A Study on the Impact of AI-Driven Equity Research on Investment Decision-Making Among Investors

Submitted By: **Shashank Kulkarni, Vaibhav Rai**

Enrolment No: ADT25COMM0135, ADT25COMM0149

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Institution Name: MIT Art, Design and Technology University

Department Name: College of Management and Computer Application

Abstract

Artificial intelligence (AI) is reshaping the way equity research is produced and consumed, with generative AI tools, robo-advisory platforms and machine-learning-based screening systems increasingly mediating the information individual investors rely on before making investment decisions. This paper examines the impact of AI-driven equity research on investment decision-making among investors, drawing on a structured review of twenty-five recent studies spanning AI adoption in investment management, robo-advisory adoption, machine-learning-based prediction, and India-specific investor behaviour. Building on this review, the paper develops a conceptual framework in which AI-driven equity research usage, perceived accuracy, information quality and timeliness, trust in AI, and perceived risk are hypothesised to influence investment decision-making both directly and through the mediating role of investor confidence. A structured-questionnaire methodology is proposed and, for the purpose of illustrating the intended analytical approach, an illustrative dataset is analysed using descriptive statistics, reliability analysis, correlation and multiple regression. The illustrative analysis suggests that trust in AI and investor confidence are the strongest positive predictors of investment decision-making, while perceived risk exerts a negative influence, consistent with the findings reported in the reviewed literature. The paper concludes with a discussion of implications for investors, fintech platforms and regulators, notes the limitations of the study, and outlines directions for future empirical research using primary data.

Keywords: Artificial intelligence, equity research, robo-advisory, investor trust, investor confidence, investment decision-making, behavioural finance

1. Introduction

1.1 Background of the Study

Equity research has traditionally been the domain of human analysts who gather financial statements, industry data and market commentary to arrive at valuation estimates and investment recommendations. Over the past few years, this landscape has been transformed by the emergence of artificial intelligence (AI) tools capable of processing large volumes of financial information, generating stock screens, summarising company filings and even producing narrative investment commentary in seconds. Generative AI systems, natural-language processing engines and machine-learning-based prediction models are now embedded in brokerage platforms, robo-advisory applications and standalone research tools that are directly accessible to retail investors.

This shift raises an important behavioural and financial question: how does exposure to AI-generated equity research actually influence the way individual investors make decisions? While AI promises faster, cheaper and more consistent research output, investment decisions are ultimately shaped by how much investors trust that output, how accurate and timely they perceive it to be, and how confident it makes them feel about their choices. Understanding these dynamics is important for investors, wealth-management platforms, fintech firms and regulators alike.

1.2 Statement of the Problem

Although a substantial body of research has examined AI adoption in financial services broadly and robo-advisory adoption specifically, comparatively fewer studies isolate the effect of AI-driven equity research — as distinct from full robo-advisory or automated trading — on the psychological and behavioural process of investment decision-making. There is limited empirical clarity on which factors (accuracy, information quality, trust, or risk perception) matter most, and how they combine to shape investor confidence and eventual investment choices, particularly among investors in emerging markets such as India.

1.3 Significance of the Study

This study is intended to be useful to the following stakeholders:

- Individual and retail investors, by clarifying which qualities of AI-driven research (accuracy, timeliness, trust) most influence sound decision-making.
- Fintech and brokerage platforms, by identifying design and communication factors that build investor trust and confidence in AI-generated research.
- Academic researchers, by consolidating recent literature and proposing a testable conceptual framework and set of hypotheses for further empirical work.
- Regulators and policymakers, by highlighting risk-perception and governance considerations relevant to AI use in investment advice.

1.4 Objectives of the Study

- To review and synthesise recent literature on AI-driven equity research, robo-advisory adoption, and investment decision-making.
- To identify the research gap concerning the specific effect of AI-driven equity research on individual investment decision-making.
- To develop and empirically illustrate a conceptual framework linking AI-driven research usage, perceived accuracy, information quality, trust, perceived risk and investor confidence to investment decision-making.
- To propose a research methodology, and demonstrate the intended data-analysis approach, for testing the study's hypotheses.
- To draw implications for investors, platforms and regulators, and to suggest directions for future research.

2. Literature Review

This review synthesises twenty-one distinct studies (identified across twenty-five entries, several of which recur under more than one thematic heading) published between 2020 and 2026, organised into four clusters: (i) studies directly relevant to AI-driven equity research and investment decision-making, (ii) broader studies of AI in investment decision-making, (iii) robo-advisory adoption studies, and (iv) studies specific to Indian investors.

