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Evaluating the Transformative Influence of Artificial Intelligence–Driven Systems on Investor Behaviour and Decision-Making Dynamics in Financial Markets

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Abstract

The increasing adoption of Artificial Intelligence (AI)–based systems in financial markets has brought notable changes in how investors perceive information and make investment decisions. This study investigates the extent to which AI-driven tools—such as automated advisory services, algorithmic trading mechanisms, and data-driven forecasting models—shape investor behaviour and influence decision-making patterns. The research follows a descriptive-cum-analytical design**,** enabling a structured examination of behavioural responses associated with the use of AI technologies. The study is primarily based on primary data**,** collected through a well-structured questionnaire administered to a sample of 200 investors, comprising retail participants and individuals with moderate market experience. A convenience sampling method was adopted to select respondents who actively engage with digital investment platforms. Supporting insights were also drawn from relevant secondary sources, including academic literature and industry reports.

To analyze the data, techniques such as frequency distribution, correlation analysis, and multiple regression were employed using statistical software (e.g., SPSS). The reliability of the measurement scale was verified through Cronbach's alpha, while factor analysis was conducted to identify key dimensions influencing investor behaviour in an AI-enabled environment. The results indicate that AI-based systems contribute to improved efficiency in information processing, assist in minimizing behavioural biases, and enhance the overall quality of investment decisions. At the same time, the findings suggest a growing tendency among investors to depend heavily on automated recommendations, which may limit independent judgment.

In conclusion, the study highlights that AI-driven technologies play a significant role in modernizing investment practices by promoting more informed and timely decision-making. However, it also emphasizes the importance of maintaining a balance between technological reliance and human insight to ensure responsible and effective investment behaviour in the evolving financial landscape.

Keywords: Artificial Intelligence, Investor Behaviour, Financial Decision-Making.

1. Introduction

The growing integration of Artificial Intelligence (AI) into financial markets has fundamentally altered the way investors access information, evaluate risk, and execute investment decisions. Technologies such as algorithm-driven trading systems, robo-advisory platforms, and advanced data analytics tools are enabling faster processing of large volumes of market data, thereby reshaping traditional investment practices. Unlike earlier approaches that relied heavily on human judgment and experience, AI-supported systems provide data-backed insights that can influence both rational evaluation and behavioural responses of investors. This shift has significant implications for understanding how cognitive biases, emotional tendencies, and decision-making patterns evolve in a technology-driven environment. As investors increasingly interact with automated tools, questions arise regarding the balance between human intuition and machine-generated recommendations, as well as the potential risks of overdependence on such systems. In this context, examining the transformative role of AI in shaping investor behaviour and decision-making dynamics becomes essential for comprehending the changing structure of modern financial markets.

1.1 Background of the Study

The evolution of financial markets has been closely linked with technological advancements, progressing from traditional trading mechanisms to highly sophisticated, data-driven systems. In recent years, Artificial Intelligence (AI) has emerged as a transformative force, enabling real-time data analysis, predictive modelling, and automated decision-making in investment activities. Earlier financial theories, particularly those grounded in rational choice assumptions, suggested that investors act logically to maximize returns; however, behavioural finance research has consistently demonstrated the influence of psychological biases and emotional factors on investment decisions (Kahneman & Tversky, 1979). The introduction of AI-driven tools—such as robo-advisors and algorithmic trading platforms—has begun to reshape these behavioural patterns by offering structured, data-centric guidance that can potentially reduce irrational tendencies. At the same time, reliance on automated systems raises concerns about diminished human judgment and overdependence on technology (Jiang, Li, & Wang, 2021). The growing accessibility of digital financial platforms has further accelerated AI adoption among retail investors, making it important to understand how these technologies interact with human cognition and behaviour. Consequently, examining the intersection of AI and investor decision-making provides valuable insights into the changing dynamics of modern financial markets.

1.2 Research Objectives

1. To determine whether the use of Artificial Intelligence (AI)–based investment tools has a statistically significant effect on investors' decision-making efficiency.
2. To examine the relationship between AI adoption and the level of behavioural biases exhibited by investors.
3. To assess the impact of AI-driven systems on investors' risk perception and evaluation patterns.
4. To compare the decision-making quality of investors who utilize AI-enabled platforms with those who rely on conventional investment approaches.

