

Research Article

Impact of AI-Based Financial Advice on Investment Preferences and Risk Perception among Salaried Investors

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Abstract: Artificial Intelligence (AI) is increasingly used to deliver financial information, investment recommendations and portfolio decision support. This study examines the proposed impact of AI-based financial advice on investment preferences and risk perception among salaried investors. The framework treats perceived usefulness, perceived accuracy, trust, personalisation and transparency as dimensions of AI-based financial advice and tests their proposed relationships with investment preference and risk perception. A quantitative cross-sectional design using a structured five-point Likert questionnaire is proposed. For demonstration of the intended empirical reporting format, a synthetic dataset of 450 hypothetical salaried investors was generated and analysed using internal-consistency assessment and regression-style structural estimates. The simulated results indicate positive associations between the five AI-advice attributes and investment preference and negative associations with risk perception. These numerical findings are illustrative only and must not be represented as observations from real respondents. The study contributes a focused framework for future primary research on AI-assisted investment decision-making among salaried investors.

Keywords: Artificial Intelligence, AI-Based Financial Advice, Investment Preferences, Risk Perception, Salaried Investors, Robo-Advisory, Investor Behaviour, Fintech

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INTRODUCTION

AI-enabled financial advice is becoming an important part of the digital transformation of financial services. Automated and intelligent systems can process large quantities of information, generate recommendations and personalise financial decision support. The research literature increasingly treats robo-advisory and AI-enabled financial advisory services as a distinct domain of financial-service interaction. Zhu *et al.* [1], identify AI-enabled financial advisory services as an emerging interdisciplinary research area, while Northey *et al.* [2], directly examine how artificial intelligence in banking influences consumer belief in financial advice.

The behavioural consequences of AI-based advice are not necessarily unidirectional. Investors may value speed, data-processing capacity, consistency and personalisation while simultaneously worrying about algorithmic error, opacity, privacy and financial loss. Silber *et al.* [3], found that perceived algorithm effectiveness and algorithm aversion were relevant to willingness to use AI advisors for complex financial decisions. Recent research on robo-advisory continues to examine trust, adoption, risk and resistance.

This study focuses on salaried investors because regular employment income provides a common basis for saving and investment while investors still differ in experience, education, income, technology familiarity and risk tolerance. The research question is whether perceived characteristics of AI-based financial advice are associated with investment preference and risk perception among this population.

Literature Review

AI-Based Financial Advice: AI-based financial advice is defined as investment-related information, recommendations or decision support produced or materially supported by AI or algorithmic systems. The category includes robo- advisory

services and newer conversational or generative-AI interfaces. Khanna and Jha [4], discuss robo-advisory as an AI-based digital financial product capable of providing customised solutions for investment, saving and retirement-related decisions. Zhu *et al.* [1], identify AI-enabled financial advisory services as a developing field requiring stronger theoretical and empirical foundations.

Perceived Usefulness and Accuracy

Perceived usefulness captures the degree to which investors believe AI advice improves their investment decision process. Perceived accuracy captures confidence that the system can process information and produce sufficiently precise recommendations. These constructs follow the logic of technology acceptance and algorithm evaluation [5,6].

Trust and Transparency

Trust is important in financial services because recommendations can influence decisions involving real monetary consequences. Northey *et al.* [2], demonstrate the relevance of AI-related beliefs in financial advice. Transparency is also important because investors may want to understand why an AI system recommends a particular investment. Zhu *et al.* [1], emphasise the need to understand technological characteristics and customer interaction in AI-enabled financial advisory services.

Personalisation

Personalisation refers to the perceived ability of AI advice to reflect an investor's goals, financial circumstances and preferences. AI systems can potentially process individual-level information quickly and provide tailored recommendations, but personalisation alone may not create trust if investors lack transparency or assurances about data use.

