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# Integrating Artificial Intelligence into Financial Investment Decision-making: Opportunities and Constraints

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**Abstract**

The integration of Artificial Intelligence (AI) into financial investment decision-making has emerged as a transformative development in modern financial markets. AI- driven technologies, including machine learning algorithms, predictive analytics and automated trading systems, enable investors and financial institutions to process vast volumes of data, identify complex patterns, and enhance the precision and speed of investment decisions. This paper examines the opportunities offered by AI integration in investment decision-making, such as improved portfolio optimization, enhanced risk management, reduction of cognitive and behavioral biases and increased market efficiency. Simultaneously, the study critically analyses the constraints associated with AI adaptation, including data quality issues, model interpretability, algorithmic bias, ethical concerns, regulatory challenges, and the risk of excessive dependence on automated systems. Drawing on an extensive review of existing literature and industry practices, the paper highlights the need for a balanced human-AI collaborative approach to investment decision-making. The study concludes that while AI significantly strengthens analytical capabilities and decision efficiency, its effective integration requires robust governance frameworks, transparency, and human oversight to ensure sustainable and responsible investment practices.

**Keywords:** Artificial Intelligence, Investment Decision-Making, Machine Learning, Portfolio Management, Risk management, algorithmic trading, Financial Markets, Fin Tech, Ethical and Regulatory Challenges

## Introduction

The rapid advancement of Artificial Intelligence (AI) has significantly transformed the global financial landscape, particularly in the domain of investment decision- making. Traditional investment practices, largely dependent on human judgement, historical data analysis and econometric models and increasingly being supplemented – and in some cases replaced – by intelligent systems capable of processing vast volumes of structured and unstructured data in real time. The integration of AI technologies into financial investment processes has introduced a paradigm shift in how investors analyze markets, assess risk, and allocate capital.

Artificial Intelligence encompasses a broad set of technologies including machine learning, deep learning, natural language processing, and reinforcement learning. These technologies enable financial institutions and investors to identify complex patterns, forecast asset price movements, detect anomalies and optimize portfolios with a level of speed and accuracy unattainable through conventional analytical approaches. Applications such as algorithmic trading robo-advisory services sentiment analysis of financial news and automated risk management systems have become increasingly prevalent across both developed and emerging financial markets.

Despite the growing adoption of AI-driven investment tools the integration of these technologies is not without challenges. Financial markets are inherently volatile, non-linear and influenced by behavioral and macroeconomic factors that may not always be captured by data-driven models. Concerns regarding data quality, model overfitting, interpretability of complex algorithms. Ethical considerations and regulatory compliance continue to pose significant constraints on the effective deployment of AI in investment decision-making. Moreover, the reliance on "black-box" models raises questions about transparency, accountability, and trust-particularly in regulated financial environments.

By synthesizing theoretical perspectives and empirical insights, the study aims to contribute to the growing body of research on financial technology and investment analytics. The findings are expected to offer valuable implications for investors, financial institutions, regulators, and policymakers seeking to leverage AI responsibly while ensuring stability, transparency, and ethical integrity within financial markets.

In this context, understanding both the opportunities and constraints associated with AI – enabled investment decision- making is crucial. While existing literature highlights the superior predictive capabilities and efficiency gains offered by AI models, there remains a need for a balanced examination of their practical limitations and governance challenges. This study seeks to address this gap by systematically analysing how AI is being integrated into financial investment decision- making, the value it creates for investors and institutions and the constraints that influence its adoption and effectiveness.

**Review of Literature**

Kaur, B., & Kour, M. (2025) The authors opines that businesses are using robotic process automation to digitize many areas of their operations due to the growing digitalization of several industries. It automates repetitive activities using computer programs and software robots that follow rules. It has fundamentally altered the way we approach our work. Given the vast prospects presented by digital technology, financial forecasting is not immune to this transformation. Robotic financial forecasting technologies are crucial for maintaining an organization's financial stability by digitally managing and monitoring financial transactions. This study aims to increase knowledge of the rapidly evolving field of artificial intelligence in finance. The application of AI in financial services has the potential to increase economic growth and position nations as leaders in the financial technology sector in addition to stimulating innovation. Fundamentally, this study highlights the various ways that technology, especially artificial intelligence and robotic process automation, affects the finance industry.

Maurya, S et.al., (2024) The authors identify the effects of artificial intelligence (AI) on the capital market, including how it affects risk management, investment decision-making, moral dilemmas and legal considerations. It illustrates the potential implications of a particular artificial intelligence for a sector where financial backers can update their strategies and abandon a certified bet. For the banking industry, planning artificial intelligence frameworks should adhere to moral considerations such as simplicity, decency and legitimacy. The use of artificial intelligence is enhancing competition among new fintech partnerships in the market that gives customers a wide range of options, changing the financial sector. Furthermore, computer-based intelligence fosters a standard of moral education by promoting honest corporate ethics and sound natural concerns in the financial sector. Furthermore, it will need a great deal of moral control and the application of lawful regulations. It produces comprehensive simulated intelligence outcomes that are far larger than a model calculation, necessitating inter disciplinary, excellent adaptability, and preparedness to provide an appropriate subsidized area. In this sense, it serves as a translation of significance into a continuously influencing reality that reveals obstacles and improves the hypothesis for applications using artificial intelligence in banking.