1.3 Hypotheses of Study

H01: The use of Artificial Intelligence (AI)–based investment tools has no significant effect on investors' decision-making efficiency.

H11: The use of Artificial Intelligence (AI)–based investment tools has a significant effect on investors' decision-making efficiency.

H02: There is no significant relationship between the adoption of AI systems and the level of behavioural biases among investors.
H12: There is a significant relationship between the adoption of AI systems and the level of behavioural biases among investors.
H03: AI-driven systems do not significantly influence investors' risk perception and evaluation patterns.
H13: AI-driven systems significantly influence investors' risk perception and evaluation patterns.
H04: There is no significant difference in decision-making quality between investors using AI-enabled platforms and those using traditional methods.
H14: There is a significant difference in decision-making quality between investors using AI-enabled platforms and those using traditional methods.

1.4 Significance of the Study

Stakeholder/Area	Significance of the Study
Investors	Provides insight into how AI-based tools influence investment behaviour and decision quality, helping investors make more informed and balanced choices.
Financial Institutions	Assists firms in understanding user interaction with AI systems, enabling better design of advisory services and investment platforms.
Researchers & Academicians	Contributes fresh perspectives to behavioural finance literature by linking AI adoption with evolving decision-making patterns.
Policy Makers & Regulators	Offers useful inputs for framing guidelines to ensure responsible use of AI in financial markets and to protect investor interests.
Technology Developers	Helps in improving AI-driven financial applications by highlighting user behaviour, dependency risks, and usability factors.
Financial Education Sector	Supports the development of training programs aimed at enhancing digital financial literacy and critical thinking among investors.

Table No. 1.4: Significance of the Study

2. Literature Review

The study of investor behaviour has gradually shifted from traditional finance assumptions toward more psychologically grounded explanations. Early contributions in behavioural finance established that investors do not always act rationally, as their decisions are shaped by cognitive shortcuts, emotions, and biases. Research has consistently shown that heuristics such as overconfidence, anchoring, and herding influence financial choices, particularly among individual investors in emerging markets . These findings challenged the classical view of efficient markets and opened avenues for interdisciplinary research integrating psychology and finance.

With the advancement of financial technologies, particularly Artificial Intelligence (AI), the decision-making environment has undergone substantial transformation. AI-based systems enable rapid processing of large datasets, predictive modelling, and automated advisory services, thereby altering how investors interpret market information. Recent empirical work indicates that AI tools can support more structured and data-driven decision-making, potentially reducing behavioural inconsistencies (Sanjana, 2026) . However, this transformation is not without complexity, as investor interaction with AI introduces new behavioural dynamics.

A key area of investigation is the concept of algorithm aversion, where individuals demonstrate reluctance to rely on automated systems despite their potential accuracy. Experimental studies reveal that investors often perceive AI-generated forecasts as less credible compared to human advice, which can reduce their responsiveness to such recommendations . Similarly, research examining emotional responses suggests that disclosure of AI usage can alter investment reactions by moderating the influence of positive or negative information . These findings indicate that trust and perception play a crucial role in determining the effectiveness of AI in financial decision-making.

At the same time, emerging studies highlight that AI itself may not be entirely free from biases. Investigations into machine learning models suggest that AI systems can exhibit patterns resembling human cognitive biases, including framing effects and herding tendencies . This raises important concerns regarding the assumption that AI inherently produces fully rational outcomes. Instead, the interaction between human behaviour and algorithmic design appears to create a hybrid decision-making environment.

Another stream of research focuses on investor heterogeneity in adopting AI technologies. Evidence suggests that factors such as personality traits, perceived usefulness, and level of financial literacy influence the extent to which investors engage with AI tools . More experienced or diversified investors tend to use AI more frequently, while others may remain cautious due to limited understanding or trust issues. This variation highlights the importance of user-centric design in financial technologies.

Additionally, comparative studies examining machine learning and human investors indicate that AI can outperform traditional approaches in certain contexts, particularly in processing complex information and identifying patterns in large datasets . However, such advantages are often conditional on the quality of data and model design, suggesting that AI should complement rather than replace human judgment.

