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Adaptive Investing in Volatile Markets: The Influence of AI Driven Analytics and Investor Experience on Portfolio Decisions

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Abstract

Purpose: The present paper discusses the application of artificial intelligence (AI) and machine learning (ML) to improve investment decision-making and portfolio management (particularly in volatile markets) as it relates to AI-based financial forecasting models, investor experience, and perception.

Motivation: With the increase of complexity and volatility in markets, it is important to learn how AI can affect investment decisions of investors alongside investor behavior. The gap in the literature on this study is considered to be the lack of understanding of how investors perceive the implementation of AI in market uncertainty.

Design/Methodology/Approach: A survey of 390 investors was carried out quantitatively. The direct and indirect effects of the adoption of AI, market volatility, and investor experience on decision-making were analyzed using Structural Equation Modeling (SEM).

Main Findings: The AI and ML models enhance investor perception, making decisions. The more experienced investors believe in AI predictions whereas the market volatility influences investor perception and decision.

Implications/Impact on Managers: The results assist financial organizations to enhance AI adoption which maximizes investor confidence owing to transparency and education.

Novelty/Contribution: This research demonstrates how AI, market volatility, and experience of investors interact, and the importance of investor perception in adopting AI.

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Keywords: AI-based financial forecasting, Investment decision-making, Market volatility, Portfolio management, Investor perception

1. Introduction

Financial markets are currently undergoing a radically new approach with artificial intelligence (AI) and machine learning (ML) models making their predictions of asset prices, anomaly discovery, portfolio allocation, and automation of trade. Market trading volumes and liquidity are becoming more and more controlled by algorithm systems (Brogaard *et al.*, 2022; Goldstein *et al.*, 2023) [13]. AI-based models have performed better than the traditional econometric models in managing portfolios and asset pricing, particularly when in a high-dimensional and volatile setting (Chen *et al.*, 2023; Gu *et al.*, 2020) [14]. Nevertheless, post-cognitive interpretation and perception applied by investors are also key factors that predetermine the result of investments, as observed in behavioral finance (Barberis, 2018; Bouri *et al.*, 2022). [2]

Market volatility also makes decision-making more complex as it leads to raising the level of uncertainty and information asymmetry as well as biases that might influence the interpretation of AI-generated signals (Baig *et al*., 2021; Pastor & Vorsatz, 2020) [1]. Although AI systems are frequently positioned as responsive to the shifts in the regime of the market, their credibility and success hinge on how the investor is familiar with the sophisticated analytics (Fuster *et al*., 2022) [11]. Recent researches point to the fact that digitalisation in financial markets is not only technological but also socio-cognitive as AI-based systems change decision-making paths (Gomber *et al*., 2023) [12]. The paper will fill this gap in the literature by discussing the relationship between AI and investor experience, market volatility, and investor perception in portfolio management decisions. It seeks to provide a more in-depth insight into the way AI technologies can be streamlined to be utilized by investors in unstable markets.

1.1. Objectives

- To assess the direct and indirect effects of AI and ML models, market volatility, and investor experience on investor perceptions in financial markets.
- To explore the mediating role of investor perceptions in the relationship between AI adoption and investment decision-making under volatile conditions.
- To evaluate the influence of investor experience on the effectiveness of AI in shaping investment decisions during market turbulence.

2. Literature Review

The combination of artificial intelligence (AI) and machine learning (ML) within the financial field has greatly enhanced financial decision-making performance concerning the portfolio management, asset pricing, and the risk analysis. AI models, particularly those based on deep learning and reinforcement learning have shown higher performance, compared to the traditional econometric models. To find complex and nonlinear relationships in financial data, these AI systems are made to capture relationships that traditional models are not able to capture very well. As an example, deep learning models have been demonstrated to be more accurate in forecasting assets prices and portfolio optimization, particularly in unstable markets (Chen *et al*., 2023; Gu *et al*., 2020) [14]. The growing application of AI in the financial markets' points to the fact that it can adjust and react to the changing market circumstances and help to make more informed decisions.

The new developments in machine learning also highlight the usefulness of AI to determine the patterns in the market based on a large scale of data. The works of Goldstein *et al*. (2023) [13] and Huang and Rust (2021) [16] have shown that AI models may analyze different categories of information (financial news and historical trends) to make more precise and timely predictions. The predictive insights that AI can offer in real time based on the mass of data it is able to process has made it an innovative instrument in modern finance.

