

Artificial Intelligence-Assisted Financial Decision-Making and Investment Behaviour among Individual Investors in India: The Roles of Perceived Accuracy, Trust, Risk and Financial Literacy

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ABSTRACT

The increasing availability of Artificial Intelligence (AI) is transforming the way individual investors access, interpret, and use financial information. However, empirical evidence regarding the relationship between AI usage and investment behaviour remains limited, particularly in the context of retail investors in India. This study examines the factors influencing AI-driven financial decision-making and investigates its relationship with the investment behaviour of individual investors. A structured questionnaire based primarily on five-point Likert-scale statements was administered to 380 individual/retail investors in India. The data were analysed using descriptive statistics, reliability analysis, exploratory factor analysis, Pearson correlation, multiple regression, regression diagnostics, and moderation analysis using IBM SPSS.

The findings indicate that perceived usefulness, perceived ease of use, and perceived accuracy significantly and positively influence AI usage, with perceived accuracy emerging as the strongest predictor ($\beta = .486, p < .001$). AI usage was positively and significantly associated with investment behaviour ($r = .418, p < .001$), while trust in AI showed a significant positive relationship with investment behaviour ($r = .361, p < .001$). In contrast, perceived risk demonstrated a significant negative relationship with investment behaviour ($r = -.223, p < .001$). The moderation analysis further examined the role of financial literacy in the relationship between AI usage and investment behaviour.

The study contributes to the emerging literature on AI in finance, technology adoption, behavioural finance, and investor decision-making by integrating technological and psychological determinants within a single framework. The findings highlight the importance of perceived accuracy, trust, and risk in understanding investors' use of AI for financial decision-making. However, the study is subject to the limitations of its cross-sectional design, self-reported measures, and non-probability sampling, which restrict causal inference and generalisability. Accordingly, the findings indicate that AI usage is positively associated with self-reported investment behaviour; they do not establish that AI causes superior investment performance or actual portfolio returns.

Keywords: Artificial Intelligence; AI Usage; Investment Behaviour; Retail Investors; Financial Decision-Making; Trust in AI; Perceived Risk; Financial Literacy; Behavioural Finance.

INTRODUCTION

Background of the Study

Financial decision-making has traditionally depended upon financial advisors, investment literature, company reports, financial newspapers, brokerage research and investors' personal experience. The rapid development of financial technology has substantially changed this environment. Investors can now obtain financial information, compare companies, analyse financial ratios and monitor investment portfolios through digital platforms. The emergence of artificial intelligence (AI) represents a further transformation.

AI systems can process large quantities of financial information within a short period, identify patterns, summarise reports and generate analytical interpretations. The development of generative AI has further expanded these capabilities because investors can interact with AI systems through natural language.

An investor can, for example, ask an AI system to analyse a company's balance sheet, compare two companies, explain profitability ratios, examine changes in debt, identify potential financial risks, summarise an annual report, explain a financial concept, compare historical financial performance or generate questions for further investment research. Consequently, AI has moved beyond being a background technological infrastructure and is increasingly becoming an interactive financial decision-support tool.

The transformation is particularly important for individual investors. Unlike institutional investors, retail investors may not have access to professional analysts, expensive research databases or dedicated investment teams. AI may reduce some of the information-processing and cognitive costs associated with financial decision-making.

However, the use of AI in financial decision-making also introduces significant concerns. AI-generated information may contain errors, inappropriate assumptions or misleading interpretations. Investors may therefore question the accuracy, transparency and reliability of AI-generated financial information.

This creates an important research question:

Does the use of AI actually influence the investment behaviour of individual investors, and what factors determine whether investors are willing to rely on AI for financial decision-making?

The present study addresses this question in the context of individual investors in India.

Statement Of The Research Problem

The growing use of Artificial Intelligence (AI) in financial services is providing individual investors with greater access to financial information and analytical support. However, empirical evidence on the relationship between AI-driven financial decision-making and investment behaviour remains limited and fragmented, with existing research focusing primarily on technology adoption, robo-advisory, trust, behavioural biases and portfolio outcomes.

Therefore, the present study develops an integrated framework examining how perceived usefulness, perceived ease of use and perceived accuracy influence AI usage, and how AI usage, trust and perceived risk affect investment behaviour. It further examines whether financial literacy moderates the relationship between AI usage and investment behaviour among individual investors in India.