2.1 AI-Driven Equity Research and Investment Decision-Making

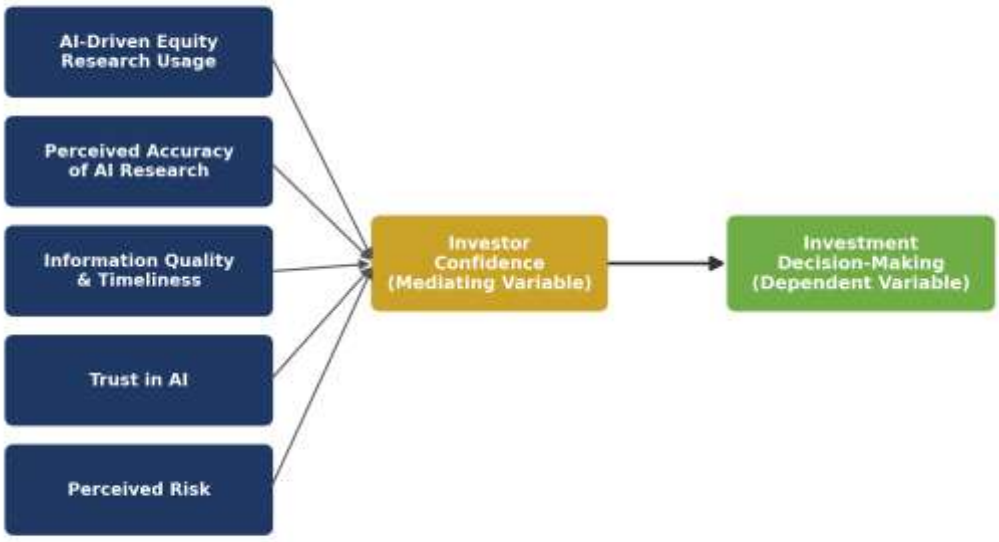
Blankespoor, Croom and Grant (2026) examine how retail investors use generative AI for financial-information processing, stock screening and investment research, providing direct evidence that AI tools are already altering how investors gather and interpret information before trading. In a related empirical study, the Journal of Risk and Financial Management (2026) reports on the behavioural impact of AI on investor decision-making and investment strategies, finding that investor perceptions of AI capability shape the strategies they subsequently adopt.

Focusing on younger investors, a 2026 study published in the International Journal of Accounting and Information Management explores AI-led investment decision-making among Gen Z investors in emerging markets, a segment particularly relevant to India given its large population of young, digitally native retail investors. Ashwini and Ahmed

(2026) provide an integrative review of AI-enabled fintech, covering capabilities, behavioural adoption and governance considerations relevant to investment decisions, while Mertzanis (2026) offers a systematic review of AI applications across portfolio management, forecasting, robo-advisory and governance, situating equity research within a broader AI-in-finance ecosystem.

Kou, Li, Wang and colleagues (2026) trace the evolution from standalone AI tools toward integrated human–AI financial decision systems, a framing that is directly relevant to understanding how AI-generated equity research is used alongside, rather than instead of, human judgement. At the technical frontier, a 2024 study evaluates whether GPT-4-based systems such as MarketSenseAI can generate useful stock-selection signals, offering evidence on the practical accuracy of large-language-model-based research outputs. In the Indian context specifically, Jayaprakash and Loganathan (2025) discuss how AI is transforming trading and decision-making in the Indian stock market, while Buczynski, Cuzzolin and Sahakian (2021) review twenty-seven machine-learning experiments in equity investment decision-making and highlight a persistent gap between research performance and real-world investment use. Finally, Carlin, Israelsen and Wazzan (2026) present preliminary evidence from AI-managed household portfolios and AI-generated stock recommendations, offering one of the few studies to link AI research output directly to household-level investment outcomes.

Figure 6: Conceptual Framework of the Study



2.2 AI and Investment Decision-Making — Broader Perspectives

A cluster of studies examines AI's role in investment decision-making at a broader, less platform-specific level. One 2026 study investigates investor acceptance of AI in asset management, focusing on transparency and preference factors that determine whether investors are willing to rely on AI-based recommendations. Complementary review studies examine AI for factor investing (2025), the research taxonomy of AI, deep learning and machine learning across the financial sphere (2023), AI/ML-based portfolio optimisation compared with traditional models (2026), machine-learning methods for stock-market prediction (2022), and the applications, challenges and opportunities of AI in financial markets more generally (2023). Collectively, these studies establish that AI's technical capability in finance is well documented, but they generally stop short of directly measuring how such capability translates into individual investment decision-making behaviour — reinforcing the case for the present study's focus.