Recent evidence also supports the relevance of financial literacy and trust in robo-advisory. An Indian study published in IIMB Management Review examined robo-advisor adoption using 445 investors and PLS-SEM, including trust, anxiety, performance expectancy and preference for human advisors. Recent international research similarly examines financial literacy, trust and risk in robo-advisory contexts. These findings support extending the present model beyond simple technology acceptance toward investor capability and perceived risk.

Zhu, Vigren and Söderberg [1], reviewed 132 articles on AI-empowered financial advisory services and identified fragmentation across technology, finance and behavioural research. Wagner [7], also reviewed research on conventional and digital investment advisory decisions. Together, these reviews indicate a need for integrated models that connect technology perceptions with investor-level outcomes.

Investment Preference and Risk Perception

Investment preference represents the inclination to consider or use AI-assisted advice when making investment decisions. Risk perception represents the investor's subjective assessment of uncertainty, possible financial loss and technology-related decision risk. These are distinct outcomes: an investor may prefer AI assistance because of convenience while still perceiving substantial risk.

Research Gap

Prior studies have examined AI advisors, robo-advisory adoption, algorithm aversion and trust, but the literature remains fragmented across technology acceptance, financial services and behavioural finance. Northey *et al.* [2], examine consumer belief in AI versus human financial advice; Silber *et al.* [3], investigate AI advisors in complex financial decisions; and Zhu *et al.* [1], identify broader research opportunities in AI-enabled financial advisory services. The present study narrows the empirical focus to salaried investors and jointly considers investment preference and risk perception as behavioural outcomes. Indian evidence is still comparatively limited and the role of financial literacy as a boundary condition for AI-assisted investment decisions deserves further examination. Accordingly, the present study extends the literature by examining financial literacy as a moderator while controlling for relevant demographic and investment-experience characteristics.

Objectives

- To examine the relationship between perceived usefulness of AI-based financial advice and investment preference
- To examine the relationship between perceived accuracy of AI-based financial advice and investment preference
- To examine the relationship between trust in AI-based financial advice and investment preference
- To examine the relationship between personalisation and investment preference
- To examine the relationship between transparency and investment preference
- To examine the relationships between these five AI-advice attributes and risk perception among salaried investors

Hypotheses

- **H1:** Perceived usefulness positively influences investment preference
- **H2:** Perceived accuracy positively influences investment preference
- **H3:** Trust positively influences investment preference
- **H4:** Personalisation positively influences investment preference
- **H5:** Transparency positively influences investment preference
- **H6:** Perceived usefulness negatively influences risk perception
- **H7:** Perceived accuracy negatively influences risk perception
- **H8:** Trust negatively influences risk perception
- **H9:** Personalisation negatively influences risk perception
- **H10:** Transparency negatively influences risk perception
- **H12:** Financial literacy moderates the relationships between AI-based financial advice attributes and risk perception
- **H11:** Financial literacy moderates the relationships between AI-based financial advice attributes and investment preference

MATERIALS AND METHODS

Research Design

The intended empirical study is a quantitative, cross-sectional survey of salaried investors. A five-point Likert scale is proposed. Eligible respondents should be salaried individuals with investment experience or active investment consideration and at least basic awareness of AI-based financial advice.

Instrument

The instrument contains seven constructs:

- Perceived Usefulness (PU)
- Perceived Accuracy (PA)
- Trust (TR)
- Personalisation (PE)
- Transparency (TP)
- Investment Preference (IP)
- Risk Perception (RP)

Each construct is represented by four items. Items should be pilot tested before actual data collection.

Financial literacy is added as a four-item moderator measuring confidence in understanding interest, inflation, diversification, investment risk and financial products. Age, gender, education, monthly income and investment experience are included as control variables. The final questionnaire should be pilot tested for wording, reliability and content validity.

Simulated-Data Protocol

For this revised manuscript only, a synthetic dataset of $N = 450$ hypothetical respondents was generated to demonstrate the intended empirical reporting format. The synthetic observations were generated from correlated latent constructs and four-item Likert scales. No real respondent data were used. These results must therefore be replaced by genuine survey results before an empirical submission.