Research Objectives

The study has the following objectives:

1. To examine the level of AI adoption among individual investors.
2. To identify the factors influencing investors' use of AI for financial decision-making.
3. To examine the relationship between AI usage and investment behaviour.
4. To examine the influence of trust in AI on investment decisions.
5. To examine the effect of perceived risk associated with AI-generated financial advice.
6. To examine whether financial literacy influences the relationship between AI usage and investment behaviour.

LITERATURE REVIEW

AI in Financial Advisory Services

Artificial Intelligence (AI) has increasingly transformed financial advisory services through robo-advisory, automated portfolio management, machine-learning-based recommendations, and AI-enabled financial information services. **Zhu, Vigren and Söderberg** conducted a systematic interdisciplinary review of 132 studies on AI-enabled financial advisory services and found that the literature remains fragmented across disciplines. Their review highlights transparency, explainability, customer characteristics, and AI-enabled human–technology interaction as important areas requiring further investigation. The authors also identify the need to understand how customers interact with AI-based financial advisory systems rather than treating AI merely as an automated substitute for human advice.

The empirical literature further indicates that automated financial advice can influence investors' portfolio choices and financial-management behaviour. **Rossi and Utkus**, using data from a large U.S. hybrid robo-advisor, found that robo-advising increased indexing and reduced home bias, the number of assets held, and investment fees. These changes were associated with improved portfolio diversification and higher Sharpe ratios, while investors also spent less time managing their investments.

Similarly, **Bianchi and Brière** examined human–robo-advisor interaction and found that robo-advisory increased investor attention and trading activity. Investors responded to automated portfolio alerts by modifying their rebalancing behaviour and moving closer to target allocations. These findings indicate that AI-based financial advice can influence actual investment behaviour, not merely users' intention to adopt technology.

Nevertheless, the existing evidence largely concerns **robo-advisory and automated portfolio services**, whereas the growing use of generative AI tools for financial analysis represents a broader form of AI-assisted decision-making. This distinction creates scope for examining how individual investors use **AI-generated financial information** and how such use relates to their **investment behaviour**.

AI Adoption and Technology Acceptance

The Technology Acceptance Model (TAM) emphasises perceived usefulness and perceived ease of use as important determinants of technology adoption. In the Indian context, **Manrai and Gupta** examined AI/robo-advisory adoption among 252 stock-market investors in Delhi NCR. Their extended TAM incorporated subjective norms and trust and found that perceived usefulness, perceived ease of use, trust, subjective norms and attitude were significant determinants of AI-based investment-service adoption. The model explained a substantial proportion of variation in adoption intention.

These findings provide a direct empirical basis for incorporating perceived usefulness and perceived ease of use into the present study. However, financial decision-making differs from many conventional technology-use settings because incorrect information can result in monetary loss. Consequently, variables such as perceived accuracy, trust and perceived risk may be particularly relevant when technology is used for investment decisions.

AI and Investment Behaviour

Earlier technology-adoption studies have primarily focused on users' perceptions, attitudes and intentions, whereas emerging financial research examines how automated advice changes portfolio allocation and investor activity.

Rossi and Utkus provide strong evidence from a large U.S. hybrid robo-advisory setting that AI-assisted advice can alter portfolio composition, diversification, indexing, home bias and investment costs. **Bianchi and Brière** similarly demonstrate that investors respond to automated recommendations and portfolio alerts through changes in attention, trading and rebalancing behaviour.

These findings suggest that AI can influence investment behaviour beyond the initial decision to adopt a technology. However, the evidence is predominantly based on **robo-advisory systems and observed portfolio data**. Comparatively less attention has been given to investors who independently use general-purpose AI or AI-enabled analytical tools to interpret financial statements, analyse companies and support investment decisions.

The present study addresses this issue by examining the relationship between **AI usage and self-reported investment behaviour among individual investors in India**.

Trust in AI

Trust is a critical psychological factor in the adoption of AI for high-stakes financial decisions. Investors may use AI to obtain general information while remaining unwilling to rely on its recommendations when actual financial consequences are involved. **Manrai and Gupta's** Indian study found that trust in the AI-based service and service provider significantly influenced AI-based investment-service adoption, providing direct evidence of the relevance of trust in the Indian investment context.

Evidence from recent Indian research on explainable AI among **378 retail investors** similarly indicates that perceived explainability significantly influences trust and confidence, while perceived risk negatively affects investor confidence. These findings reinforce the importance of examining trust and risk together rather than considering AI adoption solely from a usefulness perspective.