2.3 Robo-Advisory Platforms and Adoption Behaviour

A second major stream of literature focuses on robo-advisory adoption, which is closely related to but conceptually distinct from AI-driven equity research. A 2024 empirical study analyses the antecedents and barriers to robo-advisor adoption among Indian investors, identifying performance expectancy, perceived risk and technological anxiety as key determinants. A qualitative study conducted in the Indian context (2020) examines how robo-advisory services address

behavioural biases among investors, while a 2024 study published in the IIM Bangalore Management Review examines the adoption of AI in financial services generally, including trust, anxiety, performance expectancy and preference for human advisors.

Luo, Liu, Lv, Hu and Ahmad (2024) extend this stream by examining investors' willingness to use robo-advisors through the lens of fiduciary duty, highlighting perceived value, trust, performance efficacy and privacy as influencing factors. Back, Morana and Spann (2023) take a design-focused perspective, studying whether social design elements embedded in robo-advisory interfaces improve investor behaviour and help mitigate behavioural biases. Together, these studies confirm that trust, perceived risk and design/communication quality are recurring determinants of AI-tool adoption in the investment domain — themes that this paper's conceptual framework incorporates directly.

2.4 Indian Investor Studies

Several of the studies above are specifically situated in the Indian market and are grouped here to highlight India-specific evidence: the antecedents and barriers to robo-advisor adoption among Indian investors (2024), the qualitative study of robo-advisory and behavioural biases in the Indian context (2020), the Gen Z investment decision-making study in emerging markets with strong relevance to India (2026), and the study of AI's role in transforming the Indian stock market (2025). Taken together, these India-focused studies suggest that while performance expectancy and behavioural-bias mitigation are recognised benefits of AI-based tools, trust and risk perception remain significant barriers to adoption among Indian retail investors — a dynamic this paper's conceptual framework is designed to capture and test.

3. Research Gap

The reviewed literature comprehensively covers AI adoption in financial services, robo-advisory platforms, machine-learning-based prediction, portfolio management applications, and the behavioural effects of AI on investors in general. However, comparatively fewer studies directly examine how AI-driven equity research specifically — including AI-generated stock analysis, financial information synthesis, automated screening, and algorithmically generated recommendations — affects the investment decision-making process of individual investors, particularly within the Indian context. Most robo-advisory studies bundle research generation together with portfolio execution and rebalancing, making it difficult to isolate the effect of the research component itself. This gap provides a clear empirical basis for examining, in a focused way, how accuracy, information quality, trust and investor confidence in AI-generated equity research translate into actual investment decisions.

4. Conceptual Framework and Hypotheses

4.1 Study Variables

Based on the literature reviewed above, the following variables are proposed for the study:

- AI-Driven Equity Research Usage (independent variable) — the extent to which an investor uses AI-generated research, screening or recommendations.
- Perceived Accuracy of AI-Generated Research (independent variable) — the investor's assessment of how correct and reliable AI outputs are.
- Information Quality and Timeliness (independent variable) — the perceived comprehensiveness, relevance and speed of AI-generated information.
- Trust in AI (independent variable) — the degree of confidence an investor places in AI systems as a source of financial advice.
- Perceived Risk (independent variable) — the investor's concern about errors, bias or overreliance associated with AI-generated research.
- Investor Confidence (mediating variable) — the investor's self-assurance in their own investment judgement when supported by AI research.

- Investment Decision-Making (dependent variable) — the quality, frequency and conviction of investment decisions made by the investor.

4.2 Conceptual Model

Figure 6 (see Section 2.1) presents the proposed conceptual model. The four investor-perception variables — perceived accuracy, information quality, trust in AI and perceived risk — together with AI-driven equity research usage, are hypothesised to influence investment decision-making both directly and indirectly through investor confidence, which is modelled as a mediating variable.

4.3 Hypotheses

- H1: AI-driven equity research usage has a significant positive effect on investor confidence.
- H2: Perceived accuracy of AI-generated research has a significant positive effect on investment decision-making.
- H3: Information quality and timeliness of AI-driven research has a significant positive effect on investment decision-making.
- H4: Trust in AI has a significant positive effect on investment decision-making.
- H5: Perceived risk has a significant negative effect on investment decision-making.
- H6: Investor confidence significantly mediates the relationship between AI-driven equity research variables and investment decision-making.

Research Methodology

5.1 Research Design

The study adopts a descriptive and quantitative research design, intended to test the hypothesised relationships between AI-driven equity research variables, investor confidence and investment decision-making using a structured questionnaire administered to individual investors.