Analysis

The demonstration reports internal consistency and structural estimates. An actual PLS-SEM study should additionally report outer loadings, composite reliability, AVE, HTMT, VIF, bootstrapped confidence intervals, R^2 and f^2 using appropriate software. The numerical demonstration is not a substitute for actual empirical analysis.

For the extended model, moderation should be tested using interaction terms between financial literacy and each AI-advice construct. The final empirical analysis should report bootstrapped interaction coefficients, confidence intervals, effect sizes and conditional effects. Recommended robustness checks include common-method-bias assessment, HTMT, VIF, Q^2 , f^2 and predictive assessment such as PLS predict.

RESULTS

The Tables 1-5 are explicitly labelled SIMULATED and illustrate the presentation required after genuine data collection.

The simulated reliability values are intended to illustrate acceptable internal consistency and convergent validity. They are not empirical estimates.

Table 1: Simulated Respondent Profile

Category	Frequency	Percentage
Age 21-30	154	34.2
Age 31-40	148	32.9
Age 41-50	109	24.2
Age 51-60	39	8.7
Male	256	56.9
Female	183	40.7
Other/Prefer not to say	11	2.4
Graduate	212	47.1
Postgraduate	175	38.9
Professional/Other	63	14.0

Table 2: Simulated Measurement Statistics

Construct	Indicative loadings	Cronbach α	CR	AVE
PU	0.79, 0.82, 0.86, 0.84	0.874	0.897	0.685
PA	0.81, 0.84, 0.88, 0.85	0.882	0.909	0.715
TR	0.83, 0.86, 0.89, 0.87	0.871	0.921	0.744
PE	0.78, 0.82, 0.85, 0.83	0.888	0.892	0.673
TP	0.80, 0.84, 0.86, 0.82	0.883	0.899	0.689
IP	0.86, 0.88, 0.90, 0.87	0.901	0.931	0.770
RP	0.84, 0.87, 0.89, 0.86	0.915	0.922	0.749

Table 3: Simulated Descriptive Statistics

Construct	Mean	SD	Min	Max
PU	3.00	0.87	1	5
PA	3.00	0.88	1	5
TR	2.99	0.85	1	5
PE	3.01	0.88	1	5
TP	3.01	0.86	1	5
IP	2.99	0.88	1	5
RP	3.00	0.90	1	5

Table 4: Simulated Structural Paths

Path	β	SE	t	p
PU $\rightarrow$ IP	0.119	0.042	2.79	0.005
PA $\rightarrow$ IP	0.228	0.038	5.92	0.000
TR $\rightarrow$ IP	0.387	0.041	9.35	0.000
PE $\rightarrow$ IP	0.109	0.039	2.80	0.005
TP $\rightarrow$ IP	0.156	0.037	4.18	0.000
PU $\rightarrow$ RP	-0.064	0.058	-1.10	0.271
PA $\rightarrow$ RP	-0.203	0.053	-3.85	0.000
TR $\rightarrow$ RP	-0.212	0.057	-3.75	0.000
PE $\rightarrow$ RP	-0.068	0.053	-1.28	0.202
TP $\rightarrow$ RP	-0.096	0.051	-1.88	0.061

Simulated R^2 : Investment Preference = 0.564, Risk Perception = 0.223

Table 5: Simulated Hypothesis Decisions

Hypothesis	Path	p-value	Simulated decision
H1	PU $\rightarrow$ IP	0.005	Supported
H2	PA $\rightarrow$ IP	0.000	Supported
H3	TR $\rightarrow$ IP	0.000	Supported
H4	PE $\rightarrow$ IP	0.005	Supported
H5	TP $\rightarrow$ IP	0.000	Supported
H6	PU $\rightarrow$ RP	0.271	Not supported
H7	PA $\rightarrow$ RP	0.000	Supported
H8	TR $\rightarrow$ RP	0.000	Supported
H9	PE $\rightarrow$ RP	0.202	Not supported
H10	TP $\rightarrow$ RP	0.061	Not supported

Because the present synthetic dataset was originally generated before the moderator was added, the financial-literacy moderation statistics are not reported as empirical results in this version. In the final empirical study, the moderator and interaction terms must be generated from the actual questionnaire responses and analysed before H11 and H12 are concluded.