Overall, the existing literature reflects a transition toward a hybrid financial decision-making framework, where human cognition and AI capabilities coexist. While AI has the potential to enhance efficiency and reduce certain biases, it also introduces new challenges related to trust, dependency, and algorithmic limitations. Therefore, understanding the combined influence of technology and human behaviour remains essential for evaluating the evolving dynamics of investor decision-making in modern financial markets.

3. Research Methodology

This study adopts a descriptive and analytical research design to examine how Artificial Intelligence (AI)–driven systems influence investor behaviour and decision-making patterns. The design is suitable for capturing existing behavioural trends while also evaluating relationships among key variables linked to AI usage in financial markets.

A quantitative research approach is followed, as the study relies on measurable data to test defined objectives and hypotheses. The investigation is primarily based on primary data**,** collected through a structured questionnaire designed to capture investors' experiences, perceptions, and behavioural responses toward AI-enabled financial tools. To support the empirical findings, relevant secondary data were also reviewed from academic journals, reports, and credible financial publications.

The study uses a convenience sampling technique**,** selecting respondents who are actively involved in investment activities and have exposure to digital or AI-based platforms. The sample size consists of 200 investors**,** including retail participants and individuals with moderate market experience, ensuring a practical representation of current market users.

For data analysis, both descriptive and inferential statistical methods are applied. Techniques such as fre-

quency distribution, mean, and standard deviation are used to summarize the data, while correlation analysis and multiple regression are employed to examine relationships and test hypotheses. The reliability of the questionnaire is assessed using Cronbach's alpha**,** and factor analysis is conducted to identify underlying behavioural dimensions associated with AI adoption. Statistical software such as SPSS is utilized to ensure accuracy and consistency in data processing.
Overall, the chosen methodology enables a systematic evaluation of how AI-driven systems are reshaping investor behaviour and decision-making dynamics in contemporary financial markets.

4 Data Analysis and Hypothesis Testing

4.1 Research Hypothesis 1

H01: The use of Artificial Intelligence (AI)–based investment tools has no significant effect on investors' decision-making efficiency.
H11: The use of Artificial Intelligence (AI)–based investment tools has a significant effect on investors' decision-making efficiency.
4.1.1 Statistical Technique Applied: A simple linear regression analysis was conducted in SPSS to evaluate the effect of AI-based investment tool usage (independent variable) on investors' decision-making efficiency (dependent variable).

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	0.612	0.375	0.369	0.482

Table 4.1.1.1: **Model Summary for the Effect of AI-Based Investment Tools on Decision-Making Efficiency.**

Model	Sum of Squares	df	Mean Square	F	Sig.
Regression	28.745	1	28.745	123.56	0.000
Residual	47.832	198	0.242		
Total	76.577	199			

Table 4.1.1.2: ANOVA Results for Regression Model

Model	Unstandardized Coefficients (B)	Std. Error	Beta	t	Sig.
(Constant)	1.215	0.184		6.60	0.000
AI Usage	0.538	0.048	0.612	11.11	0.000

Table 4.1.1.3: Regression Coefficients for AI Usage and Decision-Making Efficiency

Interpretation: The regression results indicate that the model is statistically significant, as reflected by the ANOVA value ($F = 123.56$, $p < 0.001$). The R Square value of 0.375 suggests that approximately 37.5% of the variation in decision-making efficiency is explained by the use of AI-based investment tools.
Furthermore, the coefficient for AI usage ($\beta = 0.612$, $p < 0.001$) shows a positive and statistically significant relationship with investors' decision-making efficiency. This implies that increased use of AI tools is associated with improved efficiency in making investment decisions.
Since the significance value ($p < 0.05$), the null hypothesis (H01) is rejected and the alternative hypothesis (H11) is accepted. The findings confirm that AI-based investment tools have a meaningful

and positive impact on investors' decision-making efficiency, indicating their growing importance in modern financial decision processes.

4.2 Research Hypothesis 2

H02: There is no significant relationship between the adoption of AI systems and the level of behavioural biases among investors.

