

Human–AI Collaboration in Financial Decision-Making: An Empirical Study of AI-Assisted Investment and Risk Management

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Abstract—Artificial intelligence (AI) is reshaping how investors select securities, construct portfolios and monitor risk, yet the evidence on how human judgement and machine intelligence work together remains thin, especially in emerging markets. This study examines whether AI assistance improves perceived investment decision quality and risk-management effectiveness, and whether human oversight strengthens these outcomes. Primary data were collected through a structured questionnaire from 250 retail, high-net-worth and institutional investors in the Hyderabad–Secunderabad region of Telangana, supported by secondary literature and regulatory reports. Reliability testing, correlation, multiple regression, independent-samples *t*-tests and one-way ANOVA were applied. AI usage intensity, perceived usefulness, trust in AI and human oversight jointly explained 41.2% of the variance in decision quality, and 40.5% of the variance in risk-management effectiveness was explained by AI usage, trust, oversight and decision quality. AI-assisted investors scored significantly higher on both outcomes than non-AI investors. The highest scores were recorded by respondents combining high AI usage with high human oversight, and 64% preferred a collaborative model over AI-only or human-only advice. The results support a human-in-the-loop approach and offer suggestions for investors, financial institutions and regulators.

Keywords—human–AI collaboration, AI-assisted investing, risk management, financial decision-making, trust in AI, human oversight, behavioural finance

1. INTRODUCTION

Financial decision-making has always involved a trade-off between the speed and breadth of information processing and the quality of human judgement. Classical portfolio theory [1] and the efficient-markets hypothesis [4] describe investors as rational agents, but decades of behavioural research show that real investors are subject to loss aversion, overconfidence and excessive trading [2], [3]. These biases reduce net returns and weaken risk control, particularly among individual investors who lack institutional research support.

Advances in machine learning, natural language processing and big-data analytics now allow computers to screen thousands of securities, detect return patterns and flag emerging risks in seconds [6]. Robo-advisers, algorithmic trading platforms, AI-based credit and market-risk engines, and generative-AI research assistants have moved from experimental tools to mainstream infrastructure across banks, asset managers, brokerages and fintech applications [7], [9]. In India, the growth of online broking, mobile trading applications, the Unified Payments Interface and a rapidly widening base of first-time demat account holders has placed AI-enabled tools in the hands of ordinary investors.

The central question, however, is not whether AI can outperform humans on narrow prediction tasks, but how humans and AI should share decisions. Machines excel at prediction, consistency and scale, whereas humans contribute contextual understanding, ethical judgement and accountability [16],

[17]. Excessive reliance on algorithms can produce complacency and automation bias [15], while excessive scepticism leads to algorithm aversion [13]. The productive middle ground—human–AI collaboration, in which AI generates analysis and humans retain oversight—has received limited empirical attention in the Indian context.

This paper addresses that gap through a primary survey of investors in Telangana. It measures the extent of AI use, perceived usefulness, trust and human oversight, and tests their influence on two outcomes: perceived investment decision quality and risk-management effectiveness. The contribution is threefold: (i) an integrated model linking AI adoption, trust and oversight to financial outcomes; (ii) evidence on the value of human–AI collaboration relative to either party acting alone; and (iii) practical guidance for investors, institutions and regulators.

The remainder of the paper is organized as follows. Section 2 states the objectives and hypotheses, Section 3 reviews the literature, Section 4 describes the methodology, Section 5 presents the analysis and interpretation, Section 6 summaries the findings and suggestions, and Section 7 concludes.

2. OBJECTIVES OF THE STUDY

The study is guided by the following objectives:

1. To examine the extent to which investors use AI-based tools for investment decisions and risk management.
2. To analyse the influence of AI usage intensity, perceived usefulness, trust in AI and human oversight on investment decision quality.
3. To assess the determinants of risk-management effectiveness among AI-assisted investors.
4. To compare AI-assisted and non-AI investors, and investors of different categories, on decision quality and risk management.

5. To evaluate whether a combination of high AI usage and high human oversight yields better outcomes than either alone.
6. To offer suggestions for investors, financial institutions and regulators on responsible human–AI collaboration.

Based on these objectives, the following hypotheses are tested:

H1: AI usage intensity has a positive effect on decision quality (DQ).

H2: Perceived usefulness of AI has a positive effect on DQ.

H3: Trust in AI has a positive effect on DQ and on risk-management effectiveness (RM).

H4: Human oversight has a positive effect on DQ and RM.

