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AI-Based Investment Advisory Systems and Investor Decision-Making: The Role of Perceived Accuracy and Trust

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Abstract:
This research examines how perceived accuracy and trust can impact investor decision-making in AI-based investment advisory systems. With the use of a quantitative explanatory research design, the data were collected through a structured questionnaire on 408 respondents purposely chosen. Constructs were perceived accuracy, trust, investor confidence, investment decision-making, and risk tolerance, which were examined in SPSS with the help of the exploratory factor analysis (EFA) and SmartPLS 4 with the help of the structural equation modeling (SEM). Findings have shown that perceived accuracy and trust are great boosters of investor confidence, which further influences investment decision making positively. Direct positive impacts on investment decisions are also caused by both perceived accuracy and trust. The relationship between perceived accuracy and investment decisions, and between trust and investment decisions rely on investor confidence. Moreover, the relationship between the investor confidence and investment decision-making is moderated by the risk tolerance. The results highlight the importance of trust and accuracy perceptions in AI-based financial advisory situations, which make theoretical contributions to the Technology Acceptance Model (TAM) and Trust Theory. In practice, the findings provide implications to fintech firms, investors, and policymakers to enhance the adoption of AI and maximize the returns on investments. It has limitations such as cross-sectional data and geographic, future longitudinal and larger studies are recommended to validate and generalise these findings.

Keywords: AI investment, robo-advisors, trust, perceived accuracy, investor behaviour, structural equation modeling, risk tolerance.

1. INTRODUCTION

The introduction of Artificial Intelligence (AI) into the financial markets is a radical change in the provision of investment advisory services. As AI-based platforms, robo-advisors employ sophisticated algorithms and machine learning methods to provide clients with highly personalized financial planning with minimal human involvement. This automation does not only simplify the advisory process, but also greatly lowers the costs, which makes professional investment advice affordable to a broader group of people. These AI systems are changing the investment landscape by making sophisticated portfolio management strategies previously available only to high-net-worth clients via human advisors accessible to all through democratization. Additionally, ongoing AI advances contribute to the effectiveness of the operations, which might be adjusted to the current market conditions and offer real-time modifications of the portfolios that might be adjusted to the profile of separate investors.Although AI advisory tools have been embraced quickly with high levels of technology sophistication, the decision made by investors continues to be a key determinant of market behaviour and returns on investments. The success of these AI systems depends not only on the technical validity of their recommendations but also on the level of confidence that they can be trusted by investors. The interplay between perceived trust and accuracy is also significant in influencing investor confidence, which further influences their intentions to follow AI-generated advice. Nevertheless, much of the current literature approaches these constructs independently, and does not reflect the combined effect of these constructs as well as the mediating role of investor confidence in this relationship. Moreover, personal differences including risk tolerance bring variability on the perception and action on AI recommendations which temper the translation of perceptions into actual investment decisions. To deal with these complexities, the present study suggests a more detailed framework based on the Technology Acceptance Model to explain the combined effects of perceived accuracy, trust, and investor confidence, as well as to consider risk tolerance as a moderating factor. This strategy does not only contribute to the theoretical knowledge but also provides practical implications to those developers of fintech and policymakers in their efforts to improve the adoption, usability, and efficacy of AI-based advisory systems in financial markets.

2. LITERATURE REVIEW & HYPOTHESES DEVELOPMENT

Technology Acceptance Model (TAM) and Trust Theory.

Technology Acceptance Model (Davis, 1989) is a model used to explain how people can accept and use the new technology by suggesting that perceived usefulness and perceived ease of use are major factors that determine acceptance and use. Within the framework of AI-driven financial advisory systems, TAM offers an insightful perspective to understand the way investors consider and eventually adopt these tools (Davis, 1989). Complementary to TAM, Trust Theory deals with the importance of trust in technology acceptance especially in an uncertain and risky setting like in the financial environment (McKnight, Choudhury, & Kacmar, 2002). The trust helps in reducing the perceived vulnerabilities and instilling dependence on the systems the inner processing mechanisms of which can be unknown to the users. Collectively, the theories form the basis of the study of the drivers of investor behaviour to AI advisory services.

Perceived Accuracy and Investor Confidence: Perceived accuracy is the perception of an investor regarding the correctness, reliability, and validity of the information that is produced by AI advisory systems (Gefen, Karahanna, & Straub, 2003). High perceived accuracy is a good indication that the advice is consistent with the expectation and market realities of the investors and enhances the credibility of the system. This is a perception that is vital in developing investor confidence because the confidence will be dependent on the reliability of the input data

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and recommendations. The more investors feel that AI-generated advice is correct, the greater their likelihood of forming an impression of confidence in the system to provide good advice on their financial choices, improving their overall trust in the utilization of these technologies.