2.1. Artificial intelligence in Portfolio Management and Risk.

AI-based models have played a significant role in enhancing portfolio optimization strategy and risk management strategy.

The benefits of these models include their capacity to handle high-dimensional data and dynamically adjust portfolios in response to changes in the market which gives them superior risk-adjusted returns compared to the standard models. As an illustration, reinforcement learning (RL) has been extensively used in adaptive portfolio management, where AI models adapt strategies as a result of the behavior of the market to make more robust decisions in a time of uncertainty (Fuster *et al*., 2022) [11]. Such models have performed better as compared to the traditional methods especially in the periods when volatility is raised and the market is experiencing disruptions.

Besides optimization of portfolios, AI is also used in the financial risk management. It has been demonstrated that AI models have the potential to enhance the identification of possible risks because they examine a wider range of variables in the market (Gomber *et al*., 2023) [12]. These systems enable the investors to evaluate the riskiness of different financial instruments in a better way which helps them to put in place a more robust risk mitigation act.

2.2. Obstacles and shortcomings of AI in Financial Markets.

Although it has potential, the implementation of AI in the financial markets is fraught with a number of challenges especially in the area of data quality, model transparency, and interpretability. The biggest weakness is overfitting, when AI models will do well with past data, but not in reality. This problem is promoted in times of a crisis in the market when unexpected events make AI models ineffective (Pastor & Vorsatz, 2020). This explains why AI models should be able to take into consideration market uncertainty and adjust to abrupt market changes.

In addition to this, AI systems generally have a major issue with explainability, which becomes especially problematic with deep learning models. Such models tend to work as black boxes and as a result, the users are unable to comprehend the process through which decisions are being made. Such a state of non-transparency may lead to a problem of trust, since investors are reluctant to use AI-driven insights without clearly understanding the decision-making process that underlies it (Fatima & Chakraborty, 2024) [10]. The explanation of AI (XAI) frameworks is becoming an increasingly important area of focus in terms of instilling trust and enhancing the deployment of AI technologies in the finance field (Mohapatra, 2026) [19].

Besides these issues, there is an issue of data quality that is a big challenge. This is because financial data can be very noisy, incomplete, or biased and as such, can make poor predictions and poor investment policies. These problems are further compounded by the volatility that the market experiences and financial data may not be reliable in periods of drastic changes in the market. The presence of these data quality problems is critical in addressing whether the AI models are functional in the field of finance (Gomber *et al*., 2023) [12].

2.3. Experience with and Perception of AI Models by investors.

The success and the effectiveness of AI-based financial tools largely depend on investor experience and perception. Established investors will be more confident and comprehend AI models to apply them in their decision-making.
Bianchi *et al*. (2021) [3] raised the importance of offering financial
literacy in the process of adopting AI-based systems because informed investors are in a better position to perform a critical analysis of the AI-generated recommendations. Alternatively, novice investors can overtrade using the AI cues, which can be very destructive, particularly in unstable market environment (Verma *et al*., 2025) [21].
The perception of investors is also a major factor in the adoption of AI. Anxiety, trust, and performance expectancy are also important psychological constructions that determine the adoption of AI by investors. The problem of algorithm aversion, when investors show distrust in AI-based forecasting, is fairly reported (Chang & Wang, 2023) [7]. The solution to this aversion is to increase the interpretability and transparency of AI models. With the development of AI technologies and the emergence of more transparent technologies, the level of investor confidence should rise, and the situation will promote the implementation of AI in financial markets on a larger scale.

2.4. Market Turmoil and AI Implementation.

The problem of market volatility is one of the significant challenges of AI systems. Uncertainty and risk in volatile markets make it hard to have AI models that are able to generate consistent accurate predictions. Barberis (2018) [2] suggested that in the times of high volatility, investors might have a problem of loss aversion and overreaction, which may affect how they perceive AI-generated predictions. Even though AI systems can be flexible, they might not cope with the unexpected shifts in the market, and this fact raises the question about their efficiency when it comes to forecasting the market trends during the extreme events (Baig *et al*., 2021) [1].