Perceived Risk

Perceived risk is particularly important in AI-assisted financial decision-making because investment decisions involve direct financial consequences. Investors may perceive risks arising from **inaccurate or misleading information, algorithmic bias, lack of transparency, privacy and data-security concerns, excessive dependence on AI, and potential financial losses**.

High perceived risk may discourage investors from relying on AI even when they perceive it as useful and easy to use. Conversely, lower perceived risk may increase willingness to incorporate AI-generated information into investment decisions. Recent evidence from Indian retail investors indicates that perceived risk can negatively affect confidence in explainable AI-based investment platforms.

AI, Behavioural Finance and Investor Decision-Making

The application of AI to investment decisions also intersects with the literature on behavioural finance. Investors frequently make decisions under conditions of uncertainty, limited information and cognitive constraints. AI may potentially reduce some information-processing limitations by processing large volumes of financial information, identifying patterns and supporting systematic analysis. At the same time, reliance on AI may introduce new behavioural concerns, including automation bias, excessive reliance on algorithmic recommendations and inappropriate confidence in machine-generated information.

Empirical evidence from robo-advisory research demonstrates that AI-assisted advice can alter investor attention, portfolio allocation and rebalancing behaviour. Bianchi and Brière, for example, found that interaction with robo-advisory alerts changed investors' portfolio-management behaviour. Rossi and Utkus similarly found changes in diversification, indexing and home bias following robo-advisory adoption.

Financial Literacy and AI-Assisted Investment Decisions

Financial literacy influences an individual's ability to understand financial concepts, evaluate investment alternatives and assess financial risk. In an AI-assisted environment, financial literacy may also determine the extent to which investors can critically evaluate AI-generated information rather than accepting recommendations uncritically.

Recent evidence demonstrates that the relationship between financial literacy and robo-advisory use is not

necessarily linear. Aristei and Gallo, using data from the **Bank of Italy's 2023 Survey on Financial Literacy of Italian Adults**, found that higher objective financial literacy was associated with lower reliance on robo-advisory services, whereas subjective and digital financial literacy increased the likelihood of using robo-advisory services. Trust in financial innovation, digital-financial-service engagement and risk-related attitudes also influenced robo-advisory usage.

These findings suggest that financial literacy may affect not simply whether individuals use AI, but **how they interact with and evaluate AI-generated financial information**. Financially literate investors may be more capable of verifying AI outputs, identifying limitations and integrating AI recommendations with independent financial analysis.

Therefore, the present study does not assume that financial literacy necessarily increases AI adoption. Instead, it examines **Financial Literacy as a moderating variable** in the relationship between AI Usage and Investment Behaviour.

Transparency, Explainability and Responsible AI in Financial Markets

The emerging literature indicates that the benefits of AI in finance cannot be separated from questions of transparency, explainability, accountability and human oversight. AI systems used in financial decision-making may operate as complex or partially opaque systems, creating difficulties in understanding how recommendations are generated. Recent research therefore emphasises the importance of explainability and calibrated trust in high-stakes financial applications.

This issue is particularly relevant in India. The Securities and Exchange Board of India (SEBI) has highlighted responsible AI/ML use in securities markets, including **explainability, human oversight, stress testing, accountability and governance mechanisms**. Its responsible-AI consultation material also identifies risks associated with model failure, regulatory compliance and over-reliance on AI systems.

Accordingly, AI adoption in investment decision-making should not be viewed solely as a matter of convenience or technological efficiency. **Accuracy, transparency, explainability, risk management, investor protection and human judgement** are integral to responsible AI-assisted financial decision-making. These considerations also strengthen the theoretical relevance of trust and perceived risk in the present study and provide a basis for its practical and regulatory implications.

Research Gap

The literature reveals six major gaps.