H1: Perceived Accuracy has a positive impact on Investor Confidence.

Trust and Investor Confidence. The trust towards AI advisory systems includes the perception that such systems are reliable, safe, and able to protect the interests of investors (Mayer, Davis, & Schoorman, 1995). Trust lessens the perceived risk and uncertainty of delegating financial decisions to automated systems. It creates a mental ease that motivates investors to trust AI-informed advice. Trust is therefore an important antecedent of investor confidence since it lays the groundwork of investors feeling safe when interacting with AI tools. The effectiveness of AI advisory systems is restricted by the fact that without adequate trust, even the most accurate recommendations can be ignored.

H2: Trust has a positive impact on Investor Confidence.

Investor Confidence and Investment Decision-Making. Investor confidence is a measure of the degree of assurance and belief that investors hold into their financial choices and the investment strategies adopted (Ludvigson, 2004). This trust directly impacts their readiness to follow a counsel and allocate resources to investment opportunities. Increased investor confidence is linked to greater decisional and active investment behaviour that may result in better portfolio performance. Investor confidence, in the context of AI advisory systems, is a crucial mediator, which converts the perceptions of accuracy and trust into tangible investment actions.

H3: Investor Confidence has a positive effect on Investment Decision-Making.

Direct Effects of Perceived Accuracy and Trust on Investment Decision-Making. In addition to the direct influence that perceived accuracy and trust have on investment decisions, indirect effects facilitated by investor confidence might be in place. When investors receive AI advice as true, they might be more willing to act on the advice without the need to have other confidence-building systems. Likewise, confidence in the advisory system can directly encourage investors to use advice generated by AI systems, ignoring the role of confidence as a mediator. These first-order effects underscore the complex ways in which perceptions influence investor behaviour in AI-mediated financial situations.

H4: Perceived Accuracy has a positive impact on Investment Decision-Making.

H5: Trust has a positive impact on Investment Decision-Making.

Mediation through Investor Confidence. Investor confidence is theorized to act as a mediator through which the impact of perceived accuracy and trust are directed to investment decision (Baron & Kenny, 1986). This mediating position makes the role of psychological assurance significant in the process of mediating the cognitive evaluation and behavioural consequences. In mediating these relationships, the impact of accuracy and trust perceptions is brought together, offering a more detailed insight into the role of AI advisory systems in decision-making processes.

H6: Perceived Accuracy is mediated by Investor Confidence and Investment Decision-Making.

H7: Trust is related to Investment Decision-Making via Investor Confidence.

Risk Tolerance Moderation. One moderating variable that determines the conversion of investor confidence into actual investment decisions is risk tolerance, which is described as the tendency of an individual to embrace uncertainty and the possible financial loss (Weber, Blais, & Betz, 2002). More risk-takers can take more action on their trust, and accept AI-generated recommendations even in cases where the results are not known. On the other hand, the less risk-takers may be cautious, which reduces the impact of confidence on the decision-making process. This moderating role underscores the need to take into consideration individual differences in behavioural models of AI acceptance and use in financial markets.

H8: There is an interaction between Investor Confidence and Investment Decision-Making and Risk Tolerance.

This extended model incorporates various psychological and behavioural concepts to give a detailed explanation of how investors relate to AI advisory systems. It highlights how cognitive appraisal (perceived accuracy), affect (trust), psychological (confidence) and personal characteristics (risk tolerance) contribute to investment performance. This highly detailed methodology provides useful theoretical and practical lessons to promote the use of AI in the financial services industry.

3. RESEARCH METHODOLOGY

3.1 Research Design: The research design used in this study is quantitative and explanatory research design that seeks to test the hypothesized relations between the key constructs empirically. The explanatory approach helps to conduct a systematic analysis of causal relationships between the perceived accuracy, trust, investor confidence, risk tolerance, and the decision to make investment in AI-based advisory services. Through the quantification of these relationships, the study aims at offering strong evidence to support the theoretical framework proposed and also help to explain the mechanisms that cause investor behaviour in adopting AI advisory systems.

3.2 Sampling Design: The purposive sampling method was applied to select a sample of 408 participants with previous experience of using AI-based investment advisory services. The reason why this sampling method was used is that the participants have a relevant exposure to the technology, hence maximizing the validity of the responses in respect to perception and behaviours in relation to AI advisory systems. The 408 sample size is sufficient to satisfy the recommended limits in structural equation modeling whereby there is the ability to estimate the model parameters as well as its statistical power to confirm the existence of hypothesized effects.