The simulated coefficients are directionally aligned with the proposed hypotheses. Because the observations are synthetic, the p-values and significance statements must not be presented as findings from real investors.

DISCUSSION

The simulated pattern illustrates how favourable evaluations of AI-based financial advice could be associated with stronger investment preference among salaried investors. Positive coefficients for usefulness, accuracy, trust, personalisation and transparency indicate that investors may be more willing to consider AI-assisted investment decisions when they perceive the system as valuable and credible. This is consistent with the broader literature on AI advisors, including the evidence that perceived algorithm effectiveness and algorithm aversion influence willingness to use AI advisors [3].

The simulated negative relationships with risk perception illustrate a possible behavioural mechanism: investors who perceive AI advice as useful, accurate and trustworthy may perceive less uncertainty in AI-assisted decisions. This does not mean that AI objectively reduces financial risk; it only illustrates a hypothesised relationship in investor perception.

Transparency is especially relevant because investors may resist recommendations they cannot understand. Financial advice involves high-stakes decisions, so providers should not assume that technological sophistication alone creates acceptance. The broader financial-advisory literature similarly calls for research into customer interaction and the implementation of AI-enabled advisory services [1].

The financial-literacy extension is theoretically important because investors may differ in their ability to interpret AI-generated recommendations, evaluate uncertainty and distinguish advice from guaranteed returns. Recent robo-advisory research has explicitly examined financial literacy alongside demand for human advice, suggesting that investor capability should not be treated as uniform across users [8]. The proposed moderation therefore provides a basis for testing whether the same AI-advice characteristic has different behavioural implications for investors with different levels of financial literacy.

Theoretical Implications

The framework connects technology acceptance with behavioural investment research by treating AI advice as more than a generic technology. Usefulness and accuracy represent functional evaluation, while trust, personalisation and transparency capture relational and interpretive aspects of AI-assisted financial decision-making. Separating investment preference from risk perception provides a more nuanced model than relying on a single adoption-intention outcome.

The extended model combines technology-acceptance logic with behavioural-finance and investor-capability perspectives. Usefulness and accuracy represent functional evaluations; trust and transparency represent confidence and explainability; personalisation represents individual fit; and financial literacy represents an investor-level capability that may condition these relationships.

Managerial Implications

Financial institutions and fintech providers should communicate how AI-generated recommendations are produced, provide understandable explanations and allow users to review recommendations against their financial goals and risk tolerance. Providers should distinguish decision support from guaranteed outcomes and maintain appropriate human oversight for complex or high-stakes financial decisions.

Providers should also design explanations for investors with different levels of financial knowledge. Educational prompts, risk explanations and plain-language disclosures may be particularly relevant where users have limited familiarity with investment products or algorithmic recommendations.

Limitations and Future Research

The principal limitation of this revised manuscript is that all numerical results are simulated. They demonstrate the intended statistical presentation but do not constitute empirical evidence. The final research must collect genuine responses and rerun every analysis. Further research could use longitudinal data, experiments comparing human and AI advice, actual investment behaviour, financial literacy as a moderator and cross-country samples. The moderator hypotheses should be treated as proposed relationships until the financial-literacy items are collected and tested with genuine observations.

CONCLUSION

AI-based financial advice is becoming an important component of digital financial services. This paper develops a focused framework for examining how usefulness, accuracy, trust, personalisation and transparency relate to investment preferences and risk perception among salaried investors. The simulated analysis demonstrates how the

empirical paper can be presented after data collection. The numerical results must be replaced with genuine observations before they are used as evidence in a journal submission. The inclusion of financial literacy and relevant controls provides a more nuanced framework for understanding heterogeneity among salaried investors.

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