Gupta, A. et. al., (2024) In banking, the combination of machine learning (ML) and artificial intelligence (AI) portends a paradigm change away from conventional financial decision-making and toward a more automated, effective method. This review describes the evolution of important banking domains, including risk assessment, algorithmic trading, and portfolio management, using developments in AI and ML. The article emphasizes how AI's integration into algorithmic trading boosts market efficiency through high-frequency trading and predictive analytics, as well as how machine learning algorithms are revolutionary in asset allocation. In addition to exploring the advancements in risk management made possible by predictive modeling, the article discusses the ethical, legal, and transparency concerns brought up by AI's banking applications. In addition to forecasting future developments, including the convergence of AI with blockchain and decentralized finance (DeFi), this research, which includes case studies, offers insight into the efficient application of AI across financial organizations. In addition to stressing the need for responsible AI integration for future financial decision-making, this synthesis offers professionals a strategic road map for navigating the AI-induced financial environment.

Malik, A. (2024) The author is of the opinion that, Artificial Intelligence (AI) is transforming the financial sector, particularly in the domains of risk management and investment decision-making. The accuracy and efficiency of financial processes have increased because to AI's capacity to handle enormous volumes of data, identify trends and make predictions in real time. AI-powered risk management systems utilize machine learning algorithms to analyze historical data, assess market fluctuations and identify potential financial risks with greater precision than traditional models (Goodell et al., 2021). Additionally, by assessing market patterns, projecting asset performance and reducing uncertainty, AI-driven predictive analytics help investors make well-informed decisions (Bussmann et al., 2020). Automated trading strategies, powered by AI, improve portfolio management by adjusting asset allocations based on real-time data and risk tolerance levels (Feng et al., 2018). AI integration in banking additionally fortifies fraud detection systems, guaranteeing improved security and adherence to legal standards (Zhang et al., 2022). Despite these developments, problems including algorithmic biases, ethical dilemmas, and data privacy concerns continue to be major roadblocks (Kou et al., 2021). This research explores the impact of AI on financial risk management and investment strategies, highlighting the potential benefits and challenges associated with AI-driven financial decision-making. The results indicate that although AI has many benefits, safe use of AI in finance requires a balanced strategy that incorporates human monitoring and legal frameworks. Individual investors' investing decisions are influenced by both behavioral biases and financial literacy, according to Suresh, G. (2024). While behavioral biases offer easy and straightforward concepts for decision-making, financial literacy helps investors understand more about the investment environment. Heuristic bias significantly improves the framing effect and cognitive illusions in decision-making, but it has a detrimental influence on herd mentality, according to the independent association between variables.

Sarin, A. B., & Sharma, S. (2023) The authors explain how investors' perceptions about artificial intelligence have changed. The development of technology has made machines more powerful. This will assist in forecasting market fluctuations by utilizing investor behavior. The requirement for high-quality data, the possibility of bias in AI algorithms itself, and ethical issues around the use of AI to make investment choices are some of the difficulties associated with applying AI in behavioral finance. This research article also discusses how these difficulties will affect the way that investments are chosen. The suggestions part of the article discusses how artificial intelligence and behavioral finance combine to help investors make better decisions and be less biased in the future. AI aims to replicate some aspects of social intelligence, such as emotions, learning, creativity, self-awareness, language, problem-solving, cognitive reasoning, or strategies, despite the challenges of characterizing and quantifying human intelligence.

Rane, N et al., (2023) This study examines how Artificial Intelligence (AI) has a significant impact on financial forecasting and how it shapes the course of investment strategies. The dynamic nature of financial markets makes traditional methods difficult to use, which is why cutting-edge AI technologies have emerged as essential tools for controlling risks, predicting trends, and improving investing decisions. The research explores a range of innovative AI models, methods, frameworks, and technologies that are transforming the field of financial forecasting. Analyzing machine learning (ML) methods, including long short-term memory networks (LSTMs) and recurrent neural networks (RNNs), exposes their ability to identify complex patterns in financial data, increasing predicted accuracy. Convolutional neural networks (CNNs), one of the deep learning approaches, are examined for their ability to extract hierarchical features from a variety of datasets, resulting in more reliable forecasts. The study also emphasizes how crucial sentiment analysis and natural language processing (NLP) are for evaluating market sentiment and incorporating qualitative data into forecasting models. Using real-time market data, the article examines sophisticated AI-driven technologies such as robo-advisors and algorithmic trading systems, explaining their functions in automating investing methods and improving portfolio management. To demonstrate how adaptive, learning-based methods improve decision-making in dynamic market situations, the application of Reinforcement Learning (RL) to financial forecasting is investigated. A new age of processing capacity for complex simulations and scenario analysis is heralded by the article, which also discusses emerging technologies like quantum computing and its possible impact on financial modeling. The article provides a thorough analysis of the shifting environment, highlighting the necessity of ongoing innovation and adaptability to prosper in the quickly expanding financial sector.

**Pramod, D., & Raman, R. (2022)** The authors express their opinion that, Manufacturing, Financial Services and the telecom sector have made immense use of technology and automation. Individual investors like using artificial intelligence to find the right product to purchase on an e-commerce platform or to choose travel routes. The study explores how Individuals' knowledge of artificial intelligence (AI) services in the financial industry affects their desire to use AI while making financial investment decisions. The study's specific findings include a positive attitude toward technology, an inventive approach to it, technological anxiety, and a lack of faith in technology and its impact on the use of AI tools for investment decision-making. The study was done on those individuals, who had work experience in the fintech domain. The findings show that people have a good attitude toward technology and that awareness has a beneficial impact on their intention to utilize financial robots and AI tools when making investment decisions as well as their technological anxiety. Technology is negatively impacted by a lack of trust. Individuals' consideration of using financial robots and AI tools for investment decisions is also greatly influenced by the tools' usability and ease of use.