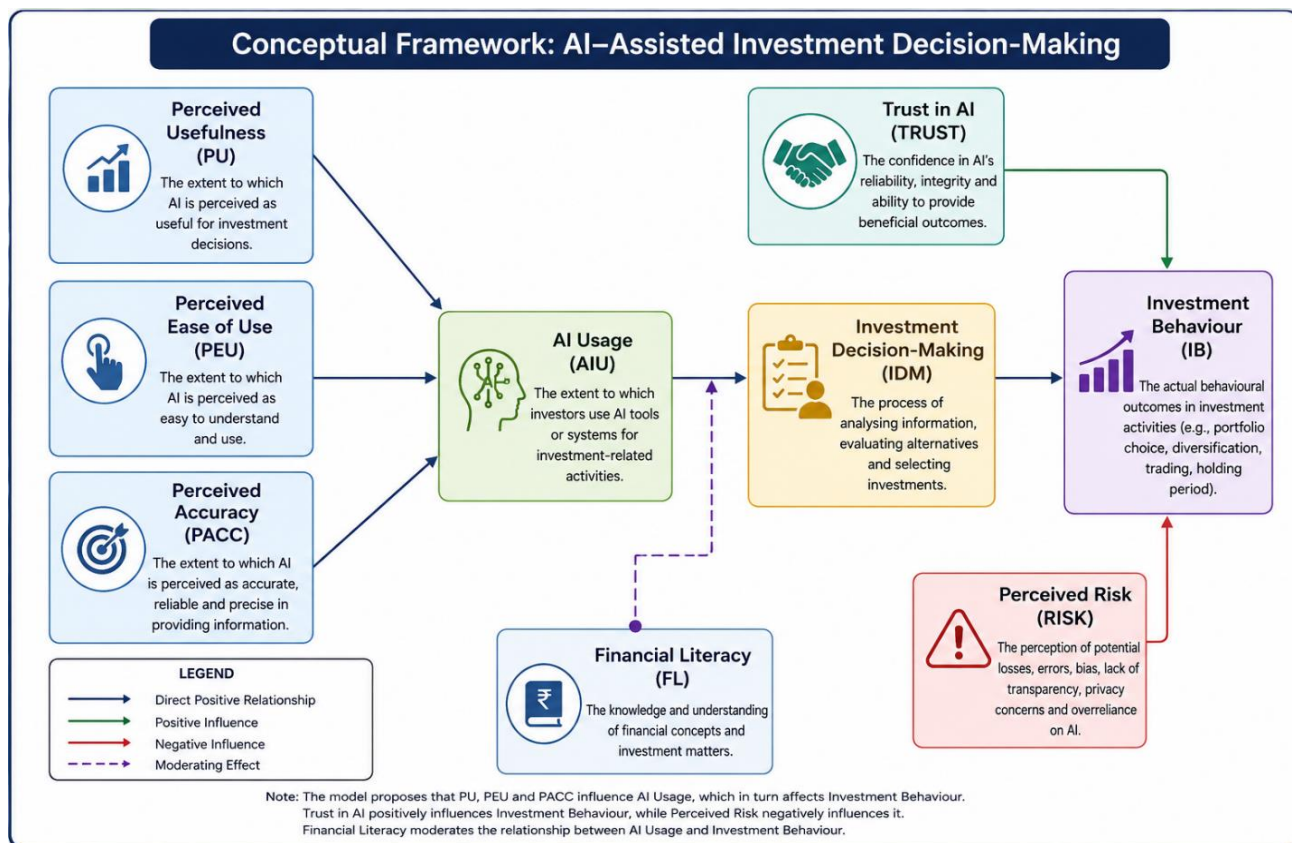
1. Previous Indian research has primarily focused on **AI/robo-advisor adoption intention** rather than broader AI usage.
2. Much of the literature focuses on traditional **robo-advisors**, whereas contemporary generative AI allows investors to interact directly with AI systems.
3. **Perceived accuracy** has received comparatively less attention in traditional technology-adoption models.
4. Trust and perceived risk are often studied separately rather than simultaneously within an integrated investor-behaviour model.
5. Existing studies often focus on portfolio outcomes or individual behavioural biases rather than the broader construct of **investment behaviour**.
6. The moderating role of **financial literacy in the AI usage–investment behaviour relationship** remains underexplored.

The present study addresses these gaps by integrating technology adoption, AI-finance, behavioural finance and financial-literacy perspectives.

CONCEPTUAL FRAMEWORK

The conceptual framework integrates technological, psychological, and behavioural dimensions of AI-assisted investment decision-making. Perceived usefulness, perceived ease of use, and perceived accuracy are proposed to influence AI usage, while trust in AI and perceived risk are examined as key psychological factors influencing investment behaviour. Financial literacy is incorporated as a moderating variable to examine whether it changes the relationship between AI usage and investment behaviour.