2.5. Mixed Solutions to AI and Investor Confidence.

To overcome the shortcomings of AI and develop more confidence in AI-based financial tools, numerous scholars have suggested a hybrid solution to the problem, involving using AI potentials with human intelligence. These models utilize the power of AI as a data analysis tool and pattern recognition as well as human judgment to offer context and interpretation of market conditions. This is because hybrid solutions can be used to increase the credibility of AI systems, as they will enable human control and lessen the dependence on the algorithms to make decisions (Fatima & Chakraborty, 2024) [10]. Such a strategy is likely to enhance investor confidence and give rise to more balanced and robust format of investment decisions.

2.6. Theoretical Framework:

This study is grounded in the Technology Acceptance Model (TAM) and the Theory of Planned Behavior (TPB). TAM posits that perceived ease of use and perceived usefulness are key factors in determining technology adoption (Davis, 1989). In the context of financial decision-making, investors' perceptions of AI systems as useful and easy to use directly influence their willingness to adopt these technologies. TPB adds another layer by emphasizing the role of perceived behavioral control, which in this case, corresponds to the investor's experience and understanding of AI systems, as well as the external factors such as market volatility (Ajzen, 1991).

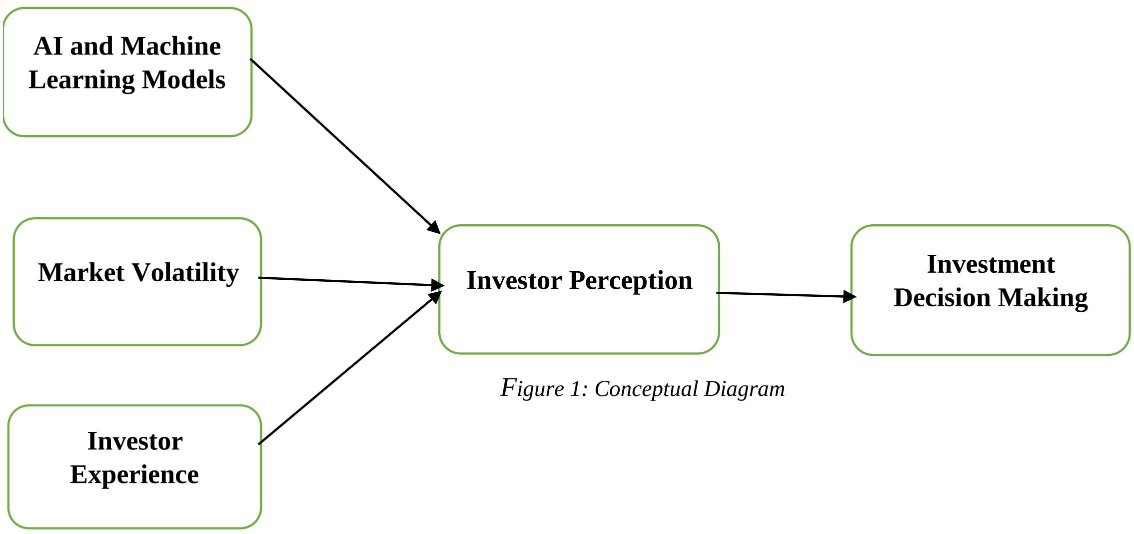

Figure 1: Conceptual Diagram

Fig 1: Conceptual Diagram

3. Methodology

This study employs a quantitative research design, analyzing data collected from 390 investors through a structured questionnaire. The survey captures variables such as AI adoption, market volatility perception, investor experience, and investment decision-making. SPSS and Structural Equation Modelling (SEM) using AMOS is applied to assess direct, indirect, and mediating relationships.

The model is evaluated through confirmatory factor analysis (CFA), composite reliability, and discriminant validity, ensuring the robustness of the constructs.

- **Sample Description:** The sample consists of investors with varying levels of experience in the financial markets, which enables the analysis of how experience mediates the relationship between AI adoption and decision-making under different market conditions.
- **Reliability and Validity:** The adequacy of sampling was confirmed through the KMO and Bartlett's Test (KMO = 0.935, $p < 0.001$), and the CFA results demonstrate strong convergent and discriminant validity. Additionally, the Cronbach's alpha value of 0.848 indicates good internal consistency.

