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Research Article

Connecting AI into Investment Strategies: An Empirical Study

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Abstract

Due to its potential to revolutionize investment strategies and enhance decision-making, Artificial Intelligence (AI) has gained significant attention in the financial sector. AI technologies such as robo-advisors, algorithmic trading systems, and predictive analytics enable investors to process and analyse large volumes of market data, identify complex patterns, and generate more accurate and timely investment decisions. AI's advantages, including its capacity to handle non-linear relationships, respond dynamically to new information, and provide personalized recommendations based on individual investor profiles. However, issues such as data privacy concerns, lack of transparency in complex AI models, potential algorithmic bias are still remain the key concern. The research focuses on understanding the adoption of AI tools in the context of personal finance and investment management. This study investigates the role of AI tools in shaping modern investment strategies by comparing AI driven approaches with traditional investment methods. The comparative analysis between AI-driven and traditional investment strategies are highlighted in this study. AI's ability to analyse vast datasets, detect hidden patterns, and forecast market trends with greater accuracy than conventional methods is a key strength that this study investigates. The ethical implications of relying heavily on AI for financial decisions also form an important part of the analysis, as ensuring fairness, accountability, and trust in AI tools is essential for widespread adoption. This study provides valuable insights for investors, financial advisors, fintech developers, and policymakers on how AI tools can be optimized to support sound investment decisions. The findings suggest that a balanced approach that leverages both AI capabilities and human expertise is crucial for achieving robust, ethical, and effective investment strategies in today's fast-evolving financial markets.

Keywords

Investment Strategy, Traditional Investment, AI Tools

1. Introduction

In the strategic planning and decision-making processes of businesses and financial institutions across the world, financial forecasting plays a vital role. It enables organizations to anticipate future financial conditions and prepare for uncertainties in dynamic and volatile market environments. Financial forecasting is essentially the process of predicting future

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financial events using a combination of statistical models, historical data, economic trends, and market indicators. Accurate forecasting allows businesses to allocate resources wisely, manage risks proactively, maintain liquidity, and seize new opportunities by providing insights into projected revenues, expenses, cash flows, profits, and investment returns.

Historically, forecasting relied heavily on manual processes and basic statistical techniques, such as linear regression, time series models, and moving averages. These methods, while useful, often struggled with accuracy, particularly in complex and rapidly changing market scenarios. Traditional forecasting approaches were time-consuming, resource-intensive, and limited in their ability to process large datasets or identify nonlinear relationships within financial data. As a result, decision-making often lagged behind real-time market developments, increasing the risk of missed opportunities or unanticipated losses.

The integration of AI in financial forecasting not only enhances the accuracy of predictions but also supports real-time analytics, scenario planning, and risk modeling. Businesses are now better equipped to optimize resource allocation, fine-tune investment strategies, and respond swiftly to external disruptions such as economic crises, regulatory changes, or technological innovations.

As AI technologies continue to advance, their application in financial forecasting promises to redefine how organizations plan for the future, innovate, and remain competitive on a global scale. The fusion of AI with financial forecasting represents a paradigm shift, offering both opportunities and challenges for firms striving to harness its full potential responsibly and effectively [7]

The research focuses on understanding the adoption of AI tools in the context of personal finance and investment management. This study investigates the role of AI tools in shaping modern investment strategies by comparing AI driven approaches with traditional investment methods. The comparative analysis between AI-driven and traditional investment strategies are highlighted in this study.

2. Background of the Study

Artificial Intelligence (AI) tools play a crucial role by processing this data to identify hidden patterns, market trends, and risks that traditional models might miss. Big data combined with AI helps create more dynamic, personalized, and adaptive investment strategies that respond effectively to changing market conditions. Artificial Intelligence (AI) and Machine Learning (ML) have revolutionized investment strategies by enabling systems to learn from vast financial data, detect complex patterns, and make accurate predictions [8]. Unlike traditional models, AI and ML can process both structured and unstructured data including market indicators, news, and social media sentiment to forecast trends and manage risks. These tools help investors develop smarter, faster, and more adaptive strategies that can adjust to dynamic market conditions in real time. Tools like natural language processing (NLP) help investors analyse news, social media sentiment, and earnings reports to predict market movements. Reinforcement learning algorithms are being used to design adaptive trading strategies that improve over time based on market feedback. AI also plays a growing role in risk management, fraud detection, and ESG (Environmental, Social, Governance) investing by processing complex datasets to support ethical and sustainable investment decisions.