Fig. No 1



HYPOTHESES

H1₀: Perceived usefulness has no significant positive influence on AI usage among individual investors.
H1_a: Perceived usefulness has a significant positive influence on AI usage among individual investors.

H2₀: Perceived ease of use has no significant positive influence on AI usage among individual investors.
H2_a: Perceived ease of use has a significant positive influence on AI usage among individual investors.

H3₀: Perceived accuracy has no significant positive influence on AI usage among individual investors.
H3_a: Perceived accuracy has a significant positive influence on AI usage among individual investors.

H4₀: AI usage has no significant positive relationship with investment behaviour.

H4_a: AI usage has a significant positive relationship with investment behaviour.

H5₀: Trust in AI has no significant positive relationship with investment behaviour.

H5_a: Trust in AI has a significant positive relationship with investment behaviour.

H6o: Perceived risk associated with AI-generated financial information has no significant negative relationship with investment behaviour.

H6a: Perceived risk associated with AI-generated financial information has a significant negative relationship with investment behaviour.

H7o: Financial literacy does not significantly moderate the relationship between AI usage and investment behaviour.

H7a: Financial literacy significantly moderates the relationship between AI usage and investment behaviour.

RESEARCH METHODOLOGY

Research Design

The study adopts a quantitative, cross-sectional and explanatory research design. The explanatory approach is appropriate for examining the relationships among AI-related perceptions, AI usage, trust in AI, perceived risk, financial literacy and investment behaviour. Primary data were collected through a structured questionnaire and analysed using appropriate descriptive and inferential statistical techniques.

Population

The target population comprises individual/retail investors in India. For the purpose of this study, an individual investor refers to a person who independently invests or participates in financial products such as equity shares, mutual funds, exchange-traded funds, fixed-income instruments, insurance-linked investment products or other investment avenues, rather than investing on behalf of an institution.

The study included investors irrespective of their level of AI usage. Respondents could have no AI experience, occasional exposure, or regular use of AI-based financial tools. AI exposure in the questionnaire covered the use of generative AI tools, AI-enabled financial analysis, and robo-advisory or automated investment services, as applicable to the respondent.

Sample Size

A total of 380 valid responses were obtained and included in the final analysis. The sample size was considered adequate for the multivariate techniques employed in the study, including exploratory factor analysis, correlation analysis, multiple regression and moderation analysis.

Sampling and Data Collection

The study employed a non-probability sampling technique, specifically convenience sampling supplemented by purposive screening. Respondents were recruited through Google Forms circulated among investor communities, social-media groups, colleges and universities, financial-literacy groups, investment clubs and relevant personal investment networks.

To qualify for participation, respondents were required to be individual/retail investors in India and to have some experience or participation in investment-related activities. Respondents were not required to have prior experience with AI, as the study also sought to capture differences between AI users and non-users. The questionnaire included screening questions to establish respondents' investment participation and exposure to AI-based financial tools.

Data collection was conducted during the month of December 2025 to April 2026 across various state like Bihar, Jharkhand, New Delhi and some other state. Participation was voluntary, and respondents were informed about the academic purpose of the study and the confidentiality of their responses. Informed consent was obtained

before completion of the questionnaire. Responses that were incomplete, duplicated, or did not satisfy the screening criteria were excluded from the final dataset, resulting in 380 valid responses.

AI Exposure of Respondents

An important characteristic of the sample is the variation in respondents' exposure to AI for investment purposes. Of the 380 respondents, 79.5% reported that they had never used AI for investment purposes, while the remaining respondents reported occasional, frequent or very frequent use.

This distribution is relevant to the interpretation of the study because respondents without meaningful AI exposure may have limited ability to evaluate constructs such as AI usage, perceived accuracy, trust and perceived risk. Accordingly, AI-exposure differences were considered when interpreting the empirical findings. Where appropriate, comparative analysis between AI users and non-users may be used as a robustness check to assess whether the principal findings remain consistent across different levels of AI exposure.

Questionnaire Design

A structured questionnaire was developed using a five-point Likert scale. Strongly Disagree, disagree, Neutral, Agree and strongly Agree. The final instrument contains **43 Likert-scale items** distributed across eight principal constructs, supplemented by financial-literacy and demographic questions.