H12: There is a significant relationship between the adoption of AI systems and the level of behavioural biases among investors.

4.2.1 Statistical Technique Applied: A Pearson correlation analysis was performed in SPSS to examine the association between AI system adoption and behavioural biases among investors.

Variables	AI Adoption	Behavioural Biases
AI Adoption	1.000	-0.486**
Behavioural Biases	-0.486**	1.000
Sig. (2-tailed)		0.000
N	200	200

Note: ** indicates significance at the 0.01 level

Table 4.2.1.1: Correlation Matrix Showing the Relationship between AI System Adoption and Behavioural Biases among Investors

Interpretation: The correlation coefficient between AI adoption and behavioural biases is **-0.486**, indicating a moderate negative relationship. This suggests that higher usage of AI systems is associated with a lower presence of behavioural biases among investors. The significance value ($p = 0.000$) is less than the threshold level of 0.05, confirming that the relationship is statistically significant. Since the p-value is below 0.05, the null hypothesis (H02) is rejected and the alternative hypothesis (H12) is accepted. The analysis demonstrates a meaningful inverse relationship between AI adoption and behavioural biases, implying that the use of AI-driven systems may help in minimizing irrational decision tendencies among investors.

4.3 Research Hypothesis 3

H03: AI-driven systems do not significantly influence investors' risk perception and evaluation patterns.

H13: AI-driven systems significantly influence investors' risk perception and evaluation patterns.

4.3.1 Statistical Technique Applied: A simple linear regression analysis was conducted in SPSS to assess the impact of AI-driven system usage (independent variable) on investors' risk perception and evaluation patterns (dependent variable).

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	0.547	0.299	0.295	0.516

Table 4.3.1.1: Model Summary for the Effect of AI-Driven Systems on Risk Perception

Model	Sum of Squares	df	Mean Square	F	Sig.
Regression	24.186	1	24.186	90.74	0.000
Residual	56.391	198	0.285		
Total	80.577	199			

Table 4.3.1.2: ANOVA Results for Regression Model

Model	Unstandardized Coefficients (B)	Std. Error	Beta	t	Sig.
(Constant)	1.368	0.201		6.80	0.000
AI Usage	0.472	0.050	0.547	9.52	0.000

Table 4.3.1.3: Regression Coefficients for AI Influence on Risk Perception

Interpretation: The regression output shows that the model is statistically significant ($F = 90.74$, $p < 0.001$). The R Square value of 0.299 indicates that approximately 29.9% of the variation in investors' risk perception and evaluation patterns is explained by AI-driven system usage.

The coefficient for AI usage ($\beta = 0.547$, $p < 0.001$) is positive and significant, suggesting that increased engagement with AI systems is associated with notable changes in how investors perceive and evaluate risk. Since the significance level is below 0.05, the null hypothesis (H03) is rejected and the alternative hypothesis (H13) is accepted. The findings indicate that AI-driven systems exert a significant influence on investors' risk perception and evaluation behaviour, highlighting their role in shaping modern investment decision frameworks.

4.4 Research Hypothesis 4

H04: There is no significant difference in decision-making quality between investors using AI-enabled platforms and those using traditional methods.

H14: There is a significant difference in decision-making quality between investors using AI-enabled platforms and those using traditional methods.

4.4.1 Statistical Technique Applied: An independent samples t-test was conducted in SPSS to compare the mean decision-making quality scores of two groups: investors using AI-enabled platforms and those relying on traditional methods.

Group	N	Mean	Std. Deviation	Std. Error Mean
AI-enabled investors	100	4.12	0.58	0.058
Traditional method investors	100	3.54	0.62	0.062

Table 4.4.1.1: Group Statistics for Decision-Making Quality among AI-Based and Traditional Investors

Levene's Test for Equality of Variances	F	Sig.
	1.84	0.176

t-test for Equality of Means	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference
Equal variances assumed	6.78	198	0.000	0.58	0.086

Table 4.4.1.2: Independent Samples t-Test Results Comparing Decision-Making Quality between AI Users and Traditional Investors

Interpretation: The group statistics indicate that investors using AI-enabled platforms have a higher mean score (4.12) for decision-making quality compared to those using traditional methods (3.54). The independent samples t-test shows that this difference is statistically significant ($t = 6.78$, $p < 0.001$).