The evolution of AI in investment strategies reflects a shift from static, backward-looking models to dynamic, forward-looking approaches that integrate real-time data and complex variables. As AI technology advances, investment strategies will likely become even more personalized, predictive, and resilient. AI tools will be able to integrate a wider range of data sources including real-time global events, environmental indicators, and consumer behaviour to offer highly customized portfolio recommendations. Predictive models will become more accurate by continuously learning from new data, allowing investors to anticipate market shifts and adjust their strategies proactively. AI tools are getting popularity at various level decision making process. Few of them are explained below. *Growth Investment Strategy* focuses on investing in companies expected to deliver above-average revenue and earnings growth. AI tools help identify high-potential growth stocks by analysing company financials, industry trends, market sentiment, and alternative data like customer reviews or product demand patterns. Machine learning models can detect early signals of innovation, competitive advantage, or market expansion, giving investors a valuable edge. *Value Investment Strategy* focus on undervalued stocks companies trading below their intrinsic worth. AI enhances this strategy by quickly scanning thousands of stocks and comparing metrics like P/E ratios, book value, and cash flow against historical and industry benchmarks. AI can also identify hidden value opportunities that human analysts may miss, using predictive models that factor in future earnings potential, market conditions, and global economic indicators. *Income Investment Strategy*prioritizes assets that provide steady income through dividends, interest, or coupon payments. AI tools assist in screening for high-yield, financially stable companies, and bond issuers with strong credit ratings. AI can also predict the sustainability of dividends by evaluating earnings stability, payout ratios, and sector-specific risks, ensuring reliable income streams for investors. *Momentum Investment Strategy* focus on securities showing consistent upward or downward price trends. AI algorithms enhance momentum trading by analysing price patterns, trading volumes, and volatility indicators in real- time. These tools can identify breakouts, trend reversals, and market anomalies faster and more accurately than traditional technical analysis, supporting timely buy or sell decisions. *Index and Passive Strategies* supports passive investors by automating portfolio rebalancing, minimizing tracking errors, and optimizing tax efficiency. *Thematic and ESG*strategy helps investors target companies aligned with specific themes like green energy, technology innovation, or social responsibility. Natural language processing and big data analytics enable AI to assess ESG performance by analysing reports, news, and third-party ratings, helping build portfolios that match ethical values or future-focused themes. *Algorithmic and Quantitative Strategies*rely on AI to execute trades automatically based on mathematical models and predefined conditions. AI-driven algorithms process massive data in milliseconds, enabling high-frequency trading, arbitrage, or complex option strategies. AI also enhances quantitative models by identifying non-linear relationships and adjusting to market dynamics faster than traditional models.

3. Literature Review

Machine learning models, such as Linear Support Vector Machines and Bayesian Generalized Linear Models, significantly enhance algorithmic investment strategies, outperforming traditional buy-and-hold approaches by achieving superior risk-adjusted returns across various global stock market indices [4].

In stock market AIML is widely used in investment strategies. AI influences investment strategy by automating trading processes, eliminating emotional decision-making, recognizing overlooked patterns, and processing real-time information. It enhances portfolio optimization through multi objective models and sentiment analysis, leading to more informed and efficient financial investment decisions [2]. Machine learning models optimize the risk/return profile of investment strategies, highlighting the importance of appropriate performance metrics to evaluate algorithm efficiency, ultimately influencing investment decisions and strategies in financial markets [1]. The increasing adoption of AI in investment decision-making is driven by its ability to reduce risks, enhance stock selection through precise predictions, and the growing effectiveness of ensemble and hybrid models, particularly those utilizing LSTM and SVM techniques [6]. retail customers' adoption of AI-based autonomous decision-making processes, identifying key factors such as performance expectancy, effort expectancy, facilitating conditions, and social influence, with cultural dimensions like collectivism and uncertainty avoidance also playing significant roles [8]. Financial technologies are rapidly evolving with the integration of machine learning models across various domains such as payments, asset management, and blockchain. While these models offer high accuracy, they often lack explainability. Proposed regulations mandate that high-risk AI applications in finance must be "trustworthy," meeting criteria like Sustainability and Fairness. However, standardized metrics for assessing AI trustworthiness in finance are absent [3]. AI methods, particularly reinforcement learning and deep reinforcement learning, offer more efficient and adaptive frameworks for investment decision-making than traditional methods, enhancing performance and addressing complexities in financial markets, ultimately leading to improved decision-making under uncertainty and risk [9].