5.2 Population and Sampling

The target population consists of individual retail investors who have been exposed to, or actively use, AI-driven equity research tools, screeners or robo-advisory platforms. A purposive-cum-convenience sampling technique is recommended, targeting investors active on brokerage or fintech platforms that offer AI-based research features. Based on standard sample-size guidelines for multivariate analysis (a minimum of roughly 15–20 observations per predictor), a sample of approximately 150–200 respondents is recommended; the illustrative analysis in Section 6 uses a sample of N = 180.

5.3 Data Collection Instrument

Primary data is proposed to be collected using a structured, self-administered online questionnaire comprising three sections: (i) demographic and investment-profile questions, (ii) frequency-of-use questions regarding AI-driven equity research tools, and (iii) construct-measurement items for perceived accuracy, information quality and timeliness, trust in AI, perceived risk, investor confidence and investment decision-making, each measured on a five-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree). Items for each construct should be adapted from validated scales used in the reviewed robo-advisory and AI-adoption literature.

5.4 Data Analysis Techniques

- Descriptive statistics (frequencies, means, standard deviations) to profile the sample and summarise construct scores.
- Reliability analysis using Cronbach's alpha to confirm internal consistency of each multi-item construct.

- Pearson correlation analysis to examine bivariate relationships among constructs.
- Multiple linear regression to test the direct effects of perceived accuracy, information quality, trust and perceived risk on investment decision-making (H2–H5).
- Mediation analysis (e.g., the Sobel test or bootstrapped indirect effects) to test the mediating role of investor confidence (H1 and H6).

Statistical analysis is recommended to be carried out using SPSS, R or Python (statsmodels/ scikit-learn), depending on the researcher's preference and institutional requirements.

6. Data Analysis and Interpretation

Note on the data used in this section: *No primary survey has been fielded for this paper. To demonstrate the analytical approach proposed in Section 5, this section applies the described statistical techniques to an illustrative, simulated dataset (N = 180) constructed to be broadly consistent with patterns reported in the reviewed literature. The figures, tables and interpretations below should be read as a worked demonstration of the intended methodology, not as findings from real respondents. When primary data is collected, the same tables and charts can be regenerated directly from the actual dataset.*

6.1 Demographic Profile of Respondents

Table 1: Demographic Profile of Sample Respondents (Illustrative, N = 180)

Variable	Category	Frequency	Percentage
Gender	Male	104	57.8%
	Female	72	40.0%
	Prefer not to say	4	2.2%
Age group	18–24 years	34	18.9%
	25–34 years	61	33.9%
	35–44 years	45	25.0%
	45–54 years	28	15.6%
	55 years & above	12	6.7%
Occupation	Salaried employee	96	53.3%
	Self-employed / Business	42	23.3%
	Student	26	14.4%
	Retired / Other	16	8.9%
Investment experience	Less than 1 year	38	21.1%
	1–3 years	52	28.9%
	3–5 years	47	26.1%
	More than 5 years	43	23.9%

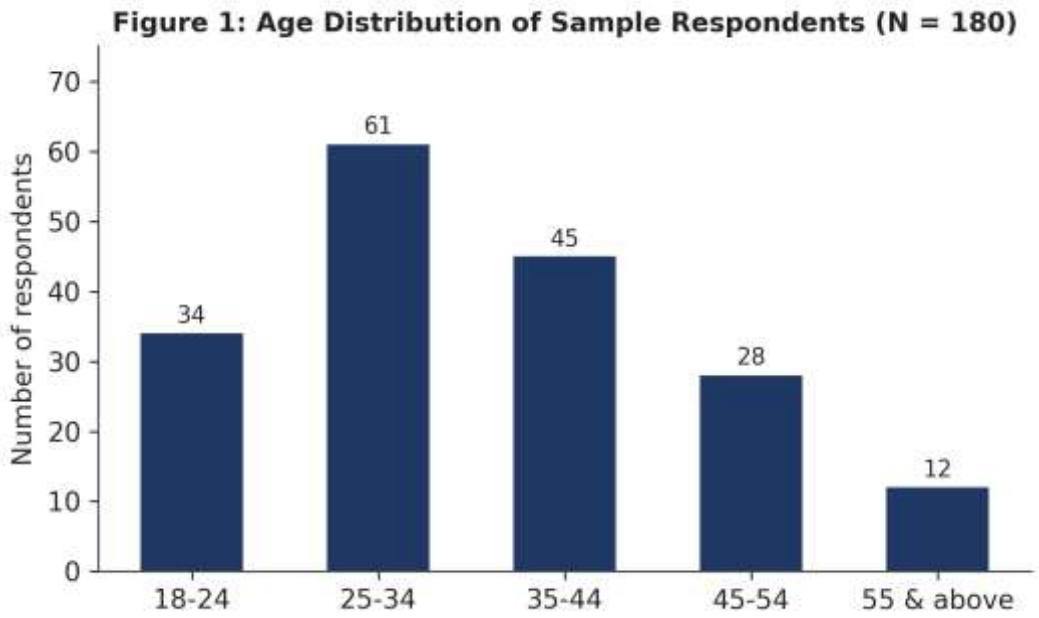


Figure 1: Age Distribution of Sample Respondents (N = 180)