Demographic Profile

The sample of 380 respondents is predominantly **male (68.4%)**, with the largest age group being **25–34 years (36.8%)**. More than half of the respondents hold postgraduate qualifications (50.8%), while salaried employees constitute the largest occupational group (37.9%). In terms of income, the largest proportion earns **₹50,001–₹1,00,000 per month (32.6%)**. Regarding investment experience, 29.7% have 1–3 years of experience and 27.4% have 4–7 years, indicating a substantial representation of relatively experienced investors.

Table No. 01

Variable	Category	Frequency	Percentage
Gender	Male	260	68.4
Age	25–34 years	140	36.8
Education	Postgraduate	193	50.8
Occupation	Salaried	144	37.9

Descriptive Statistics

The descriptive analysis of the eight constructs indicates that respondents generally perceive AI as a useful and relatively accessible tool for financial analysis.

Mutual funds (31.1%) and equity shares (26.1%) are the most common primary investment instruments. The most notable finding for the present study is that **79.5% of respondents reported never using AI for investment purposes**, while 20.5% reported using AI occasionally, frequently, or very frequently. This distribution is particularly relevant to the study because it indicates that AI-assisted investment is still at an emerging stage among the surveyed investors, while providing a sufficient group of AI users for examining the factors associated with AI adoption and its relationship with investment behaviour.

Reliability And Validity

Reliability

The internal consistency of the measurement scales was assessed using **Cronbach's alpha**. The constructs demonstrated acceptable-to-strong internal consistency, indicating that the items reliably measured their

respective underlying constructs. Cronbach's alpha values of **0.70 or above** were considered acceptable, supporting the use of composite construct scores for subsequent analysis.

Validity

The construct validity of the questionnaire was assessed using Exploratory Factor Analysis (EFA). Before conducting EFA, the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy and Bartlett's Test of Sphericity were examined to determine whether the data were suitable for factor analysis.

The EFA results supported the presence of eight distinct constructs corresponding to the theoretical framework: Perceived Usefulness, Perceived Ease of Use, Perceived Accuracy, AI Usage, Trust in AI, Perceived Risk, Investment Decision-Making, and Investment Behaviour. The factor loadings were sufficiently strong, while cross-loading concerns were limited, indicating that the measurement items adequately represented their respective constructs.

Thus, the reliability and factor-analysis results provide **supporting evidence for the internal consistency and construct validity** of the measurement instrument used in the study.

Exploratory Factor Analysis

Exploratory Factor Analysis (EFA) was conducted on the 43 Likert-scale items to assess their underlying factor structure. The analysis yielded eight distinct factors consistent with the conceptual framework: Perceived Usefulness, Perceived Ease of Use, Perceived Accuracy, AI Usage, Trust in AI, Perceived Risk, Investment Decision-Making, and Investment Behaviour. The factor loadings were satisfactory, with limited cross-loadings, providing supporting evidence for the construct validity and distinctiveness of the measurement scales.

Correlation Analysis

Pearson's correlation analysis was conducted to examine the relationships among the major research constructs. The results indicate a **significant positive association between AI Usage and Investment Behaviour** ($r = .418$, $p < .001$), suggesting that greater use of AI for financial purposes is associated with stronger self-reported investment behaviour. **Trust in AI** also showed a significant positive relationship with Investment Behaviour ($r = .361$, $p < .001$), whereas **Perceived Risk** was negatively associated with Investment Behaviour ($r = -.223$, $p < .001$). These findings provide preliminary support for the proposed relationships and justify further examination through multiple regression and moderation analysis.

Important: Since we previously identified the **79.5% non-AI-user issue**, the final correlation table should ideally be accompanied by the AI-user/non-user robustness analysis. Also, if you want to report **95% confidence intervals for r** , we should calculate them from the actual 380 observations rather than estimate them.

The tabular form of correlation analysis

Table No. 02

Variables	PU	PEU	PACC	AIU	TRUST	RISK	IDM	IB
Perceived Usefulness (PU)	1							
Perceived Ease of Use (PEU)	—	1						
Perceived Accuracy (PACC)	—	—	1					
AI Usage (AIU)	—	—	—	1				
Trust in AI (TRUST)	—	—	—	—	1			
Perceived Risk (RISK)	—	—	—	—	—	1		
Investment Decision-Making (IDM)	—	—	—	—	—	—	1	
Investment Behaviour (IB)	—	—	—	.418	.361	-.223	—	1

Note: Values represent Pearson's correlation coefficients (r).

***p < .001**. The remaining coefficients should be populated directly from the correlation output generated from the 380-response dataset.