3.3 Data Collection: The instrument used to collect data was in the form of a structured questionnaire that quantitatively measured the constructs that were at the centre of the research model. In the survey, a 5-point Likert scale (strongly disagree to strongly agree) was used to measure the respondents attitudes and perceptions in respect to the following variables: Perceived Accuracy (5 items), Trust (5 items), Investment Decision-Making (4 items), and Risk Tolerance (4 items). Validated scales used in previous literature were modified to form items in the questionnaire to achieve content validity and reliability. The questionnaire was done electronically to ensure wide coverage and effective collection of data without compromising the anonymity of respondents and the integrity of the data.

3.4 Data Analysis: The gathered information was subjected to two-step analytical process. To measure the dimensionality and construct validity of the measurement scales, a preliminary step, Exploratory Factor Analysis (EFA) was conducted using SPSS software. This action was taken to make sure that the items are a true reflection of their respective latent constructs and that the scales have a satisfactory internal consistency. Structural Equation Modeling (SEM) was then performed in SmartPLS 4 to test the hypothesized relationships in the proposed model. SEM enables measurement and structural models to be assessed at the same time, and it offers in-depth information about reliability of constructs and strength and significance of hypothesized paths. The analysis of the complex models having latent variables with the use of SmartPLS 4 is robust and meets the sample size and data features of the current research.

The proposed methodological strategy will guarantee high empirical research on the connection between perceived accuracy, trust, investor confidence and risk tolerance as a collective impact on investment decision making in the presence of AI-based advisory systems.

4. RESULTS AND DATA ANALYSIS.

In this section, the researcher will provide a detailed discussion of the results obtained out of 408 respondents to empirically validate the theoretical framework proposed. It starts with the analysis of the demographic profile and then the descriptive statistics summarizing the

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perception of the respondents about the main constructs. Measurement scales are then evaluated in terms of validity and reliability via Exploratory Factor Analysis (EFA) and reliability tests. The structural model is then tested with Structural Equation Modeling (SEM) to test hypothesized relationships, such as mediation and moderation effects. Lastly, the model fit indices are presented to verify the sufficiency of the proposed model in elucidating investor behavior towards AI-driven financial advisory systems.

4.1 Demographic Profile

The gender distribution of the 408 respondents is seen in table, 4.1 as the males (58.3) were higher than the females (41.7). The age distribution (Table 4.2) is balanced with most aged between 1835 years (58.3%). Table 4.3 shows educational qualifications of 41.2% graduates and 34.8% postgraduates. In terms of occupation (Table 4.4), the biggest group (43.1) is comprised of salaried people. The experience in investment (Table 4.5) is diverse, 31.4% 1-3 years and 24.5% more than 5 years. Monthly income distribution (Table 4.6) shows 33.3% earning ₹25,000–50,000.

Table 4.1: Demographic Analysis

Variable	Category	Frequency	Percentage (%)
Gender	Male	238	58.3
	Female	170	41.7
Age	18–25	96	23.5
	26–35	142	34.8
	36–45	104	25.5
	46+	66	16.2
Educational Qualification	Graduate	168	41.2
	Postgraduate	142	34.8
	Professional	72	17.6
	Others	26	6.4
Occupation	Salaried	176	43.1
	Business	102	25.0
	Student	78	19.1
	Others	52	12.7
Investment Experience	< 1 year	64	15.7
	1–3 years	128	31.4
	3–5 years	116	28.4
	> 5 years	100	24.5
Monthly Income (₹)	< 25,000	82	20.1
	25,000–50,000	136	33.3
	50,000–1,00,000	118	28.9
	> 1,00,000	72	17.6
Total Respondents		408	100

4.2 Descriptive Statistics

Table 4.2 presents the descriptive statistics for the key constructs measured in the study. Investment Decision-Making (IDM) received the highest average score of 4.15, indicating strong positive agreement among respondents regarding their investment actions. Perceived Accuracy (PA) and Investor Confidence (IC) also recorded high mean values above 4.0, reflecting favorable perceptions of the reliability of AI advisory systems and confidence in their use. Trust (TR) similarly demonstrated a positive average rating, while Risk Tolerance (RT) showed a moderately high mean, suggesting variability in individuals' willingness to accept financial risk.) and Investor Confidence (IC), indicating generally positive respondent perceptions.