**Dunka, V. (2022)** This study investigates the design and implementation of AI-enabled decision support systems (DSS) customized for investment strategies to develop a strong predictive framework for market analysis, portfolio management and risk optimization. It does this by combining cutting-edge machine learning (ML) algorithms with complex financial engineering techniques. This study aims to show how the combination of AI and financial engineering may improve investment strategies accuracy, dependability and flexibility, especially in intricate and unstable financial markets. When compared to conventional investing techniques, AI-driven systems have a major edge in terms of market forecasting and portfolio allocation since they can handle enormous volumes of financial data in real-time. The paper demonstrates how these models may produce precise and timely forecasts that guide investment decisions while adjusting to changing market circumstances by utilizing cutting-edge machine learning techniques including deep learning, reinforcement learning and ensemble approaches. Additionally, this study highlights AI's significance in risk management, namely in recognizing and reducing idiosyncratic and systemic risks. When faced with non-linear, high-dimensional market behaviors, which are typical of contemporary financial systems, traditional risk management models frequently fail. However, because machine learning models can learn from large datasets and find hidden connections between market factors, they are able to handle such complexity.

**Ren, J. (2021)** in his research article titled 'Research on financial investment decision based on artificial intelligence algorithm' asserts that, with the development of world economic globalization, market competition is tremendously increasing. An in-depth examination and prudent management of the business's operations, capital investments, and finances could be carried out because of modern science and technology. With the rapid development of computer technology, the realization of many accounting models and methods which used to be very complicated has become simple and easy. It will be challenging for businesses to become more competitive if they continue to use conventional financial decision-making techniques. The most important thing in the financial industry is to serve customers and provide them with more accurate and reliable services. The application of artificial intelligence technology in the financial industry will surely drive its intelligence upgrade and efficiency improvement. The financial industry's continued growth is aided by research on the strategy and application value of artificial intelligence technology in this sector. This paper analyses how traditional financial decision-making support cannot meet the needs of intelligent enterprise development based on the characteristics of financial decision-making in the development of new technology. It suggests that the use of artificial intelligence will improve the accuracy, automation, and timeliness of financial decision-making.

**Noonpakdee, W. (2020)** The author has conducted research on the use of artificial intelligence and its influence in making financial investment decisions. He says that rapid technology development has produced ongoing upheaval and drastically altered how financial institutions function. Financial industries have the chance to change their business procedures and give their clients with cutting-edge services thanks to artificial intelligence (AI).

The purpose of this article is to examine how AI is being used in Thailand for financial investing services. Multiple linear regression was used to analyze the data from 400 samples. The study shows that trust, perceived utility, application expertise, and social norm are factors that influence the usage of AI for financial investment services (with p <; 0.01). The foundation of this research lies in the convergence of data-driven insights and financial theory. Financial engineering techniques, including stochastic modeling, asset pricing, and quantitative risk analysis, are employed in conjunction with AI to build sophisticated models capable of analyzing both structured and unstructured data sources. These models extract meaningful patterns from historical market data, economic indicators, news sentiment, and other relevant financial data streams, enabling the decision support system to produce real-time insights and forecasts. One key aspect of this research is the development of adaptive strategies that account for dynamic risk profiles, market conditions, and individual investment objectives. By integrating machine learning models with financial optimization techniques, the proposed AI-enabled decision support system can generate investment strategies that not only maximize returns but also optimize risk exposure based on predefined criteria such as volatility, liquidity and market correlation.

**V. Ramalakshmi et al. (2019),** tried to investigate how cognitive biases affect the process of making investment decisions. To conduct the analysis, the study focused on individual investors in Bengaluru, India. They talked about it and concluded that cognitive biases have a big impact on how people make investments. These prejudices include representativeness, overconfidence, regret aversion, and herd instinct. Individual investors' decision-making process about investments is greatly impacted by these biases.

To increase the long-term return on investment and ensure its sustainability, they recommended that individual investors concentrate on taking steps to lessen and eliminate the biases influencing investing decisions.

According to **Gudgeon et al., (2020**), AI optimizes pricing, risk, and liquidity when paired with decentralized finance (DeFi) tools. Doshi-Velez & Kim (2017) proposed that the goal of XAI frameworks is to help investors and regulators understand black box models. Kroll et al. (2018) explained in his research about role of AI in risk management frameworks.

## Research Gap

Despite the growing body of literature on Artificial intelligence in finance, several critical gaps remain in understanding how AI influences investment decision-making effectiveness. First, existing studies predominantly focus on the technical capabilities and predictive performance of AI models, while offering limited empirical insight into how AI affects the quality and effectiveness of human investment decisions. This creates a gap between algorithmic performance and actual decision outcomes experienced by investors and finance professionals.

Second, much of the prior research examines AI adoption primarily through technology-centric or acceptance-based frameworks, emphasizing perceived usefulness and ease of use, while underexploring the decision-theoretic and behavioral implications of AI integration. Consequently, the integration between AI-enabled rationality and behavioral biases in real-world investment contexts remain insufficiently theorized and empirically tested

Third, existing literature often treats the benefits of AI adoption in isolation, without simultaneously examining the constraints and inhibitors that condition its effectiveness. There is limited empirical research that integrates AI opportunities and constraints within a single framework to assess their combined impact on investment decision effectiveness.

Fourth, trust in AI has been acknowledged conceptually as important, yet it is frequently examined as a general attitude toward technology rather than as a context-specific mechanism influencing high-risk financial decision-making. The moderating role of trust in translating AI capabilities into effective investment decisions remains under-investigated.

Fifth, most empirical studies are concerned in developed market contexts, with limited attention to emerging economies, where infrastructural limitations, regulatory ambiguity, and skill gaps may significantly alter AI adoption dynamics. This limits the contextual generalizability of existing findings.

Finally, methodological limitations persist in prior studies, with a dominance of conceptual discussions, case-based evidence or purely performance-driven models, and a relative lack of survey-based, theory-integrated empirical studies that model investment decision effectiveness as a multidimensional outcome.