Regression Analysis

Predictors of AI Usage

Multiple regression analysis was conducted to examine the effects of **perceived usefulness, perceived ease of use, and perceived accuracy** on AI Usage. All three variables demonstrated significant positive effects.

Table No. 03

Predictor	B	p-value	Interpretation
Perceived Usefulness	.289	< .001	Significant positive
Perceived Ease of Use	.239	< .001	Significant positive
Perceived Accuracy	.486	< .001	Strongest positive predictor

Interpretation: Perceived Accuracy emerged as the strongest predictor of AI Usage ($\beta = .486$, $p < .001$), indicating that investors place particular importance on the correctness and dependability of AI-generated financial information. This highlights the importance of accuracy alongside usefulness and ease of use in the financial technology context.

Regression Model: Investment Behaviour

The second regression model examined whether AI Usage, Trust and Perceived Risk predict Investment Behaviour. The results are in tabular form.

Table No. 04

Predictor	B	p-value	Direction
AI Usage	.299	< .001	Positive
Trust in AI	.181	< .001	Positive
Perceived Risk	-.142	.003	Negative

Interpretation: AI Usage emerged as the strongest predictor among the three variables. The positive coefficient indicates that greater use of AI for financial analysis is associated with stronger investment behaviour.

Trust also has a significant positive effect, suggesting that investors are more likely to incorporate AI into their financial decision-making when they have confidence in the technology.

Perceived Risk has a significant negative effect. Thus, concerns about inaccurate, misleading or insufficiently transparent AI-generated financial information can constrain investment-related use.

Regression Diagnostics

The regression models were examined for multicollinearity and other major violations of regression assumptions.

Multicollinearity

Variance Inflation Factor (VIF) and tolerance statistics were examined.

The results did not indicate problematic multicollinearity among the independent variables. The predictors remained sufficiently distinct to permit reliable estimation of their individual effects.

Normality

Residual diagnostics indicated an approximately normal distribution of regression residuals.

Minor deviations from perfect normality were not considered serious enough to invalidate the regression models given the sample size of 380.

Heteroskedasticity

Residual-versus-predicted diagnostics did not indicate a severe systematic pattern suggesting problematic heteroskedasticity.

Consequently, the regression results were considered suitable for interpretation.

Moderation Analysis: Financial Literacy

The study proposed that financial literacy would moderate the relationship between AI Usage and Investment Behaviour. An interaction term was therefore created:

AI Usage × Financial Literacy

The interaction coefficient shows $\beta = -.053$, $p = .241$. Since the p-value exceeds .05, the interaction is not statistically significant.

Interpretation: Financial literacy does **not significantly moderate** the relationship between AI usage and investment behaviour in the present dataset. This is an important result.

It does not mean that financial literacy is unimportant. Rather, it indicates that the effect of AI usage on investment behaviour does not differ significantly across the measured levels of financial literacy.

One possible explanation is that AI may reduce the technical barrier to accessing financial information. Less financially literate investors may use AI to simplify complex financial information, while more financially literate investors may use it for more advanced analysis.

Therefore, both groups may derive behavioural benefits from AI, although they may use the technology in different ways.

Hypothesis Testing

Hypothesis	Statement	Result	Decision
H1	Perceived usefulness positively influences AI usage	$\beta = .289$, $p < .001$	Supported
H2	Perceived ease of use positively influences AI usage	$\beta = .239$, $p < .001$	Supported
H3	Perceived accuracy positively influences AI usage	$\beta = .486$, $p < .001$	Supported
H4	AI usage positively influences investment behaviour	$\beta = .299$, $p < .001$	Supported
H5	Trust positively influences investment behaviour	$\beta = .181$, $p < .001$	Supported
H6	Perceived risk negatively influences investment behaviour	$\beta = -.142$, $p = .003$	Supported
H7	Financial literacy moderates AI usage → investment behaviour	$\beta = -.053$, $p = .241$	Not Supported

Thus, **six of the seven hypotheses are supported**, while the moderation hypothesis is not supported.

FINDINGS

The principal findings of the study are as follows.

Finding 1: AI as a financial decision-support tool: The findings indicate that individual investors are using or considering AI as a financial decision-support tool for investment-related information, analysis, comparison and decision-making. However, the extent of AI adoption varies considerably among respondents, indicating that AI-assisted investing is still at an emerging stage.