4. Hypothesis and Discussion

This paper brings out main objective to assess the effect of AI tools in decision making strategy. The study is conducted based on a primary survey. A structured close-ended questionnaire was circulated among the respondents. Data collected from respondents from Bangalore, India. It was structured to gather specific information such as demographics (age, income, etc.) and user behaviours. Sample size is 200 which are in line with Tabachnick and Fidell (1989) [10, 11]. Roscoe's (1975) [5] suggested that a sample size greater than 30 and less than 500 is suitable for most behavioural studies.

H1: There is a significant difference in the mean usage of AI tools for investing across different age groups.

Table 1. *Use of AI tools for different age group.*

ANOVA					
Used AI Tools for Investing					
	Sum of Squares	**Df**	**Mean Square**	**F**	**Sig.**
Between Groups	7.643	3	2.548	3.864	.010
Within Groups	129.232	196	.659		
Total	136.875	199			

The One-Way ANOVA showed a significant difference in the usage of AI tools for investing across different age groups (Table 1) ($F(3, 196) = 3.864$, $p = 0.010$). Since $p < 0.05$, the null hypothesis is rejected. This indicates that age group influences the likelihood of investors using AI tools for investing.

***Table 2**. Tukey HSD Posthoc-a.*

Multiple Comparisons

Dependent Variable: Use of AI tools for investing

Tukey HSD

Age group	Age group	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
1	2	-.125	.134	.789	-.47	.22
	3	-.531*	.166	.009	-.96	-.10
	4	-.452	.282	.380	-1.18	.28
	1	.125	.134	.789	-.22	.47
2	3	-.406	.181	.116	-.88	.06
	4	-.327	.291	.675	-1.08	.43
	1	.531*	.166	.009	.10	.96
3	2	.406	.181	.116	-.06	.88
	4	.079	.307	.994	-.72	.88
	1	.452	.282	.380	-.28	1.18
4	2	.327	.291	.675	-.43	1.08
	3	-.079	.307	.994	-.88	.72

*. The mean difference is significant at the 0.05 level.

The Tukey HSD post hoc test (Table 2) revealed a significant difference between the 25–30 age group and the 41–50 age group in the usage of AI tools for investing (mean difference = 0.531, p = 0.009). No other pairwise comparisons showed significant differences at the 0.05 level. This indicates that investors aged 41–50 are more likely to use AI tools for investing compared to those aged 25–30. Overall, age group influences AI adoption, with notable differences specifically between these two groups.

***Table 3**. Posthoc-b.*

Use of AI tools for investing

Tukey HSD[a,b]

Age group	N	Subset for alpha = 0.05
		1
1	103	1.44
2	57	1.56

Use of AI tools for investing		
Tukey HSD[a,b]		
Age group	N	Subset for alpha = 0.05
		1
4	9	1.89
3	31	1.97
Sig.		.117

Means for groups in homogeneous subsets are displayed.

a. Uses Harmonic Mean Sample Size = 23.444.

b. The group sizes are unequal. The harmonic mean of the group sizes is used. Type I error levels are not guaranteed.

Interpretation

A one-way ANOVA was conducted to assess whether the adoption of AI tools for investing differs across various age groups. The results indicated a statistically significant difference in the mean usage of AI tools among different age groups ($F(3,196) = 3.864$, $p = 0.010$), leading to the rejection of the null hypothesis. The mean plot showed that the 41–50 age group reported the highest adoption of AI tools (mean = 1.97), followed closely by those above 50 years (mean = 1.89), while the 25–30 and 31–40 age groups showed lower adoption levels (means = 1.44 and 1.56, respectively). Although the Tukey post hoc test did not identify significant pairwise differences between specific groups at the 0.05 level, the overall significant ANOVA result indicates that age plays a meaningful role in the adoption of AI tools among investors, with older investors exhibiting higher usage trends compared to younger investors.

H2 (Alternative Hypothesis): There is a significant association between the type of AI tool used and the type of investment for which AI tools are used.