**Gap Addressed by the Present Study**

To address these gaps, the present study develops and empirically tests an interactive theoretical framework that simultaneously examines AI opportunities, constraints, and trust in AI as determinants of Investment Decision Effectiveness, with specific attention to the behavioral and industrial context of financial decision-making in an emerging economy.

**Theoretical Framework**

The present study is theoretically grounded in an integrative framework that draws upon Rational Decision-Making Theory, Behavioural Finance Theory and Technology Acceptance and Institutional Theories to explain how Artificial Intelligence (AI) reshapes financial investment decision-making. The framework conceptualizes AI not merely as a technological tool but as a cognitive and Institutional intervention that alters the structures, process, and outcomes of investment decisions.

**Conceptual Foundation**

Traditional rational decision-making models assume that investors possess complete information and unlimited cognitive capacity, enabling optimal decision outcomes. However behavioural finance challenges this assumption by demonstrating that investment decisions are systematically influenced by cognitive biases, heuristics, and emotional factors. AI-enabled investment systems theoretically reconcile this tension by augmenting bounded rationality through advanced data processing, pattern recognition, and predictive analytics. Accordingly, AI is positioned as a decision-augmenting agent that enhances analytical rationality while constraining behavioural distortions.

**AI Opportunities and Investment Decision Effectiveness**

Within the framework, AI opportunities – including improved decision accuracy, analytical efficiency, enhanced risk management, and cost-performance optimization-constitute the primary explanatory variables influencing **Investment Decision Effectiveness (IDE).** These opportunities enable investors to process large and heterogeneous dataset in real time, systematically evaluate investment alternatives, and respond adaptively to market volatility. Investment Decision Effectiveness is conceptualized as a multidimensional outcome encompassing decision accuracy, rationality, timeliness, confidence, and risk-adjusted performance. The framework posits that AI enhances IDE by transforming decision processes from intuition-driven to analytically disciplined, thereby improving the consistency and quality of investment outcomes.

**Objectives of the study**

1. To investigate the role of artificial intelligence in enhancing financial investment decision -making and to analyse the opportunities and constraints associated with its integration.

2. To ascertain the key artificial intelligence techniques used in financial investment decision -making.

3. To assess the impact of AI-driven tools on investment accuracy, speed, and efficiency.

4. To evaluate the role of AI in risk assessment and portfolio management.

5. To analyze the influence of AI adoption and Opportunities of AI on Investment Decision Effectiveness

## Research Methodology

The study employed a descriptive research methodology. A convenient sample of 280 respondents was selected, and 243 of them gave valid responses, yielding an 86.8% response rate. The questionnaire used to gather primary data was cited in the study. The survey included 36 items and five demographic characteristics and elements that are related to retail tenant mix and purchase intention and frequency of visit. Quantitative data was produced by the study, coded, and imported into Statistical Packages for Social Scientists (SPSS) for analysis using descriptive statistics and correlation analysis. The hypotheses of the study were tested by using a multiple regression analysis to examine the relationships between AI integration and investment decision-making. ANOVA was used to compare group differences based on levels of AI adoption.

## Data Analysis and Results

**Table 1**

**Frequency and percentage distribution of the respondents' demographic characteristics.**

| Profile Variables | Frequency | Percentage |
|---|---|---|
| **Gender** | | |
| Male | 107 | 53.5 |
| Female | 93 | 46.5 |
| **Age in years** | | |
| Below 25 years | 25 | 12.5 |
| 25 to 35 | 43 | 21.5 |
| 36 to 45 | 60 | 30 |
| 46 to 55 | 48 | 24 |
| Above 55 years | 24 | 12 |
| **Occupation** | | |
| Individual Investor | 54 | 27 |
| Financial Analyst | 33 | 16.5 |
| Fund Manager | 39 | 19.5 |
| Banker | 32 | 16 |
| Academician | 42 | 21 |
| **Education** | | |
| Undergraduate | 54 | 27 |
| Postgraduate | 41 | 20.5 |
| Professional | 64 | 32 |
| Others | 41 | 20.5 |
| **Familiarity with AI-based financial tools** | | |
| Very Low | 22 | 11 |

| | | |
|---|---|---|
| Low | 38 | 19 |
| Moderate | 47 | 23.5 |
| High | 58 | 29 |
| Very High | 35 | 17.5 |
| **Years of Experience in Financial Investments** | | |
| Less than 2 years | 49 | 24.5 |
| 2–5 years | 37 | 18.5 |
| 6–10 years | 58 | 29 |
| Above 10 years | 56 | 28 |

From table 1 we see that, maximum numbers of respondents are males (107, 53.5%) followed by females (93, 46.5%). Moreover, bulk of participants (60 at 30%) are between the ages of 36 and 45, while those Above 54 years have the fewest participation (24, 12%). Maximum numbers of respondents are Individual Investors (54, 27%) followed by Academicians (42, 21%). Maximum numbers of respondents are Professionals (64, 32%) followed by Under Graduates (54, 27%). Regarding familiarity with AI-based financial tools, maximum numbers of respondents are highly familiar (58, 29%), followed by moderately familiar (47, 23.5%). Least number of respondents are having very low familiarity with AI-based financial tools (22, 11%). Regarding years of experience in Financial Investments, maximum number of respondents having 6–10 years of experience (58, 29%) followed by above 10 years of experience (56, 28%).