4. Results

4.1. Socio-Economic Profile of Respondents

The respondents in this study were selected from various sectors of the financial market, including retail investors, institutional investors, and financial advisors. The socio-economic characteristics of the participants are summarized below:

Table 1: Socio-Economic Profile of Respondents

Characteristic	Category	Number (n=390)	Percentage (%)
Age	18-25 years	59	15%
	26-35 years	117	30%
	36-45 years	98	25%
	46-60 years	78	20%
	Above 60 years	38	10%
Gender	Male	253	65%
	Female	137	35%
Educational Qualification	High School	19	5%
	Undergraduate	97	25%
	Postgraduate (Master's)	156	40%
	Professional Qualification	118	30%
Annual Income	Less than ₹5,00,000	58	15%
	₹5,00,000 - ₹10,00,000	117	30%
	₹10,00,000 - ₹20,00,000	137	35%
	Above ₹20,00,000	78	20%
Investment Experience	1-3 years	47	12%
	4-6 years	117	30%
	7-10 years	137	35%
	More than 10 years	89	23%
Type of Investment	Stocks and Shares	156	40%
	Bonds and Debentures	59	15%
	Mutual Funds	98	25%
	Real Estate	39	10%
	Cryptocurrency	39	10%

Source: Survey Data and author calculation

Interpretation: The social-economic background of the respondents demonstrates a rich and skilled sample of investors. Most of them (55%), 26-45 age group, are of sufficient financial market experience, and 20% of all are within the 46-60 years old category, with relatively more of the younger generations entering financial markets. The sample size in terms of gender is predominantly male, 65 percent, which also corresponds to the global tendencies in terms of the financial market participation, yet also opens the ways to develop the gender-specific differences in the use of AI further. Regarding education, 40 and 30 percent of respondents have postgraduate degrees and professional certifications such as the Chartered Financial Analyst (CFA), respectively, and this indicates an educated sample. The income of the respondents is diverse, with 30% in between 5,00, 000 - 10,00,000 and 35% in between 10,00,000 - 20,00,000, which suggests a middle and upper-middle-class profile and is well-placed to use AI-driven investment instruments. Also, most of the respondents (68%) have more than 4 years of investment experience indicating that there are experienced investors who have gone through the portfolio management and risk evaluation process. Finally, the respondents are showing diversified investment preferences as 40% invest in stocks and shares, 25% in mutual funds and 35% in bonds, real estate or cryptocurrency, and such an approach to investment strategy is diverse.

4.2 Measurement Model Assessment

Table 2: Rotated Component Matrix[a]

	Component			
	1	2	3	4
AIMLM1		.702		
AIMLM2		.734		
AIMLM3		.686		
AIMLM4		.717		
MV1				.775
MV2				.812
MV3				.530
MV4				.501
MV5				.762
IE1			.801	
IE2			.780	
IE3			.815	
IE5			.827	
IP1	.727			
IP2	.701			
IP3	.669			
IP4	.623			
IP5	.692			
IDM1	.803			
IDM2	.818			
IDM3	.815			
IDM4	.812			
IDM5	.809			

Source: Survey Data and author calculation
Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.
Rotation converged in 7 iterations

Interpretation: The component matrix that was obtained after the Principal Component Analysis with the Varimax rotation shows a definite and clear factor structure. The rotation stabilized after seven iterations, which signified the stability of the model. Items have high loading on their respective components with the factor loadings meeting the acceptable threshold of 0.50 and above. The AI and Machine Learning items measure on one factor, Market Volatility items assess on another, and Investor Experience items constitute a factor. The Investor Perception and Investment Decision Making items have a high loading on the primary behavioral component. The low cross-loadings show that the construct is clear and the dimensional validity of the measurement model.

Table 3: KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.935
Bartlett's Test of Sphericity	Approx. Chi-Square	5151.238
	df	253
	Sig.	.000

Source: Survey Data and author Calculation

- **Interpretation:** The Kaiser-Meyer-Olkin (KMO) measure of adequacy of sampling is 0.935, which is above the recommended level of 0.60 and shows outstanding sampling adequacy. This implies that this data can be subjected to factor analysis and that the variables have a high-percentage of common variance.The Test of Sphericity by Bartlett is not significant (kh2 = 5151.238, df = 253, p < 0.001) and therefore does not support the null hypothesis of the correlation matrix being an identity matrix. The combination of these outcomes proves that the dataset can be utilized in terms of factor extraction and that the significant underlying factor structures can be identified in a reliable way.