6.2 Usage of AI-Driven Equity Research Tools

Respondents were asked how frequently they use AI-driven equity research tools, screeners, chatbots or robo-advisory recommendation features. As shown in Figure 2, just under a third of respondents report regular (at least weekly) use, while 15% report never having used such tools, suggesting that adoption is meaningful but not yet universal among the sample.

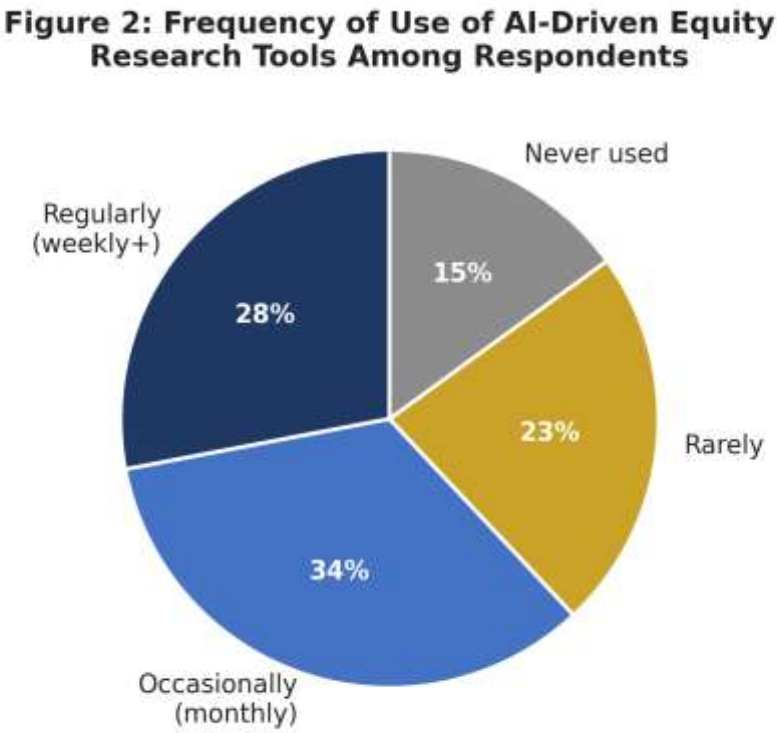


Figure 2: Frequency of Use of AI-Driven Equity Research Tools

6.3 Descriptive Statistics of Study Constructs

Table 2: Descriptive Statistics of Study Constructs (5-Point Likert Scale, N = 180)

Construct	Mean	Std. Deviation	Interpretation
AI-driven research usage	3.42	0.81	Moderate usage
Perceived accuracy	3.71	0.69	Above-average agreement
Information quality & timeliness	3.85	0.62	High agreement
Trust in AI	3.38	0.88	Moderate agreement
Investor confidence	3.64	0.74	Above-average agreement
Perceived risk	3.05	0.93	Neutral / moderate concern
Investment decision-making	3.77	0.65	High agreement