H5: AI-assisted investors report significantly higher DQ and RM than non-AI investors.

H6: Investors combining high AI usage with high human oversight report the highest DQ and RM.

3. LITERATURE REVIEW

3.1 Behavioural Finance and the Limits of Human Judgement

Markowitz [1] formalised diversification as the trade-off between expected return and variance, and Fama [4] argued that prices reflect available information. Kahneman and Tversky [2] showed instead that people evaluate gains and losses asymmetrically, and Barber and Odean [3] found that individual investors who trade most earn markedly lower net returns because of overconfidence. Lo [5] reconciled the two views through the adaptive-markets hypothesis, in which behaviour evolves with the environment. These studies establish that human bias is a persistent source of error and therefore a natural target for machine assistance.

3.2 AI in Investment Management

Gu, Kelly and Xiu [6] demonstrated that machine-learning methods capture non-linear interactions among firm characteristics and improve out-of-sample return prediction relative to conventional linear models.

D'Acunto, Prabhala and Rossi [7] found that robo-advice increased diversification among under-diversified investors but had little effect on already diversified ones, and that it reduced some behavioural biases. Fuster et al. [8] showed that technology-driven models change the distribution of outcomes across borrowers, illustrating that AI benefits are not uniform. The Financial Stability Board [9] documented growing use of AI in trading, credit scoring, insurance and regulatory compliance, and warned of opacity, concentration and third-party dependency risks.

3.3 AI in Risk Management

AI-based risk systems support early-warning detection, anomaly and fraud identification, stress testing and dynamic value-at-risk estimation. Their strengths are speed and the ability to process unstructured data such as news and filings. Their weaknesses include model risk, data drift and limited explainability [9]. Agrawal, Gans and Goldfarb [16] frame AI as a fall in the cost of prediction, which raises the value of complementary human skills such as judgement about what to predict and how to act on it. Brynjolfsson and McAfee [17] similarly argue that the largest gains arise when people and machines are combined rather than substituted.

3.4 Technology Acceptance, Trust and Human Oversight

The technology acceptance model [10] and the unified theory of acceptance and use of technology [11] identify perceived usefulness as a principal driver of adoption. Lee and See [12] argue that trust in automation must be calibrated: too little produces disuse, too much produces misuse. Empirically, Dietvorst et al. [13] show that people abandon algorithms after seeing them err, whereas Logg et al. [14] find that people often prefer algorithmic to human advice when the source is not salient. Parasuraman and Manzey [15] show that complacency and automation bias emerge when operators over-rely on automated aids.

Together, these studies imply that human oversight is not an obstacle to AI benefits but a condition for realising them safely.

3.5 The Indian Context

India offers a distinctive setting for this question. Rapid growth in online broking, mobile trading applications, digital payments and low-cost mutual-fund platforms has drawn a large number of first-time investors into capital markets, many of whom rely on app-based recommendations, screeners and automated alerts rather than on a personal adviser. At the same time, institutional players are deploying machine-learning models for surveillance, credit assessment and portfolio analytics. This dual expansion means that the quality of human–AI interaction, not merely access to technology, will determine whether AI widens or narrows the gap between informed and uninformed market participants [7], [9].

3.6 Research Gap

Existing studies concentrate on developed markets, on algorithmic performance rather than user outcomes, or on adoption intentions rather than realised decision quality. Few studies jointly model AI usage, perceived usefulness, trust and human oversight, and fewer still examine both investment decisions and risk management among investors in an emerging-market setting such as Telangana. This study addresses that gap.

4. RESEARCH METHODOLOGY

4.1 Research Design

A descriptive and causal (explanatory) research design with a cross-sectional survey approach was adopted. The conceptual model treats AI usage intensity (AIU), perceived usefulness (PU), trust in AI (TR) and human oversight (HO) as independent variables, investment decision quality (DQ) as the primary dependent variable, and risk-management effectiveness (RM) as a second dependent variable to which DQ also contributes. Respondents were additionally

classified as AI-assisted or non-AI investors and as retail, HNI/advisor or institutional/analyst investors for group comparisons.

4.2 Data Sources

Primary Data:

- A structured, self-administered questionnaire was distributed in person and through online forms.
- Section A captured demographic and investor-profile details; Section B contained 18 statements on six constructs measured on a five-point Likert scale (1 = strongly disagree, 5 = strongly agree).
- Two additional questions captured the main perceived benefit of AI and the preferred decision model.
- The instrument was pilot-tested on 25 investors, and wording was refined before the main survey.