Table 4: Normality Test (Shapiro-Wilk)

Statistic	p
0.995	0.289

Source: Survey Data and author calculatio

- **Interpretation:** Shapiro-Wilk Test of Normality gives a Statistic of 0.995 and a p-value of 0.289. Because the p-value exceeds the standard significance level of 0.05 we do not reject the null hypothesis. This shows that the data is normally distributed that is, it satisfies the normality assumption of most tests in statistics such as regression analysis. Therefore, the data is deemed to be fitable in the model without worrying about breach of the normality.

Table 5: Model Estimates and Psychometric properties of Constructs

Construct	Items	Factor Loadings	Sum of Factor Loadings	Item Reliability (Squared Factor Loadings)	Delta (Error Variance)	Sum of Delta	AVE (Average Variance Extracted)	CR
AI and Machine Learning Models	AIMLM1	0.765	2.983	0.585	0.415	1.776	0.556	0.834
	AIMLM2	0.731		0.534	0.466			
	AIMLM3	0.742		0.55	0.45			
	AIMLM4	0.745		0.555	0.445			
Market Volatility	MV1	0.709	3.021	0.502	0.498	3.242	0.412	0.793
	MV2	0.77		0.592	0.408			
	MV3	0.404		0.163	0.837			
	MV4	0.406		0.165	0.835			
	MV5	0.732		0.536	0.464			
Investor Experience	IE1	0.772	3.02	0.597	0.403	1.726	0.571	0.844
	IE2	0.721		0.519	0.48			
	IE3	0.783		0.613	0.387			
	IE4	0.744		0.554	0.456			
Investor Perception	IP1	0.818	4.057	0.67	0.33	1.76	0.659	0.881
	IP2	0.819		0.672	0.328			
	IP3	0.831		0.691	0.311			
	IP4	0.802		0.644	0.372			
	IP5	0.787		0.62	0.418			
Investment Decision Making	IDM1	0.823	4.842	0.677	0.323	1.741	0.72	0.9
	IDM2	0.865		0.749	0.307			
	IDM3	0.859		0.738	0.292			
	IDM4	0.845		0.714	0.259			
	IDM5	0.85		0.723	0.248			

Source: Survey Data and author calculation

- **Interpretation:** The psychometric properties and model estimates depict that there is good reliability and validity among the constructs. The factor loadings are all above the advised loading of 0.50, which verifies that they have adequate contribution to the latent constructs. The total factor loading indicates high levels of internal consistency and especially with Investment Decision Making and Investor Perception.

The values of item reliability (squared loadings) tend to be over 0.50 which is acceptable explained variance of most indicators. Market Volatility contains two comparatively lower-loading items (MV3 and MV4), which makes it slightly lower its Average Variance Extracted.

The AVE scores are greater than 0.50 of AI and Machine Learning Models (0.556), Investor Experience (0.571), Investor Perception (0.659), and Investment Decision Making (0.720), which prove convergent validity. Whereas Market Volatility indicates that AVE is less than 0.50 (0.412), the Composite Reliability (0.793) is greater than the suggested level of 0.70, which indicates an acceptable level of construct reliability.

The values of Composite Reliability are between 0.793 and 0.900, indicating that there is high internal consistency of constructs. In general, the measurement model has a high level of psychometric adequacy and can be furthered to structural model analysis.

Table 6: Discriminant Validity of Constructs (Fornell–Larcker Criterion)

Construct	AIMLM	MV	IE	IP	IDM
AI and Machine Learning Models	**0.94**				
Market Volatility	0.52	**0.79**			
Investor Experience	0.48	0.44	**0.94**		
Investor Perception	0.71	0.63	0.67	**0.95**	
Investment Decision Making	0.69	0.58	0.61	0.9	**0.97**

Source: Survey Data and author calculation

- **Interpretation:** Fornell-Larcker criterion was used to determine the discriminant validity of the constructs. The square root of the Average Variance Extracted (AVE) which are shown on the diagonal of the matrix is higher than the respective inter-construct correlations in all instances. As an example, AI and Machine Learning Models (0.94), Investor Experience (0.94), Investor Perception (0.95) and Investment Decision Making (0.97) have greater diagonal values than their associations with other constructs. Market Volatility records relatively lower correlations, but its diagonal figure (0.79) is also greater than all the other inter-construct correlations. The results prove that all constructs are empirically different and discriminant validity is satisfactory.