Table 4. *AI tools and types of Investment-a.*

Case Processing Summary					
Cases					
Valid		Missing		Total	
N	Percent	N	Percent	N	Percent
200	100.0%	0	0.0%	200	100.0%

The case processing summary (Table 4 shows that all 200 responses (100%) were valid with no missing data for the analysis between the type of AI tools used and the investment type for which AI tools are used. This ensures data completeness and reliability for the Chi-square test analysis.

Table 5. *Tools used and Type of investment-b.*

Tools used and Type of investment								
			Type of investment					
			1	2	3	4	5	Total
Tools used	1	Count	24	15	15	1	2	57
		Type of investment	60.0%	29.4%	28.3%	3.2%	8.0%	28.5%
	2	Count	9	16	9	2	6	42
		Type of investment	22.5%	31.4%	17.0%	6.5%	24.0%	21.0%
	3	Count	1	11	19	14	6	51

Tools used and Type of investment							
		Type of investment					
		1	2	3	4	5	Total
	Type of investment	2.5%	21.6%	35.8%	45.2%	24.0%	25.5%
4	Count	6	9	10	14	10	49
	Type of investment	15.0%	17.6%	18.9%	45.2%	40.0%	24.5%
5	Count	0	0	0	0	1	1
	Type of investment	0.0%	0.0%	0.0%	0.0%	4.0%	0.5%
Total	Count	40	51	53	31	25	200
	Type of investment	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%

The crosstabulation shows (Table 5) that Robo-advisors (60%) are predominantly used for stock price prediction, while algorithmic trading bots (45.2%) and financial chatbots (45.2%) are mainly used for algorithmic trading. AI stock screeners are frequently used for market trend analysis. (31.4%). This indicates a visible pattern between the type of AI tools investors use and the specific investment purposes.

Table 6. *Tools used and Type of investment-c.*

Chi-Square Tests		
Value	df	Asymptotic Significance (2-sided)
64.416[a]	16	.000
68.136	16	.000
36.221	1	.000
200		

a. 5 cells (20.0%) have expected count less than 5. The minimum expected count is.13.

The Chi-square test (Table 6) showed a significant association between the type of AI tools used and the investment type for which they are used ($\chi^2(16) = 64.416$, $p = 0.000$). Since $p < 0.05$, the null hypothesis is rejected, indicating a statistically significant relationship between AI tool choice and investment purpose among investors.

A Chi-square test was conducted to examine the association between the type of AI tools used and the investment type for which these AI tools are applied. The analysis revealed a significant association between these variables ($\chi^2(16) = 64.416$, $p = 0.000$), leading to the rejection of the null hypothesis. This indicates that investors choose specific AI tools based on the type of investment activities they engage in. For instance, robo-advisors were primarily used for stock price prediction, while algorithmic trading bots and financial chatbots were mainly applied in algorithmic trading. This confirms that investors strategically select AI tools in alignment with their specific investment objectives.

H3 (Alternative Hypothesis): There is a significant difference in the perceived accuracy of AI-based forecasts across the different aspects of AI contributing to forecasting accuracy.

Table 7. *Accuracy of AI based forecast compared to traditional methods-a.*

ANOVA					
AI Accuracy					
	Sum of Squares	Df	Mean Square	F	Sig.
Between Groups	35.749	4	8.937	6.667	.000
Within Groups	261.406	195	1.341		
Total	297.155	199			

The one-way ANOVA showed (Table 7) a significant difference in perceived accuracy of AI-based forecasts across different aspects of AI contributing to forecasting accuracy ($F(4,195) = 6.667$, $p = 0.000$). Since $p < 0.05$, the null hypothesis is rejected, indicating that the perceived accuracy of AI forecasts varies depending on which AI aspect investors value most.

Table 8. Accuracy of AI based forecast compared to traditional methods-b.

Multiple Comparisons						
Dependent Variable: Accuracy of AI based forecast compared to traditional methods						
Tukey HSD						
(I) 15 Which Aspect of AI contribution most to its forecasting Accuracy?	(J) 15 Which Aspect of AI contribution most to its forecasting accuracy?	Mean Difference (I-J)	Std. Error	Sig.	95% Interval Confidence	
					Lower Bound	Upper Bound
1	2	-.072	.270	.999	-.81	.67
	3	-.545	.250	.192	-1.23	.14
	4	-.828*	.264	.016	-1.55	-.10
	5	-1.236*	.294	.000	-2.04	-.43
2	1	.072	.270	.999	-.67	.81
	3	-.474	.242	.293	-1.14	.19
	4	-.756*	.256	.029	-1.46	-.05
	5	-1.164*	.287	.001	-1.95	-.37
	1	.545	.250	.192	-.14	1.23
	2	.474	.242	.293	-.19	1.14
	4	-.282	.236	.752	-.93	.37
	5	-.690	.269	.080	-1.43	.05
4	1	.828*	.264	.016	.10	1.55
	2	.756*	.256	.029	.05	1.46
	3	.282	.236	.752	-.37	.93
	5	-.408	.281	.596	-1.18	.37
5	1	1.236*	.294	.000	.43	2.04
	2	1.164*	.287	.001	.37	1.95
	3	.690	.269	.080	-.05	1.43
	4	.408	.281	.596	-.37	1.18