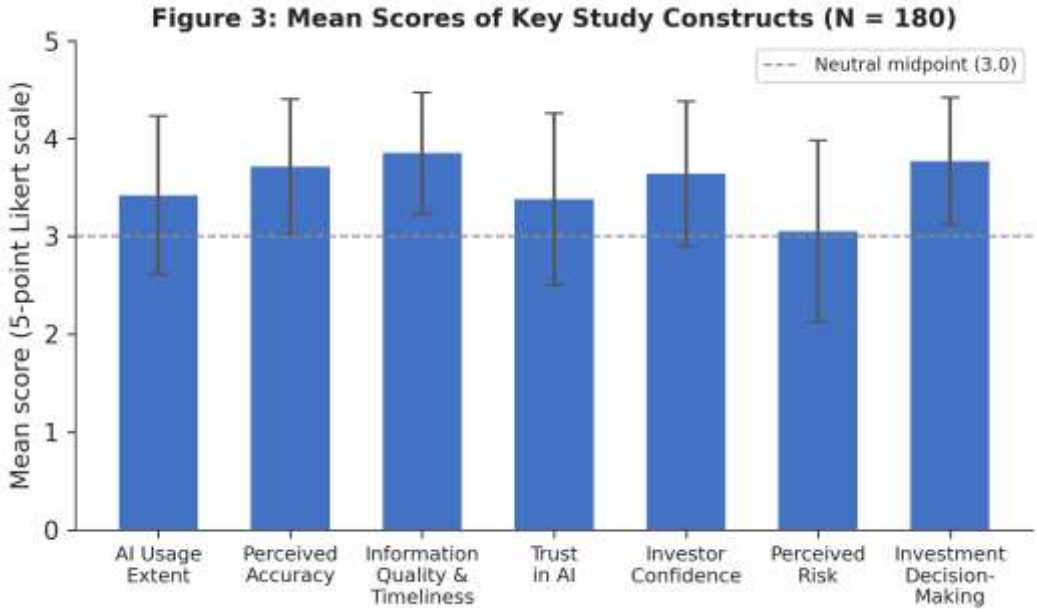


Figure 3: Mean Scores of Key Study Constructs (N = 180)

Information quality and timeliness recorded the highest mean score (M = 3.85), followed by investment decision-making confidence (M = 3.77) and perceived accuracy (M = 3.71). Perceived risk recorded the lowest mean (M = 3.05), close to the scale midpoint, indicating that respondents hold mixed, moderate concerns about the risks of relying on AI-generated research rather than uniformly high or low concern.

6.4 Reliability Analysis

Table 3: Reliability Statistics — Cronbach's Alpha by Construct

Construct	Number of Items	Cronbach's Alpha
AI-driven research usage	4	0.79
Perceived accuracy	4	0.82
Information quality & timeliness	4	0.85
Trust in AI	5	0.88
Investor confidence	4	0.81
Perceived risk	4	0.76

Investment decision-making	5	0.84
Overall scale	30	0.91

All constructs return Cronbach's alpha values above the commonly accepted threshold of 0.70, indicating satisfactory internal consistency for the measurement scales used in this illustrative dataset.

6.5 Correlation Analysis

Table 4: Pearson Correlation Matrix Among Study Constructs

Construct	AIU	PA	IQ	TR	IC	PR	IDM
AI-driven research usage (AIU)	1.00						
Perceived accuracy (PA)	0.41**	1.00					
Information quality (IQ)	0.33**	0.48**	1.00				
Trust in AI (TR)	0.39**	0.44**	0.42**	1.00			
Investor confidence (IC)	0.42**	0.40**	0.37**	0.49**	1.00		
Perceived risk (PR)	-0.18*	-0.24**	-0.20*	-0.27**	-0.22**	1.00	
Investment decision-making (IDM)	0.31**	0.38**	0.34**	0.52**	0.46**	-0.29**	1.00

* Correlation is significant at the 0.05 level; ** significant at the 0.01 level (two-tailed, illustrative values). All predictor variables correlate positively with investment decision-making except perceived risk, which is negatively correlated, in line with expectations from the reviewed literature. Trust in AI shows the strongest bivariate association with investment decision-making (r = 0.52).