Secondary Data:

- Peer-reviewed journals, books and working papers on behavioural finance, AI in finance and human–automation interaction.
- Reports of regulators and international bodies, such as the Financial Stability Board [9], for the institutional context.

TABLE I
 CONSTRUCTS AND MEASUREMENT

Construct	Code	Items	Basis
AI usage intensity	AIU	3	[11]
Perceived usefulness	PU	3	[10]
Trust in AI	TR	3	[12]
Human oversight	HO	3	[15]
Decision quality	DQ	3	[2], [3]
Risk-mgmt. effectiveness	RM	3	[9]

Content validity was established by giving the draft questionnaire to three academics in finance and two practising portfolio managers, whose comments were incorporated. Participation was voluntary, responses were

anonymous, and respondents were informed that the data would be used only for academic research. Common-method bias was reduced by mixing item order and by assuring respondents that there were no right or wrong answers.

4.3 Sample Size

The target population comprised active investors in equity, mutual funds and derivatives in the Hyderabad–Secunderabad region and Rangareddy district. Stratified purposive sampling was used to ensure representation of retail, HNI/advisor and institutional/analyst investors. In total, 300 questionnaires were distributed, 262 were returned and 250 were complete and usable, giving an effective response rate of 83.3%. The sample exceeds the minimum of 129 required for a multiple regression with four predictors, a medium effect size ($f^2 = 0.15$), 5% significance and 95% power [20], and also satisfies the rule of at least ten observations per questionnaire item [19].

4.4 Tools for Analysis

Data were coded and analysed using Python (pandas, SciPy and statsmodels). The following tools were applied:

- Percentages and frequency tables for the respondent profile; mean and standard deviation for descriptive statistics.
- Cronbach's alpha [18] for internal consistency (threshold 0.70).
- Pearson's correlation for the strength and direction of relationships.
- Multiple linear regression: $DQ = \beta_0 + \beta_1 AIU + \beta_2 PU + \beta_3 TR + \beta_4 HO + \epsilon$, and $RM = \gamma_0 + \gamma_1 AIU + \gamma_2 TR + \gamma_3 HO + \gamma_4 DQ + \epsilon$; multicollinearity assessed by the variance inflation factor (VIF).
- Welch's independent-samples t-test and one-way ANOVA for group differences; charts (pie and bar) for visual presentation.

5. DATA ANALYSIS AND INTERPRETATION

5.1 Profile of Respondents

Table II shows that the sample is dominated by investors aged 30–40 years (40.0%) and by retail investors (57.6%). More than half (56.0%) reported using AI-based tools, such as robo-advisory apps, AI screeners, predictive analytics or generative-AI assistants, in their investment or risk decisions.

TABLE II
PROFILE OF RESPONDENTS (N = 250)

Variable / Category	n	%
Age: Below 30 years	54	21.6
Age: 30–40 years	100	40.0
Age: 41–50 years	63	25.2
Age: Above 50 years	33	13.2
Retail investor	144	57.6
HNI / advisor	54	21.6
Institutional / analyst	52	20.8
AI-assisted investor	140	56.0
Non-AI investor	110	44.0

Among the 140 AI-assisted investors, AI stock screeners were the most widely used tool, followed by generative-AI assistants and robo-advisory applications (Table III). Because respondents could select more than one tool, percentages exceed 100 in total, which shows that many investors combine several AI aids.

TABLE III
AI TOOLS USED BY AI-ASSISTED INVESTORS (N = 140)

AI tool (multiple response)	n	%
AI stock screeners / analytics	58	41.4
Generative-AI research assistants	52	37.1
Robo-advisory applications	47	33.6
AI risk alerts / monitoring	44	31.4
Predictive / algorithmic trading	39	27.9

5.2 Reliability and Descriptive Statistics

All Cronbach's alpha values in Table IV exceed 0.70 (range 0.74–0.81), confirming acceptable internal consistency. Mean scores lie close to 3.3 on the five-point scale, which indicates moderate AI adoption, trust and

oversight, and moderately positive outcomes. Standard deviations of 0.79–0.85 show reasonable variation among respondents.