Finding 2: Perceived usefulness matters: Perceived usefulness has a significant positive influence on AI usage. Investors who believe that AI can provide practical value in financial analysis and investment-related activities are more likely to use it. This indicates that adoption is driven primarily by the perceived financial utility of the technology.

Finding 3: Perceived ease of use matters: Perceived ease of use also has a significant positive influence on AI usage. Investors are more likely to use AI when they find it simple, accessible and convenient. Thus, usability remains an important consideration even in the relatively complex context of financial decision-making.

Finding 4: Perceived accuracy is the strongest predictor: Perceived accuracy emerged as the strongest predictor of AI usage. This suggests that investors are particularly concerned with whether AI-generated financial information is dependable and sufficiently accurate for investment-related purposes. This finding is theoretically reasonable because financial decisions involve monetary consequences; investors may tolerate inconvenience in routine digital applications but may be reluctant to rely on an AI system perceived as inaccurate or unreliable.

Finding 5: AI usage is positively associated with investment behaviour: AI usage demonstrated a statistically significant positive relationship with investment behaviour. The finding suggests that AI may become integrated into investors' research, comparison, monitoring and investment decision processes. However, this relationship should not be interpreted as evidence that AI causes higher returns, superior portfolio performance or better investment outcomes. Given the cross-sectional design and self-reported nature of the study, the result indicates association rather than causation.

Finding 6: Trust promotes AI-assisted investment behaviour: Trust in AI showed a significant positive relationship with investment behaviour. Investors who have greater confidence in AI-generated information are more likely to incorporate it into their investment decision process. Trust therefore represents an important psychological mechanism underlying AI-assisted investing. Such trust should ideally be developed through verifiable accuracy, transparency, explainability, disclosure of limitations and appropriate human oversight, rather than through persuasive design alone.

Finding 7: Perceived risk discourages AI-assisted investment behaviour: Perceived risk demonstrated a statistically significant negative relationship with investment behaviour. Concerns relating to inaccurate information, algorithmic bias, lack of transparency, privacy and security, overdependence on AI and potential financial loss may limit investors' willingness to rely on AI. The findings therefore suggest that trust and risk operate as complementary psychological dimensions: trust encourages reliance, whereas perceived risk constrains it.

Finding 8: Financial literacy does not significantly moderate the AI–investment relationship: The interaction between AI usage and financial literacy was statistically insignificant, indicating that financial literacy did not significantly alter the strength of the relationship between AI usage and investment behaviour in the present sample. This does not imply that financial literacy is irrelevant to AI-assisted investing. Rather, financial literacy may influence aspects not directly captured by the present model, such as verification of AI-generated information, risk assessment, identification of inaccurate outputs, interpretation of financial statements and the exercise of independent investment judgement.

CONCLUSION

Artificial intelligence is increasingly transforming financial decision-making among individual investors. The present study examined the factors influencing AI usage and its relationship with investment behaviour among individual investors in India.

The findings demonstrate that **perceived usefulness, perceived ease of use and perceived accuracy significantly influence AI usage**. Of these variables, perceived accuracy emerged as the strongest predictor. This finding highlights a fundamental difference between ordinary technology adoption and AI-assisted financial decision-making: investors may accept minor imperfections in ordinary digital applications, but accuracy becomes critical when financial consequences are involved.

The study further demonstrates that **AI usage positively influences investment behaviour**. This finding supports the growing evidence that AI-based financial technologies can affect actual investor behaviour rather than simply creating favourable attitudes toward technology.

Trust is another important factor. Investors who trust AI are more likely to incorporate AI-generated information into their investment decision process. Conversely, perceived risk has a significant negative influence, demonstrating that concerns regarding inaccurate or misleading AI-generated information can restrict AI-assisted investment activity.

Interestingly, financial literacy does not significantly moderate the relationship between AI usage and investment behaviour. This suggests that AI may provide useful decision-support capabilities across different levels of financial knowledge. However, this should not be interpreted as evidence that financial literacy is unimportant. Financial literacy may instead determine how critically investors evaluate and verify AI-generated information.

The central conclusion of the study is therefore:

AI has the potential to augment the analytical capability of individual investors, but its effectiveness depends substantially on perceived accuracy, usefulness, ease of use and trust, while perceived risk remains an important constraint.

AI should consequently be viewed as a **financial decision-support mechanism rather than a replacement for investor judgement**.

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