4.3. Structural Model Evaluation.

Model Fit Indices

There are good explanatory power and overall fit results of the proposed model, which is indicated by the comprehensive structural equation model fit results. Both Investor Perception (0.859) and Investment Decision Making (0.860) have R values of 0.859 and 0.860, indicating the existence of strong associations between predictors and endogenous constructs.

The R^2 of 0.738 and 0.739 of both constructs show that about 74 percent of the variance in both constructs is predicted by the model which has a high predictive power.
The chi-square to the degrees of freedom ratio ($kh^2/df < 3.00$) is at a reasonable level, which confirms that the model is adequate. The value of RMSEA (0.037) and the small range of confidence (0.029-0.045) indicates that the model is a great fit to the population covariance matrix. Close model fit is also shown by the high value of PCLOSE (0.998). The ECVI value is significantly less than the independence model implying parsimony and generalizability. Hoelter indices of more than 200 are used to indicate adequate sample size and structural stability. Lastly, structural paths are all significant ($p < 0.001$), which supports the strength of the model.

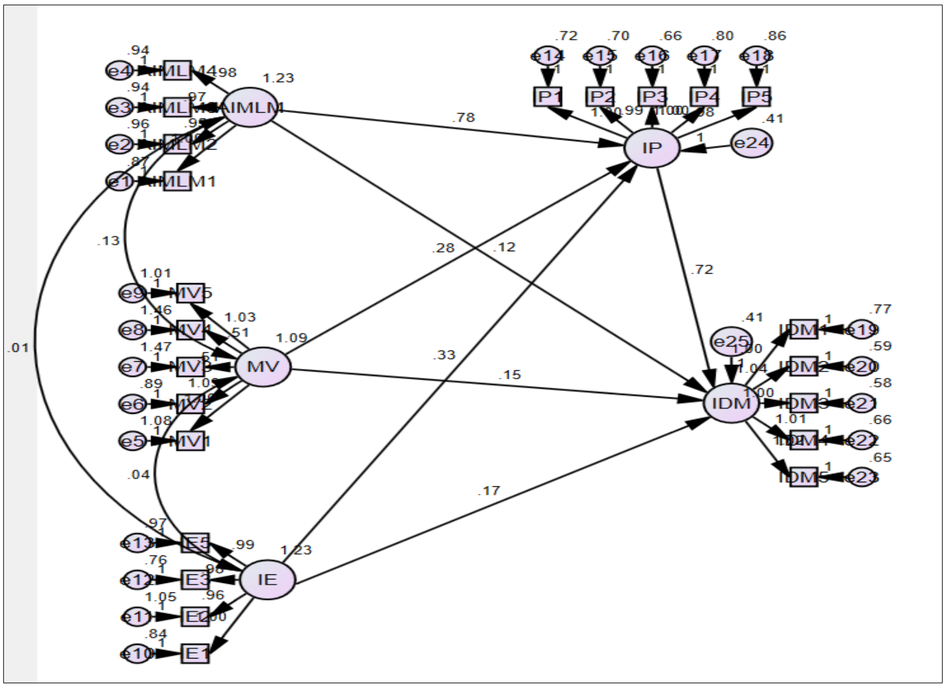

Fig 2: Structural Equation Model

4.4. Summary of Structural Equation Model.

The structural equation model as illustrated in figure 2 demonstrates how AI and Machine Learning Models relate to Market Volatility, Investor Experience, Investor Perception, and Investment Decision Making. The model shows that there is a strong positive correlation between AI models and Investor Perception (b = 0.720). Perceptions of investors have a significant influence on Investor Experience (b = 0.306) and Market Volatility (b = 0.241) with an explanation of 73.8 percent of it (R2 = 0.738). The direct effect of Investor Perception on the Investment Decision Making (b = 0.685) is greater than that of AI models (b = 0.102), Market Volatility (b = 0.121), and Investor Experience (b = 0.149). The regression model explains 73.9 percent of the variance in Investment Decision Making (R2 = 0.739). Indirect effects present that the Investor Perception mediates the effects of AI models (b = 0.493), Investor Experience (b = 0.210), and Market Volatility (b = 0.165). The fit of the model is also excellent (RMSEA = 0.037; PCLOSE = 0.998), which proves the validity of the cognitive decision-making framework.