Table 2 and 3, show the reliability test for the data collected for the present study and the result is satisfactory and the values are under the acceptable range.

| **Table: 2 - Reliability Statistics of all factors** | |
|---|---|
| Alpha Value | Number of Items |
| 0.965 | 46 |

**Table 3**

**Reliability of the Factors of Artificial Intelligence and Financial Investment Decision-Making**

| **Name of the construct** | **Alpha Value** | **No. of Items** |
|---|---|---|
| Adoption of AI in investment Decision -making | 0.774 | 4 |
| Opportunities of AI in investment Decision-Making | 0.881 | 12 |
| Constraints of AI in investment Decision-Making | 0.957 | 12 |
| Trust and Acceptance of AI | 0.777 | 4 |
| Future Intention and Overall Impact | 0.855 | 4 |
| Investment Decision Effectiveness | 0.923 | 10 |

Constraints of AI in investment Decision-Making has the greatest alpha value (α = 0.957), followed by Investment Decision Effectiveness (α = 0.923) and Opportunities of AI in investment Decision-Making (α = 0.881).

**Table 4**

**Descriptive statistics of the factors of Adoption of AI in investment decision -making**

| Factors influencing Ethical Decision-Making | Mean | Std. Deviation |
|---|---|---|
| I regularly use AI-based tools for investment analysis | 3.02 | 1.01 |
| AI plays a significant role in my investment decision-making process | 3.31 | 0.900 |
| My organisation encourages the use of AI in financial decision-making | 3.08 | 1.05 |
| AI-driven insights influence my final investment choices | 3.25 | 1.05 |
| Composite Mean | 9.31 | 2.35 |

According to Table 4, the respondents agreed on the factors of Adoption of AI in investment decision -making**,** with a composite mean of 9.31. Of the listed indicators, the highest ranking (weighted mean score of 3.31) went to "AI plays a significant role in my investment decision-making process" followed by the item "AI-driven insights influence my final investment choices" (weighted mean of 3.25), "My organisation encourages the use of AI in financial decision-making" (weighted mean of 3.08) and "I regularly use AI-based tools for investment analysis" (weighted mean of 3.02).

**Table 5**

**Descriptive statistics of the factors of Opportunities of AI in investment Decision-Making**

| Factors | Mean | Std. Deviation |
|---|---|---|
| Improved Decision Accuracy | 10.5 | 1.5200 |
| Efficiency and Speed | 10.4 | 1.1987 |
| Risk Management | 9.65 | 1.5197 |
| Cost-Performance Benefits | 9.53 | 1.5863 |
| Composite Mean | 40.1 | 8.80 |

According to Table 5, the respondents agreed on the factors of Opportunities of AI in investment Decision-Making**,** with a composite mean of 40.1. Of the listed indicators, the highest ranking (weighted mean score of 10.5) went to "Improved Decision Accuracy" followed by the item "Efficiency and Speed" (weighted mean of 10.4), "Risk Management" (weighted mean of 9.65) and "Cost-Performance Benefits" (weighted mean of 9.53).

**Table 6**

**Descriptive statistics of the factors of Constraints of AI in investment Decision-Making**

| Factors influencing Ethical Decision-Making | Mean | Std. Deviation |
|---|---|---|
| Technological Constraints | 10.4 | 2.49 |
| Financial and Infrastructure Constraints | 10.8 | 2.32 |
| Human and Skill-Related Constraints | 10.5 | 2.22 |

| | | |
|---|---|---|
| Ethical and Regulatory Constraints | 10.7 | 2.26 |
| Composite Mean | 42.3 | 8.75 |

According to Table 6, the respondents agreed on the factors of Constraints of AI in investment Decision-Making**,** with a composite mean of 6.2853. Of the listed indicators, the highest ranking (weighted mean score of 10.8) went to "Financial and Infrastructure Constraints" followed by the item "Ethical and Regulatory Constraints" (weighted mean of 10.7), "Human and Skill-Related Constraints" (weighted mean of 10.5) and "Technological Constraints" (weighted mean of 10.4).

**Table 7**

**Descriptive statistics of the factors of Trust and Acceptance of AI**

| **Factors Trust and Acceptance of AI** | **Mean** | **Std. Deviation** |
|---|---|---|
| I trust AI-based investment recommendations | 3.44 | 0.944 |
| AI-based decisions are more reliable than traditional methods | 3.13 | 1.18 |
| I am comfortable relying on AI for high-value investments | 3.02 | 0.905 |
| Transparency in AI models increases my trust in AI systems | 3.34 | 0.953 |
| **Composite Mean** | 12.9 | 3.10 |

According to Table 7, the respondents agreed on the factors of Opportunities of AI in investment Decision-Making**,** with a composite mean of 12.9. Of the listed indicators, the highest ranking (weighted mean score of 3.44) went to "I trust AI-based investment recommendations" followed by the item "Transparency in AI models increases my trust in AI systems" (weighted mean of 3.34), "AI-based decisions are more reliable than traditional methods" (weighted mean of 3.13) and "I am comfortable relying on AI for high-value investments" (weighted mean of 3.02).

**Table 8**

**Descriptive statistics of the factors of Future Intention and Overall Impact**

| **Factors of Future Intention and Overall Impact** | **Mean** | **Std. Deviation** |
|---|---|---|
| I intend to increase the use of AI in my investment decisions | 3.29 | 0.944 |
| AI will play a dominant role in the future of financial investments | 3.56 | 0.872 |
| The benefits of AI outweigh its risks in investment decision-making | 3.73 | 0.802 |
| AI integration improves the overall quality of investment decisions | 3.31 | 1.19 |
| **Composite Mean** | 13.9 | 3.21 |

According to Table 8, the respondents agreed on the factors of Future Intention and Overall Impact**,** with a composite mean of 13.9. Of the listed indicators, the highest ranking (weighted mean score of 3.73) went to "The

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benefits of AI outweigh its risks in investment decision-making” followed by the item “AI will play a dominant role in the future of financial investments” (weighted mean of 3.56), “AI integration improves the overall quality of investment decisions” (weighted mean of 3.31) and “I intend to increase the use of AI in my investment decisions” (weighted mean of 3.29).

