measures can be performed by including more or new questions to survey focusing on machine learning, sentiment analysis, and algorithmic trading techniques.

Future research could use different samples and research communities covering countries with well-developed and efficient financial markets. One can also argue that altering some of the questions in the survey by focusing on machine learning, sentiment analysis, and algorithmic trading techniques in portfolio investment might be used in future studies on the same topic as the current paper. Building new measures on the use of AI in financial issues through Google Trends or social media and Python software can be used in future studies to model the appropriate links between AI and investment strategies.

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