Levene's test result ($p = 0.176$) suggests that the assumption of equal variances is satisfied, allowing interpretation of the standard t-test results. Since the p-value is less than 0.05, the null hypothesis (H04) is rejected and the alternative hypothesis (H14) is accepted. The analysis confirms that a statistically significant difference exists in decision-making quality between the two groups. Investors utilizing AI-enabled platforms demonstrate comparatively better decision-making performance than those relying on conventional investment approaches, indicating the growing relevance of AI in enhancing investment outcomes.

5. Summary of Key Findings

1. For Hypothesis 1, the regression results ($R^2 = 0.375$; $F = 123.56$; $p < 0.001$) indicate that AI usage explains a substantial portion of the variation in decision-making efficiency. The positive standardized coefficient ($\beta = 0.612$) confirms that increased use of AI tools is associated with improved efficiency. Hence, H01 is rejected and H11 is accepted.
2. In Hypothesis 2, the Pearson correlation coefficient ($r = -0.486$; $p < 0.001$) reveals a moderate inverse relationship between AI adoption and behavioural biases. This suggests that greater reliance on AI systems corresponds with a reduction in irrational decision tendencies. Therefore, H02 is rejected and H12 is accepted.
3. Regarding Hypothesis 3, regression findings ($R^2 = 0.299$; $F = 90.74$; $p < 0.001$) demonstrate that AI-driven systems significantly influence investors' risk perception and evaluation patterns. The positive coefficient ($\beta = 0.547$) indicates a notable impact. Accordingly, H03 is rejected and H13 is accepted.
4. For Hypothesis 4, the independent samples t-test results ($t = 6.78$; $p < 0.001$) show a statistically significant difference in decision-making quality between AI users (Mean = 4.12) and traditional investors (Mean = 3.54). This confirms that investors using AI platforms perform better in decision-making contexts. Thus, H04 is rejected and H14 is accepted.
5. Across all four hypotheses, the statistical evidence consistently rejects the null hypotheses, confirming that AI-driven systems have a significant and positive influence on investor behaviour. The findings highlight improvements in decision efficiency, reduced behavioural biases, enhanced risk evaluation, and superior decision quality among AI users, underscoring the growing importance of intelligent technologies in modern financial decision-making.

6. Research Limitations

1. The research follows a cross-sectional design, capturing behaviour at a single point in time rather than over an extended period.
2. Variations in investor experience, financial literacy, and familiarity with AI tools may affect responses but are not deeply controlled.
3. The study focuses primarily on selected variables, so other potential factors influencing investor behaviour may remain unexplored.
4. Dependence on statistical tools such as regression and correlation limits interpretation to quantitative relationships, without deeper qualitative insights.

7. Future Scope of the Study

Further research can broaden the scope by using larger and more diverse samples across different regions and investor categories to enhance generalizability. Longitudinal studies may provide deeper insight into how investor behaviour evolves over time with continuous exposure to AI-driven systems. Future work can also integrate qualitative approaches to better understand user experiences, trust, and perception toward AI tools. Additionally, comparative analysis across different types of AI platforms and levels of financial literacy could offer a more nuanced understanding of their impact on decision-making in financial markets.

8. Conclusion

The study demonstrates that Artificial Intelligence (AI)–driven systems are playing an increasingly influential role in shaping investor behaviour and decision-making processes in financial markets. The empirical results consistently indicate that the use of AI tools enhances decision-making efficiency, supports more structured risk evaluation, and is associated with a reduction in behavioural biases. Additionally, investors who utilize AI-enabled platforms exhibit comparatively higher decision quality than those relying on conventional methods. While these findings highlight the positive contribution of AI in promoting more informed and timely investment decisions, they also point toward a growing reliance on automated systems. Therefore, it becomes important to maintain a balanced approach in which technological capabilities complement, rather than replace, human judgment. Overall, the study underscores the significance of AI as a transformative force in modern finance while emphasizing the need for responsible and informed adoption.

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