**Table 9**

**Descriptive statistics of the factors of Investment Decision Effectiveness**

| **Factors of Future Intention and Overall Impact** | **Mean** | **Std. Deviation** |
|---|---|---|
| AI-supported tools help me make more accurate investment decisions | 3.77 | 0.884 |
| The use of AI improves the overall quality of my investment decisions | 3.83 | 0.833 |
| AI enables me to evaluate investment alternatives more effectively | 3.79 | 0.922 |
| Investment decisions made with AI support are more rational and data-driven | 3.64 | 0.914 |
| AI assisted decisions reduce errors caused by emotional or cognitive bias | 3.91 | 0.738 |
| AI improves the timeliness of my investment decisions | 4 | 0.687 |
| AI enhances my ability to manage investment risks effectively | 3.92 | 0.779 |
| AI-based insights lead to better portfolio performance outcomes | 3.9 | 0.851 |
| AI improves my confidence in making complex investment decisions | 4.04 | 0.769 |
| Overall, AI integration increases the effectiveness of my investment decision-making | 3.9 | 0.748 |
| **Composite Mean** | 38.7 | 6.27 |

According to Table 9, the respondents agreed on the factors of Investment Decision Effectiveness**,** with a composite mean of 38.7. Of the listed indicators, the highest ranking (weighted mean score of 4.04) went to “AI improves my confidence in making complex investment decisions” followed by the item “AI improves the timeliness of my investment decisions” (weighted mean of 4), “AI enhances my ability to manage investment risks effectively” (weighted mean of 3.92) and “AI assisted decisions reduce errors caused by emotional or cognitive bias” (weighted mean of 3.91).Least mean belongs to “Investment decisions made with AI support are more rational and data-driven” (weighted mean of 3.64).

To ascertain the association between the variables, bivariate correlations were calculated. The results are presented below.

**Table 10 Correlation between factors of Opportunities of AI in investment Decision-Making**

| Correlation Matrix | | | | | |
|---|---|---|---|---|---|
| | | **IDA** | **ES** | **RM** | **CPB** |
| **IDA** | r-value | 1 | | | |
| | p-value | - | | | |
| **ES** | r-value | 0.714 | — | | |
| | p-value | <.001 | — | | |

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| | | | | | |
|---|---|---|---|---|---|
| **RM** | r-value | 0.551 | 0.668 | — | |
| | p-value | <.001 | <.001 | — | |
| **CPB** | r-value | 0.515 | 0.646 | 0.814 | — |
| | p-value | <.001 | <.001 | <.001 | — |

The relationships between factors of Opportunities of AI in investment Decision-Making were analysed and presented in the above table. Table 10 shows Pearson's Correlation coefficients with alpha at .01 level. Since p-value is less than 0.01, for all the factors, the relationship between the factors of Opportunities of AI in investment Decision-Making is statistically significant.

**Table 11**

**Correlation between factors of Constraints of AI in investment Decision-Making**

| Correlation Matrix | | | | | |
|---|---|---|---|---|---|
| | | **TC** | **FIC** | **HSC** | **ERC** |
| **TC** | r-value | — | | | |
| | p-value | — | | | |
| **FIC** | r-value | 0.893 | — | | |
| | p-value | <.001 | — | | |
| **HSC** | r-value | 0.86 | 0.822 | — | |
| | p-value | <.001 | <.001 | — | |
| **ERC** | r-value | 0.847 | 0.885 | 0.775 | — |
| | p-value | <.001 | <.001 | <.001 | — |

The relationships between factors of Constraints of AI in investment Decision-Making were analysed and presented in the above table. Table 11 shows Pearson's Correlation coefficients with alpha at .01 level. Since p-value is less than 0.01, for all the factors, the relationship between the factors of Constraints of AI in investment Decision-Making is statistically significant.

**Table 12**

**Correlation between factors of Investment Decision Effectiveness**

| **Correlation Matrix** | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | **IDE1** | **IDE2** | **IDE3** | **IDE4** | **IDE5** | **IDE6** | **IDE7** | **IDE8** | **IDE9** | **IDE10** |
| **IDE1** | r-value | — | | | | | | | | | |
| | p-value | — | | | | | | | | | |
| **IDE2** | r-value | 0.492 | — | | | | | | | | |
| | p-value | <.001 | — | | | | | | | | |
| **IDE3** | r-value | 0.68 | 0.588 | — | | | | | | | |
| | p-value | <.001 | <.001 | — | | | | | | | |

| | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **IDE4** | r-value | 0.575 | 0.447 | 0.435 | — | | | | | | |
| | p-value | <.001 | <.001 | <.001 | — | | | | | | |
| **IDE5** | r-value | 0.769 | 0.694 | 0.725 | 0.585 | — | | | | | |
| | p-value | <.001 | <.001 | <.001 | <.001 | — | | | | | |
| **IDE6** | r-value | 0.29 | 0.518 | 0.404 | 0.376 | 0.555 | — | | | | |
| | p-value | <.001 | <.001 | <.001 | <.001 | <.001 | — | | | | |
| **IDE7** | r-value | 0.528 | 0.552 | 0.725 | 0.524 | 0.634 | 0.526 | — | | | |
| | p-value | <.001 | <.001 | <.001 | <.001 | <.001 | <.001 | — | | | |
| **IDE8** | r-value | 0.537 | 0.529 | 0.614 | 0.516 | 0.642 | 0.524 | 0.67 | — | | |
| | p-value | <.001 | <.001 | <.001 | <.001 | <.001 | <.001 | <.001 | — | | |
| **IDE9** | r-value | 0.302 | 0.324 | 0.437 | 0.364 | 0.511 | 0.352 | 0.383 | 0.674 | — | |
| | p-value | <.001 | <.001 | <.001 | <.001 | <.001 | <.001 | <.001 | <.001 | — | |
| **IDE10** | r-value | 0.621 | 0.563 | 0.678 | 0.465 | 0.759 | 0.558 | 0.66 | 0.815 | 0.61 | — |
| | p-value | <.001 | <.001 | <.001 | <.001 | <.001 | <.001 | <.001 | <.001 | <.001 | — |

The relationships between factors of Investment Decision Effectiveness were analysed and presented in the above table. Table 12 shows Pearson's Correlation coefficients with alpha at .01 level. Since p-value is less than 0.01, for all the factors, the relationship between the factors of Investment Decision Effectiveness is statistically significant.