*. The mean difference is significant at the 0.05 level.

The Tukey post hoc test(Table 8) revealed significant differences in perceived accuracy between investors prioritizing machine learning capability (5) and those prioritizing data analysis speed (1), pattern recognition (2), and elimination of human bias (4) ($p < 0.05$). This indicates that investors who value machine learning perceive AI forecasts as significantly more accurate than those valuing other AI aspects.

***Table 9**. Accuracy of AI based forecast compared to traditional methods-c.*

Accuracy of AI based forecast compared to traditional methods			
Tukey HSD[a,b]			
Aspect of AI contribution to forecasting Accuracy	N	Subset for alpha = 0.05	
		1	2
1	35	1.80	
2	39	1.87	
3	55	2.35	2.35
4	43		2.63
5	28		3.04
Sig.		.244	.074

Means for groups in homogeneous subsets are displayed.

a. Uses Harmonic Mean Sample Size = 38.062.

b. The group sizes are unequal. The harmonic mean of the group sizes is used. Type I error levels are not guaranteed.

A one-way ANOVA (Table 9) was conducted to determine whether perceived accuracy of AI-based forecasts (Q14) differs depending on which aspect of AI investors consider most important for forecasting accuracy (Q15). The results showed a statistically significant difference ($F(4,195) = 6.667$, $p = 0.000$), leading to the rejection of the null hypothesis. The mean plot demonstrated a clear upward trend, indicating that perceived accuracy increases from investors who value data analysis speed and pattern recognition to those who value machine learning capability, which had the highest mean perceived accuracy (3.04). Although some subset differences in the post hoc test were not significant within homogeneous groups, the overall results confirm that the aspect of AI valued by investors significantly influences their perceived effectiveness of AI forecasts, highlighting the role of AI tools in shaping investment decision-making strategies.

5. Conclusion

The adoption of artificial intelligence (AI) in investment forecasting is reshaping how investors approach financial decisions by providing faster, more accurate, and efficient prediction methods. The findings indicate that a substantial portion of participants, particularly postgraduates and individuals aged 23–27, recognize the value of AI in processing large datasets and delivering real-time analysis, aligning with their preference for timely insights to make informed investment choices. While a majority perceive AI forecasts as somewhat to very accurate, a segment of respondents still views AI predictions as either comparable to or less accurate than traditional methods, highlighting the need for continuous refinement of AI models to enhance trust and reliability.

The data also shows a clear preference for using AI alongside traditional investment methods, reflecting a hybrid approach among users seeking to balance innovation with proven forecasting strategies. Simplicity, cost-effectiveness, and familiarity with AI tools emerged as critical factors influencing adoption, underscoring the need to develop user-friendly, accessible AI tools with clear value propositions to drive higher engagement. Additionally, the versatility of AI in portfolio management, market trend analysis, algorithmic trading, and compliance reporting demonstrates its widespread impact across financial services, further enhancing its relevance in modern investment practices.

In conclusion, while AI has already improved aspects of investment forecasting for many users, further development is crucial to address accuracy concerns and build broader trust among investors. Ongoing innovation, targeted education, and awareness programs will be key in helping users understand and confidently adopt AI-driven investment tools. The integration of AI into conventional investment strategies has the potential to create a more accurate, efficient, and robust forecasting ecosystem, offering long-term benefits for individual investors and the financial industry as a whole.

Author Contributions

Satarupa Misra: Conceptualization, Data curation
Indumathi Nagesh: Data curation, Methodology

Rama Narayanswami: Data curation, Formal Analysis, Methodology, Investigation

Surabhi Jha: Data curation, Validation

Conflicts of Interest

The authors declare no conflicts of Interest.

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