Table 8: Hypothesis Testing

Hypothesis	Path	β	C.R.	P-value	Decision
H1	AI and Machine Learning Models → Investor Perception	0.781	12.925	<0.001	Supported
H2	Market Volatility → Investor Perception	0.298	5.982	<0.001	Supported
H3	Investor Experience → Investor Perception	0.358	7.703	<0.001	Supported
H4	Investor Perception → Investment Decision Making	0.909	16.148	<0.001	Supported

Source: Survey Data and author calculation

The hypothesis testing findings show that there are significant connections between the constructs in the model. H1 proposes that there is a strong positive influence of AI and Machine Learning Models on Investor Perception with a b = 0.781 and C.R. = 12.925 which is significant ($p < 0.001$). H2 demonstrates a moderate positive correlation between Market Volatility and Investor Perception with the b of 0.298 and C.R of 5.982 which is also significant at $p < 0.001$. H3 shows that Investor Experience has positive effects on Investor Perception (b = 0.358, C.R. = 7.703, $p < 0.001$). Lastly, H4 is quite strong, positive correlation between Investor Perception and Investment Decision Making (b = 0.909, C.R. = 16.148, $p < 0.001$). The four hypotheses are all proven to hold, not ruling out the important role of Investor Perception in influencing Investment Decision Making as well as the role of AI/ML models, market volatility, and investor experience are all important factors in influencing perceptions.

Table 9: Mediation Analysis

Indirect Path	Effect Size	Hypothesis Testing
AI and Machine Learning Models → Investor Perception → Investment Decision Making	0.709	Supported
Market Volatility → Investor Perception → Investment Decision Making	0.271	Supported
Investor Experience → Investor Perception → Investment Decision Making	0.325	Supported

Source: Survey Data and author calculation

The table presents the indirect effect sizes for the paths involving Investor Perception as a mediator between various constructs and Investment Decision Making. The path from AI and Machine Learning Models → Investor Perception → Investment Decision Making has the strongest indirect effect size of 0.709, suggesting that AI and Machine Learning Models significantly influence Investment Decision Making through their impact on Investor Perception. The path from Market Volatility → Investor Perception → Investment Decision Making shows a moderate indirect effect size of 0.271, indicating that while Market Volatility affects Investor Perception, its overall impact on Investment Decision Making is weaker than that of AI and Machine Learning Models. Lastly, the path from Investor Experience → Investor Perception → Investment Decision Making has an indirect effect size of 0.325, reflecting a moderate influence, with Investor Experience indirectly impacting Investment Decision Making through Investor Perception, though not as strongly as AI and Machine Learning Models.

5. Discussion

The review indicates that AI and machine learning have a major influence on investment decision-making, and the attitude of an investor is a key factor in deciding to adopt an algorithmic insight. This is consistent with the studies that suggest that trust, anxiety, and performance expectancy are associated with the adoption of robo-advisors (Fatima & Chakraborty, 2024) [10], and that the psychological factors have the ability to alleviate the effect of algorithm aversion in automated wealth management (Chang & Wang, 2023) [7]. The experience of the investor increases confidence in AI outputs, as observed in recent research in India (Verma *et al*., 2025) [21]. Seeing through and explainable AI also enhances trust, which contributes to intention to adopt AI (Mohapatra, 2026) [19]. The study promotes the use of cognition to AI-mediated investing.

6. Conclusion and Future Research

AI and machine learning technologies hold the potential to revolutionize portfolio management and investment decision-making, particularly in volatile market conditions. However, the success of these technologies is highly contingent upon investor perceptions and the ability to adapt to complex market dynamics. This study contributes to the growing body of literature by exploring the interaction of AI, market volatility, and investor experience, offering practical insights for both practitioners and researchers. Future research might add to this scheme, turning it into a longitudinal design, where the researcher can observe behavioral changes and intercountry variation in AI adoption. To gain further insights into trust in AI-based financial decision-making, experimental designs that would emphasize transparency and objective performance data on portfolios would help.

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