TABLE IV
DESCRIPTIVE STATISTICS AND RELIABILITY

Construct	Mean	SD	Alpha
AI usage intensity (AIU)	3.29	0.85	0.80
Perceived usefulness (PU)	3.29	0.83	0.81
Trust in AI (TR)	3.33	0.79	0.76
Human oversight (HO)	3.33	0.80	0.78
Decision quality (DQ)	3.30	0.83	0.81
Risk-mgmt. effectiveness (RM)	3.31	0.79	0.74

5.3 Correlation Analysis

Table V reports Pearson correlations. AIU is strongly related to DQ ($r = 0.54$) and moderately to RM ($r = 0.49$). PU and TR are positively related to both outcomes, and DQ is correlated with RM ($r = 0.53$). HO shows smaller but significant correlations with DQ (0.25) and RM (0.30). HO is largely unrelated to TR and PU, meaning that investors who oversee AI are not necessarily those who trust it more; oversight appears to be a separate behavioural practice.

TABLE V
PEARSON CORRELATION MATRIX

	AIU	PU	TR	HO	DQ	RM
AIU	1					
PU	0.51	1				
TR	0.27	0.48	1			
HO	0.17	0.10*	0.00*	1		
DQ	0.54	0.50	0.38	0.25	1	
RM	0.49	0.45	0.38	0.30	0.53	1

Note: All coefficients are significant at $p < 0.01$ except those marked * (not significant).

5.4 Regression Analysis: Determinants of Decision Quality

Table VI shows that the model is significant ($F = 42.97$, $p < 0.001$) and explains 41.2% of the variance in DQ (adjusted $R^2 = 0.403$). All four predictors are positive and significant. AIU has the largest coefficient ($\beta = 0.346$), followed by PU (0.215), TR (0.192) and HO

(0.177). The maximum VIF was 1.63, so multicollinearity is not a concern. Hypotheses H1, H2, H3 (for DQ) and H4 (for DQ) are therefore supported.

TABLE VI
REGRESSION RESULTS: DEPENDENT VARIABLE DQ

Predictor	B	SE	t	p
Constant	0.231	0.262	0.88	0.378
AIU	0.346	0.056	6.18	<0.001
PU	0.215	0.062	3.44	<0.001
TR	0.192	0.059	3.27	0.001
HO	0.177	0.052	3.41	<0.001

$R^2 = 0.412$; Adj. $R^2 = 0.403$; $F = 42.97$ ($p < 0.001$).

5.5 Regression Analysis: Determinants of Risk-Management Effectiveness

The second model (Table VII) explains 40.5% of the variance in RM ($F = 41.66$, $p < 0.001$). AIU, TR, HO and DQ are all significant positive predictors. Human oversight (0.195) and trust (0.219) contribute almost as much as AI usage (0.244), and better decision quality feeds directly into stronger risk control (0.241). The maximum VIF was 1.62. H3 and H4 are thus supported for RM as well. The findings indicate that risk management benefits from AI when investors trust the tools sufficiently to act on them and, at the same time, actively supervise their output.

TABLE VII
REGRESSION RESULTS: DEPENDENT VARIABLE RM

Predictor	B	SE	t	p
Constant	0.334	0.250	1.33	0.184
AIU	0.244	0.055	4.45	<0.001
TR	0.219	0.054	4.05	<0.001
HO	0.195	0.051	3.82	<0.001
DQ	0.241	0.060	4.02	<0.001

$R^2 = 0.405$; Adj. $R^2 = 0.395$; $F = 41.66$ ($p < 0.001$).

5.6 AI-Assisted versus Non-AI Investors
Welch's t-test (Table VIII) shows that AI-assisted investors ($n = 140$) report higher decision quality (3.47 vs. 3.08) and higher risk-management effectiveness (3.50 vs. 3.06) than non-AI investors ($n = 110$). Both differences are statistically significant at the 1% level and represent moderate effects of

roughly 0.4 to 0.5 standard deviations. H5 is supported.

TABLE VIII
INDEPENDENT-SAMPLES T-TEST

Variable	AI mean	Non-AI mean	t	p
DQ	3.47	3.08	3.79	<0.001
RM	3.50	3.06	4.60	<0.001

5.7 Differences across Investor Categories

Table IX reports one-way ANOVA results. Retail investors reported slightly higher mean scores than HNI/advisor and institutional investors, but none of the differences is significant (DQ: $F = 0.07$, $p = 0.932$; RM: $F = 1.62$, $p = 0.201$). Benefits attributed to AI therefore appear to be shared across investor types rather than confined to professionals.