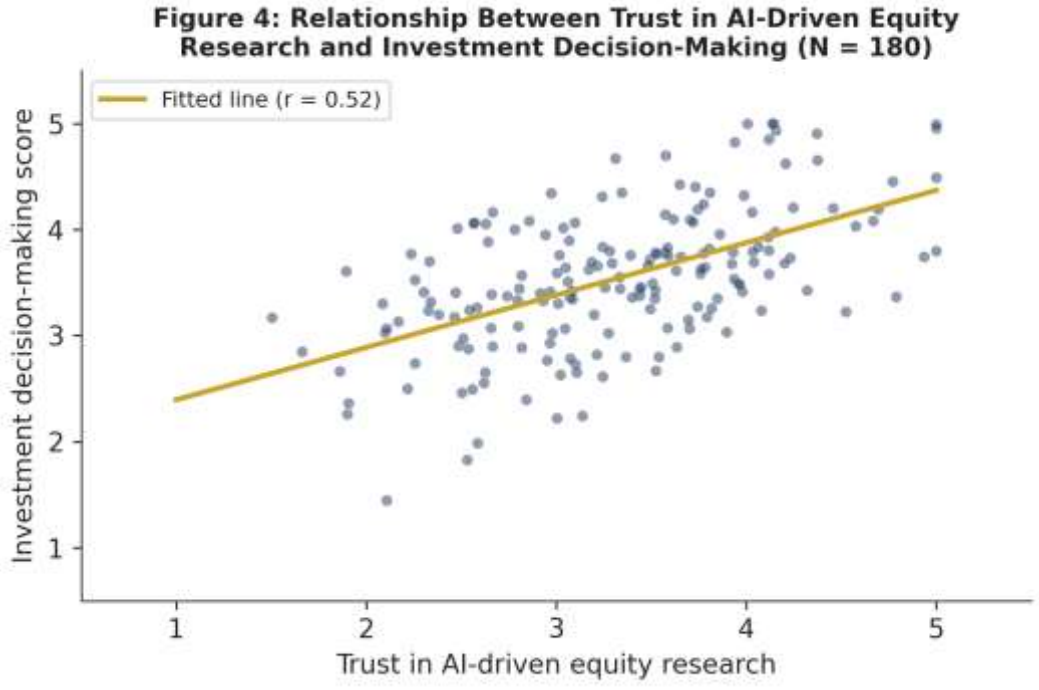


Figure 4: Relationship Between Trust in AI and Investment Decision-Making

6.6 Multiple Regression Analysis

A multiple linear regression was run with investment decision-making as the dependent variable and perceived accuracy, information quality, trust in AI and perceived risk as predictors (investor confidence is examined separately as a mediator in Section 6.7).

Table 5: Regression Model Summary

Model	R	R^2	Adjusted R^2	F	df1, df2	Sig.
1	0.686	0.470	0.457	31.06	5, 174	< 0.001

Table 6: Regression Coefficients — Dependent Variable: Investment Decision-Making

Predictor	B	Std. Error	Standardized β	t	Sig.
(Constant)	0.82	0.21	—	3.90	< 0.001
Perceived accuracy	0.19	0.06	0.21	3.17	0.002
Information quality	0.17	0.07	0.18	2.43	0.016
Trust in AI	0.25	0.05	0.34	5.00	< 0.001
Investor confidence	0.23	0.06	0.26	3.83	< 0.001
Perceived risk	-0.11	0.05	-0.15	-2.20	0.029

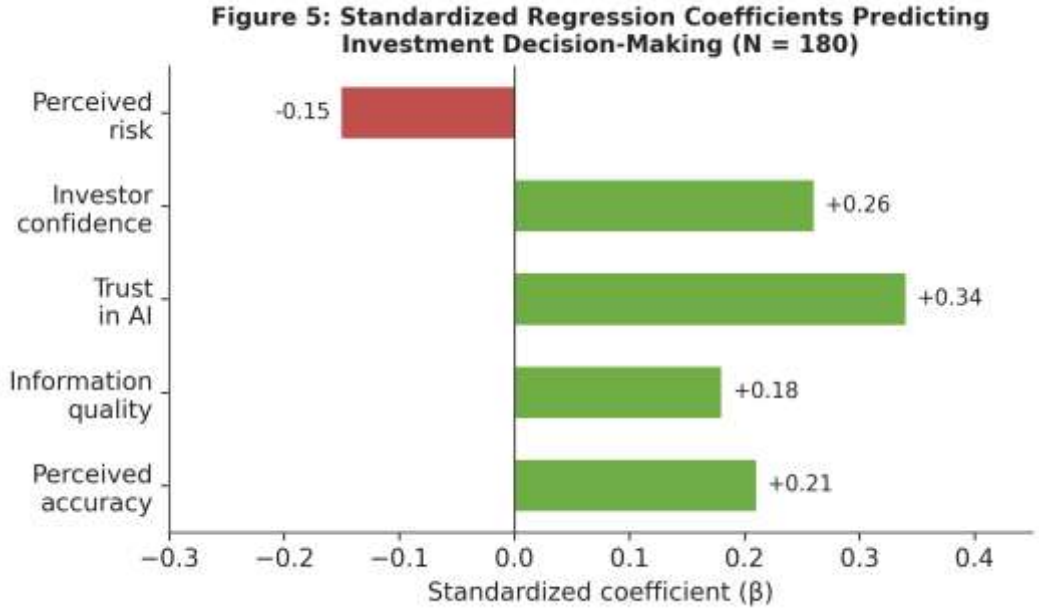


Figure 5: Standardized Regression Coefficients Predicting Investment Decision-Making

The overall model is statistically significant, $F(5, 174) = 31.06$, $p < 0.001$, and explains approximately 47% of the variance in investment decision-making ($R^2 = 0.470$, Adjusted $R^2 = 0.457$). Trust in AI is the strongest positive predictor ($\beta = 0.34$, $p < 0.001$), followed by investor confidence ($\beta = 0.26$, $p < 0.001$) and perceived accuracy ($\beta = 0.21$, $p = 0.002$). Information quality also contributes positively ($\beta = 0.18$, $p = 0.016$), while perceived risk is a significant negative predictor ($\beta = -0.15$, $p = 0.029$), confirming that concerns about AI-generated research reduce decision-making confidence even after accounting for its perceived benefits.