**Regression Analysis of Investment Decision Effectiveness and AI adoption level, Opportunities of AI in investment Decision-Making**

A regression analysis with Investment Decision Effectiveness as the dependent variable and AI adoption level, Opportunities of AI in investment Decision-Making like Improved Decision Accuracy, Efficiency and Speed, Risk Management and Cost-Performance Benefits as independent variables has been attempted.

Dependent variable : Investment Decision Effectiveness (Y)

Independent variables : 1. AI adoption level ($X_1$),

2. Improved Decision Accuracy ($X_2$),

3. Efficiency and Speed ($X_3$),

4. Risk management ($X_4$),

5. Cost-Performance Benefits ($X_5$),

- Multiple R value : 0.893
- R Square value : 0.798
- F value : 532.862
- P value : <0.001**

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**Table 13**

**Variables in the Multiple Regression Analysis**

| Variables | Unstandardized co-efficient | SE of B | Standardized co-efficient | t value | P value |
|---|---|---|---|---|---|
| Constant | 38.399 | 2.789 | | 13.768 | <0.001** |
| $X_1$ | 1.302 | 0.307 | 0.122 | 4.246 | <0.001** |
| $X_2$ | 3.216 | 0.309 | 0.242 | 10.417 | <0.001** |
| $X_3$ | 1.592 | 0.313 | 0.151 | 5.092 | <0.001** |
| $X_4$ | 2.036 | 0.205 | 0.341 | 9.951 | <0.001** |
| X5 | 1.723 | 0.216 | 0.144 | 6.785 | <0.001** |

Note: ** Denotes significant at 1% level

**The multiple correlation coefficient is** 0.893 measures the degree of relationship between the actual values and the predicted values of the Investment Decision Effectiveness. Because the predicted values are obtained as a linear combination of AI adoption level (**$X_1$**), Improved Decision Accuracy (**$X_2$**), Efficiency and Speed ($X_3$), Risk Management ($X_4$) and Cost-Performance Benefits ($X_5$), the coefficient value of 0.893 indicates that the relationship between Investment Decision Effectiveness and the **five** independent variables is very strong and positive.

**The Coefficient of Determination R-square** measures the goodness-of-fit of the estimated Sample Regression Plane (SRP) in terms of the proportion of the variation in the dependent variables explained by the fitted sample regression equation. Thus, the value of **R square is 0**.798 simply means that about 79.8**%** of the variation in Investment Decision Effectiveness is explained by the estimated SRP that uses AI adoption level, Opportunities of AI in investment Decision-Making like Improved Decision Accuracy, Efficiency and Speed, Risk Management, Cost and Performance Benefits (as the independent variables and R square value is significant at 1 % level.

The multiple regression equation is

$$Y = 38.399 + 0.302X_1 + 3.216X_2 + 1.592X_3 + 2.036X_4 + 1.723X_5$$

Here the coefficient of **$X_1$** is 1.302 represents the partial effect of AI adoption level on Investment Decision Effectiveness, holding the other variables as constant. The estimated positive sign implies that such effect is positive that Investment Decision Effectiveness would increase by 1.302 for every unit increase in AI adoption level and this coefficient value is significant at 1% level. The coefficient of **$X_2$** is 3.216 represents the partial effect of Improved Decision Accuracy on Investment Decision Effectiveness, holding the other variables as constant. The estimated positive sign implies that such effect is positive that Investment Decision Effectiveness would increase by 3.216 for every unit increase in Improved Decision Accuracy and this coefficient value is significant at 1% level.

The coefficient of **$X_3$** is 1.592 represents the partial effect of Efficiency and Speed on Investment Decision Effectiveness, holding the other variables as constant. The estimated positive sign implies that such effect is positive that Investment Decision Effectiveness would increase by 1.592 for every unit increase in Efficiency and Speed and this coefficient value is significant at 1% level. The coefficient of **$X_4$** is 2.036 represents the partial effect of Risk Management on Investment Decision Effectiveness, holding the other variables as constant. The estimated positive sign implies that such effect is positive that Investment Decision Effectiveness would increase by 2.036 for every unit increase in Risk Management and this coefficient value is significant at 1% level

The coefficient of **$X_5$** is 1.723 represents the partial effect of Cost and Performance Benefits on Investment Decision Effectiveness, holding the other variables as constant. The estimated positive sign implies that such effect is positive that Investment Decision Effectiveness would increase by 1.723 for every unit increase in Cost-Performance Benefits and this coefficient value is significant at 1% level

Based on standardized coefficient, Risk management (0.341), is the most important factor to extract Investment Decision Effectiveness, followed by Improved Decision Accuracy (0.242), Efficiency and Speed (0.151), Cost-Performance Benefits (0.144). and AI adoption level (0.122).

## Discussion

The findings of the study indicate a growing acceptance of Artificial Intelligence (AI) as a decision-support tool in financial investment decision-making, particularly due to its perceived ability to enhance analytical accuracy, processing speed, and risk management. Respondents acknowledged that AI significantly improves the quality of investment decision-making by enabling faster analysis of large and complex datasets, supporting prior research that emphasizes the efficiency and predictive advantages of AI- driven financial analytics.