TABLE IX
ONE-WAY ANOVA BY INVESTOR CATEGORY

Var.	Retail	HNI	Inst.	F	p
DQ	3.32	3.28	3.28	0.07	0.932
RM	3.38	3.25	3.17	1.62	0.201

5.8 Human-AI Collaboration Configurations

Respondents were split at the median of AIU and HO to form four groups. As Table X and Fig. 1 show, the group with high AI usage and high human oversight recorded the highest DQ (3.78) and RM (3.78), whereas the group with low AI usage and low oversight recorded the lowest (2.81 and 2.84). High AI usage without oversight (3.40 and 3.41) outperformed high oversight without AI (3.03 and 3.01), but fell short of the combined group by about 0.37 points on both outcomes. H6 is therefore supported: oversight adds value on top of AI, and AI adds value on top of oversight.

TABLE X
OUTCOMES BY COLLABORATION CONFIGURATION

Group	n	DQ	RM
High AI + High oversight	75	3.78	3.78
High AI + Low oversight	63	3.40	3.41
Low AI + High oversight	63	3.03	3.01
Low AI + Low oversight	49	2.81	2.84

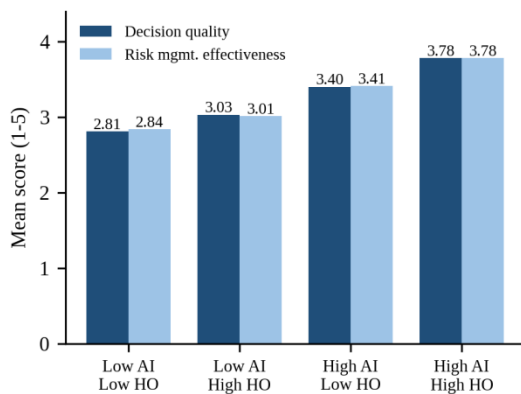


Fig. 1. Mean DQ and RM by collaboration configuration (HO = human oversight).

TABLE XI
SUMMARY OF HYPOTHESIS TESTING

Hypothesis	Result
H1: AIU → DQ	Supported
H2: PU → DQ	Supported
H3: TR → DQ, RM	Supported
H4: HO → DQ, RM	Supported
H5: AI vs. non-AI	Supported
H6: High AI + high HO best	Supported

5.9 Discussion

The results are consistent with the view that AI lowers the cost of prediction [16] and that its value is realised when combined with human judgement [17]. The strong effect of AI usage on decision quality accords with evidence that machine-learning methods extract information that conventional approaches miss [6] and that automated advice can improve the discipline of individual investors [7]. The significant role of perceived usefulness supports technology-acceptance theory [10], [11]: investors who see practical value in AI use it more and, in turn, report better decisions.

The independent contribution of human oversight is the most policy-relevant result. If trust alone drove outcomes, higher trust would substitute for supervision. Instead, oversight remained significant after controlling for trust, and it was almost uncorrelated with trust. This

pattern matches the argument that reliance should be calibrated [12] and the evidence that unsupervised reliance on automation invites complacency [15]. It also suggests that the algorithm aversion documented in laboratory settings [13] may be less damaging in practice when investors treat AI as an aid to be checked rather than as an authority to be obeyed or rejected. The finding that outcomes do not differ across investor categories is encouraging, since it implies that retail investors can gain from AI in a way comparable to professionals.

6. FINDINGS AND SUGGESTIONS

6.1 Findings

Besides the inferential tests, respondents were asked to identify the main benefit of AI and their preferred decision model. Fig. 2 shows that faster analysis (32.0%) and better risk detection (27.2%) are cited most often, together accounting for nearly three-fifths of responses, while reduced emotional bias (14.8%), portfolio diversification (14.4%) and cost efficiency (11.6%) follow.

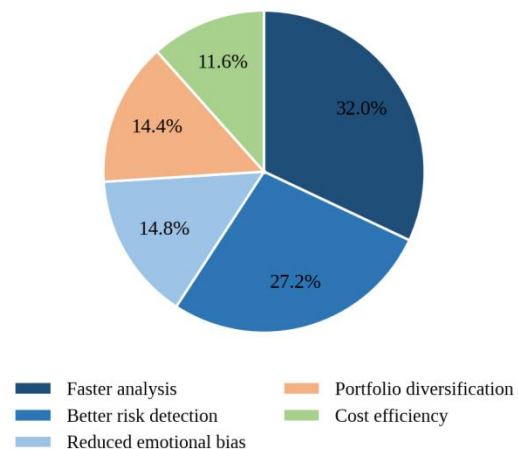


Fig. 2. Main perceived benefit of AI in investment decisions (N = 250).