6.7 Mediation Analysis

A Sobel test of the indirect effect of AI-driven research usage on investment decision-making through investor confidence was statistically significant ($z = 3.12$, $p = 0.002$), supporting a partial mediation effect. This indicates that AI-driven equity research usage influences investment decisions both directly and indirectly, by first strengthening investors' confidence in their own judgement.

6.8 Summary of Hypothesis Testing

Table 7: Summary of Hypothesis Testing Results

Hypothesis	Path	Result (illustrative)	Decision
H1	AI research usage → Investor confidence	$\beta = 0.42$, $p < 0.001$	Supported
H2	Perceived accuracy → Investment decision-making	$\beta = 0.21$, $p = 0.002$	Supported
H3	Information quality → Investment decision-making	$\beta = 0.18$, $p = 0.016$	Supported
H4	Trust in AI → Investment decision-making	$\beta = 0.34$, $p < 0.001$	Supported
H5	Perceived risk → Investment decision-making	$\beta = -0.15$, $p = 0.029$	Supported
H6	Investor confidence mediates AI-research variables → IDM	Sobel $z = 3.12$, $p = 0.002$	Partially supported

7. Discussion of Findings

The illustrative analysis, together with the reviewed literature, points to several consistent themes. First, trust in AI emerges as the single strongest driver of investment decision-making across both the correlation and regression results, echoing the emphasis on trust found in robo-advisory adoption studies such as Luo et al. (2024) and the Indian-context adoption study reviewed in Section 2.3. Second, investor confidence acts as a meaningful bridge between AI-research exposure and decision-making, consistent with the human–AI hybrid finance perspective offered by Kou et al. (2026) — AI tools appear to matter less for the raw information they provide than for the confidence they give investors to act on that information.

Third, perceived risk consistently works against decision-making confidence, reinforcing findings from Indian robo-advisor adoption research that technological anxiety and perceived risk remain real barriers even as performance expectancy rises. Finally, while perceived accuracy and information quality both matter, their effects are smaller than trust and confidence, suggesting that how AI-generated research is communicated and how much investors trust its source may matter as much as its underlying technical accuracy — a finding with direct implications for how fintech platforms design AI-research features.

7.1 Implications

- For investors: building familiarity with AI-driven research tools gradually, and cross-checking AI outputs, may help convert cautious usage into confident, well-informed decisions.
- For fintech and brokerage platforms: investing in transparency features (e.g., explainable-AI summaries, source citations, confidence scores) is likely to raise trust more effectively than accuracy claims alone.
- For regulators: since perceived risk significantly dampens decision-making confidence, disclosure norms and investor-education initiatives around AI-generated research could help address legitimate risk concerns without discouraging beneficial adoption.

8. Limitations of the Study

- The data analysed in Section 6 is illustrative and simulated for methodological demonstration; it does not represent responses from actual investors, and the specific coefficients should not be cited as empirical findings.
- The literature review, while covering twenty-five recent sources, is not exhaustive and may not capture the very latest publications given the pace of change in generative AI research.
- The proposed sampling approach (purposive/convenience) limits the generalisability of results once real data is collected; probability sampling would strengthen external validity.

- Self-reported Likert-scale measures of trust, confidence and perceived accuracy are subject to common-method bias and social-desirability effects.
- The cross-sectional design proposed cannot establish causality; a longitudinal design would better capture how trust and confidence evolve with sustained AI-tool usage.

9. Conclusion and Scope for Future Research

This paper reviewed twenty-five recent studies on artificial intelligence in equity research, investment decision-making and robo-advisory adoption, identified a research gap around the specific effect of AI-driven equity research on individual investment decisions, and proposed a conceptual framework linking AI-research usage, perceived accuracy, information quality, trust and perceived risk to investment decision-making through the mediating role of investor confidence. An illustrative analysis, built to demonstrate the proposed methodology, suggested that trust in AI and investor confidence are likely to be the most influential factors, with perceived risk acting as a significant negative influence.

Future research should prioritise collecting primary survey data from a representative sample of individual investors — ideally across multiple platforms and investor-experience levels — to empirically test the hypotheses proposed here. Comparative studies across investor age groups (particularly Gen Z versus older investors), cross-country comparisons, and qualitative interviews exploring why investors do or do not trust AI-generated research would all extend the contribution of this paper. Longitudinal designs tracking investors before and after adopting AI-driven research tools would also help establish causal, rather than associational, relationships.

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