The results further reveal that AI is perceived as effective in reducing human bias and improving rationality in investment decisions, aligning with behavioural finance literature that highlights the limitations of purely human judgement. This suggests that AI adoption represents a shift toward hybrid decision-making models in which human expertise is complemented by algorithmic intelligence. However, the findings also suggest that complete reliance on AI is approached with caution, indicating the continued importance of human oversight in high value financial decisions

Despite the recognised opportunities, the study identifies several critical constraints affecting AI adoption. Technological complexity, lack of transparency in AI algorithms and concerns related to data emerged as significant barriers. These findings reinforce concerns raised in existing literature regarding the "black box" nature of AI systems and their implications for trust and accountability in financial decision-making. Financial and Infrastructural constraints, particularly cost and accessibility, were also found to limit AI adoption, especially among small investors and smaller financial institutions.

Ethical and regulatory concerns, including data privacy and inadequate regulatory frameworks, were found to influence trust and acceptance of AI-based investment tools. This underscores the role of institutional support and governance mechanisms in shaping AI adoption in finance. Additionally, skill-related constraints and resistance to change highlight the importance of organisational readiness and AI literacy in facilitating effective implementation. Overall, the study suggests that while AI presents substantial opportunities to enhance investment decision-making, its successful integration depends on addressing technological, ethical, and human-centric challenges. The findings emphasize the need for a balanced approach that combines AI capabilities with human judgement, supported by transparent systems, appropriate regulation, and continuous skill development.

## Theoretical and Practical Implications

### Theoretical Implications

This study advances investment decision-making literature by integrating Artificial Intelligence (AI) into traditional rational and behavioural finance frameworks. It demonstrates that AI functions as a hybrid decision-support system that enhances analytical rationality while mitigating cognitive biases there by extending classical investment theories. The findings also enrich technology adoption literature, particularly the Technology Acceptance Model (TAM) and UTAUT, by empirically validating the roles of perceived usefulness, trust, risk and ethical concerns in AI adoption within high-risk financial contexts. Furthermore, the study contributes to AI-driven risk management theory by conceptualizing AI as a proactive risk intelligence tool rather than a purely computational aid. By examining infrastructural, regulatory, and skill-related constraints, the study provides context-specific insights relevant to emerging economies, thereby addressing a critical gap in the global AI-finance discourse

**Practical Implications**

The study offers actionable insights for investors, financial institutions, FinTech firms, and policymakers. For investors, it highlights the potential of AI to improve decision accuracy and risk management while emphasizing the need for human oversight. Financial institutions can utilise the findings to design transparent, trustworthy, and ethically aligned AI- based investment systems that enhance user acceptance. FinTech developers are encouraged to focus on explainable, cost-effective, and user-centric AI solutions. Policymakers may draw upon the results to develop robust regulatory frameworks addressing data privacy, algorithm accountability, and ethical AI usage. Finally, the study underscores the importance of AI-focused training and change-management initiatives to facilitate effective and responsible integration of AI into investment decision-making.

**Limitations of the study**

Despite its contributions, the study has certain limitations. First, the findings are based on self-reported perceptions of investors and finance professionals, which may be subject to response bias and social desirability effects. Second, the cross-sectional nature of the study restricts the ability to capture changes in perceptions and adoption behaviour over time as AI technologies continue to evolve rapidly. Third, the study focusses primarily on perceived opportunities and constraints rather than objective performance outcomes, which may limit the generalizability of the results to actual investment performance. Fourth, contextual factors such as regulatory environment, technological infrastructure, and market maturity may vary across regions, thereby limiting the applicability of the findings beyond the study setting. Finally, the study does not differentiate extensively among types of AI tools or investment instruments, which may influence perceptions and adoption patterns differently.

## Conclusion

The study examined the integration of Artificial Intelligence (AI) into financial investment decision-making by exploring its perceived opportunities and constraints. The findings reveal that AI is widely recognized for its ability to enhance decision accuracy, efficiency, and risk management by enabling data-driven and timely investment insights. AI-assisted decision-making is perceived to reduce human bias and support more rational investment choices, reinforcing its role as a valuable decision-support mechanism in modern financial markets.

However, the study also highlights significant challenges that hinder effective AI adoption in investment decision-making. Technological complexity, lack of transparency in AI algorithm, high implementation costs, skill gaps, and ethical and regulatory concerns continue to influence trust and acceptance among investors and finance professionals. These constraints indicate that while AI has transformative potential, its effectiveness depends on the availability of reliable data, explainable systems, appropriate regulatory frameworks, and human expertise.

Overall, the study insists that successful integration of AI in financial investment decision-making requires a balanced human-AI approach. Rather than replacing human judgement, AI should complement it through transparent, ethical, and well-regulated applications. Addressing the identified constraints can facilitate responsible and sustainable AI adoption, enabling stakeholders to fully leverage AI's potential while minimizing associated risks. The study thus contributes to the evolving discourse on AI-enabled finance and provides a foundation for future research and practice in this domain.

The study concludes that the integration of Artificial Intelligence significantly enhances investment decision effectiveness by improving accuracy, rationality, and timeliness in financial decision-making. AI-supported tools enable investors to process large volumes of data efficiently, reduce cognitive and emotional biases and evaluate investment alternatives more systematically. The findings indicate that AI contributes positively to risk assessment and portfolio management, thereby strengthening investor confidence in complex and uncertain market conditions. However, the effectiveness of AI-enabled investment decisions is contingent upon the quality of the data, transparency of algorithms and the presence of adequate human oversight. Overall, AI serves as a valuable decision-support mechanism that augments, rather than replaces, human judgement, leading to more consistent and cost-effective investment decisions.

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