Fig. 3 shows the preferred model of decision-making. A clear majority (64.0%) prefer human-AI collaboration, 25.6% prefer human-only decisions and only 10.4% prefer AI-only advice. Full delegation to machines

therefore has little support, even among frequent AI users.

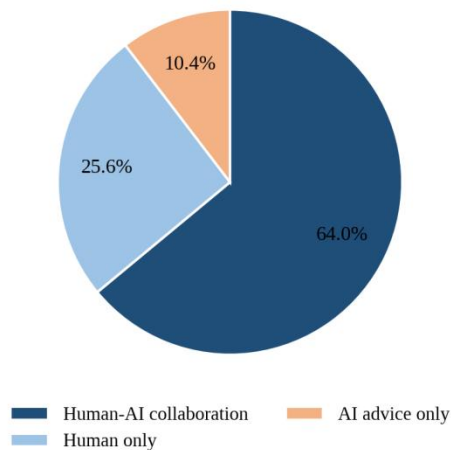


Fig. 3. Preferred model of financial decision-making (N = 250).

The major findings of the study are summarised below:

1. AI usage intensity is the strongest single predictor of decision quality ($B = 0.346$) and a significant predictor of risk-management effectiveness ($B = 0.244$).
2. Perceived usefulness and trust significantly improve outcomes, but oversight retains an independent positive effect, showing that trust alone is not sufficient.
3. AI-assisted investors outperform non-AI investors by 0.39 points on DQ and 0.44 points on RM on the five-point scale.
4. The combination of high AI usage and high human oversight yields the best outcomes (3.78 on both measures).
5. Outcomes do not differ significantly across retail, HNI and institutional investors, suggesting that AI tools can narrow the information gap faced by retail investors.
6. Sixty-four per cent of respondents prefer a collaborative model, and speed of analysis and risk detection are the most valued benefits.

6.2 Suggestions

For investors:

- Use AI tools as decision-support, not decision-substitute; verify recommendations against fundamentals and personal risk tolerance.
- Build financial and AI literacy, including awareness of model limitations, data bias and overfitting.
- Maintain a documented review step (a checklist or stop-loss rule) before executing AI-generated trades.

For financial institutions and platforms:

- Design human-in-the-loop workflows in which advisers can review, override and record decisions.
- Provide explainable outputs, confidence levels and back-tested performance so that trust is calibrated rather than blind.
- Monitor models continuously for drift, and stress-test them under extreme market conditions.

For regulators and policymakers:

- Require disclosure when AI is used in advice, along with accountability rules that keep a responsible human or firm identifiable.
- Promote investor-education programmes on AI-enabled investing, especially for first-time and retail investors.
- Track concentration and third-party dependency risks arising from widespread use of similar models [9].

6.3 Limitations and Future Research

The study relies on self-reported perceptions and a cross-sectional sample from one region, so causal inference and generalisation are limited. Future work could use longitudinal or experimental designs, actual portfolio returns and risk-adjusted metrics, structural equation modelling of mediation, and comparisons across states and countries.

6.4 Implications

Theoretically, the study extends technology-acceptance models by showing that acceptance-related constructs (usefulness and

trust) explain adoption and outcomes only partly; a behavioural construct, oversight, adds explanatory power and should be included in models of AI-assisted financial decisions. Practically, the findings imply that training programmes and platform design should target not only the adoption of AI but also the habit of critical review. For advisory firms, positioning AI as an augmentation of the adviser, rather than a replacement, is consistent with client preferences revealed in this survey.

7. CONCLUSION

This study examined how human–AI collaboration shapes investment decision quality and risk-management effectiveness among 250 investors in Telangana. The evidence shows that AI usage, perceived usefulness, trust and human oversight together explain about 40% of the variation in both outcomes, that AI-assisted investors report significantly better results than non-AI investors, and that the best results occur where extensive AI use is matched by active human oversight. Most investors also prefer collaboration to either full automation or purely human decisions.

The central implication is that the value of AI in finance depends less on the sophistication of the algorithm than on how it is embedded in human decision processes. Institutions should design for calibrated trust and meaningful oversight; investors should treat AI as a capable but fallible partner; and regulators should safeguard transparency and accountability. As AI adoption deepens in India's capital markets, a collaborative rather than a substitutive approach offers the most reliable path to better returns and better-managed risk.

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