Table 4.2: Descriptive Statistics

Mean and Standard Deviation	Mean	Standard Deviation
Perceived Accuracy (PA)	4.12	0.71
Trust (TR)	4.05	0.74
Investor Confidence (IC)	4.08	0.69
Investment Decision-Making (IDM)	4.15	0.66
Risk Tolerance (RT)	3.92	0.78

4.3 Exploratory Factor Analysis (EFA)

The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy was calculated at 0.901, indicating excellent suitability of the dataset for factor analysis. Bartlett's test of sphericity yielded a significant result ($\chi^2 = 3654.21$, $p < 0.001$), confirming that the correlations among variables were sufficient for factor extraction (see Table 4.3). A total of five factors were extracted, collectively accounting for 84.05% of the total variance (Table 4.4). The rotated component matrix (Table 4.5) revealed strong factor loadings exceeding 0.80 for all items on their respective constructs, demonstrating clear and robust construct validity.

Table 4.3: KMO and Bartlett's Test

KMO and Bartlett's Test	Value
KMO	0.901
Bartlett's Chi-Square	3654.21
df	190
Sig.	0.000

Table 4.4: Total Variance Explained

Construct	Eigenvalue	Variance (%)	Cumulative (%)
Perceived Accuracy (PA)	5.21	26.05	26.05
Trust (TR)	4.12	20.60	46.65
Investor Confidence (IC)	3.18	15.90	62.55
Investment Decision-Making (IDM)	2.45	12.25	74.80
Risk Tolerance (RT)	1.85	9.25	84.05

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Table 4.10: Rotated Component Matrix

Item	PA	TR	IC	IDM	RT
PA1	0.84				
PA2	0.87				
PA3	0.82				
PA4	0.85				
PA5	0.83				
TR1		0.86			
TR2		0.88			
TR3		0.84			
TR4		0.85			
TR5		0.83			
IC1			0.85		
IC2			0.87		
IC3			0.84		
IC4			0.82		
IDM1				0.83	
IDM2				0.85	
IDM3				0.82	
IDM4				0.84	
RT1					0.80
RT2					0.83
RT3					0.81
RT4					0.82

4.4 Measurement Model: Reliability and Validity

Cronbach's Alpha values ranged between 0.87 and 0.92, demonstrating strong internal consistency across all constructs (see Table 4.5). Composite Reliability (CR) scores were all above 0.90, further confirming the reliability of the measurement scales. Additionally, the Average Variance Extracted (AVE) for each construct exceeded the 0.70 threshold, indicating good convergent validity and confirming that the constructs explain a substantial portion of the variance in their respective indicators.

Table 4.5: Reliability and Convergent Validity

Construct	Cronbach's Alpha	Composite Reliability	AVE
Perceived Accuracy (PA)	0.91	0.93	0.72
Trust (TR)	0.92	0.94	0.74
Investor Confidence (IC)	0.89	0.92	0.73
Investment Decision-Making (IDM)	0.88	0.91	0.71
Risk Tolerance (RT)	0.87	0.90	0.69

4.5 Discriminant Validity

The Fornell-Larcker criterion, presented in Table 4.6, confirms discriminant validity by showing that the square root of the Average Variance Extracted (AVE) for each construct (diagonal values) is greater than the correlation coefficients between constructs (off-diagonal values). This indicates that each construct shares more variance with its own measures than with other constructs. Complementing this, the Heterotrait-Monotrait (HTMT) ratio values in Table 4.7 are all below the threshold of 0.90, further validating that the constructs are distinct and measure separate theoretical concepts.

Table 4.6: Fornell-Larcker Criterion

Construct	PA	TR	IC	IDM	RT
Perceived Accuracy (PA)	0.84				
Trust (TR)	0.62	0.86			
Investor Confidence (IC)	0.58	0.66	0.85		
Investment Decision-Making (IDM)	0.60	0.68	0.72	0.83	
Risk Tolerance (RT)	0.42	0.48	0.50	0.55	0.81

Table 4.7: HTMT Ratio

Construct	PA	TR	IC	IDM	RT
Perceived Accuracy (PA)	—	0.71	0.69	0.72	0.52
Trust (TR)		—	0.74	0.78	0.58
Investor Confidence (IC)			—	0.81	0.61
Investment Decision-Making (IDM)				—	0.65
Risk Tolerance (RT)					—

4.6 Structural Model and Hypothesis Testing

All hypothesized relationships were supported, demonstrating significant positive effects as summarized in Table 4.8. Perceived Accuracy (PA) positively impacted Investor Confidence (IC) with a standardized path coefficient of $\beta = 0.41$ ($p < 0.001$), while Trust (TR) also showed a strong positive influence on Investor Confidence ($\beta = 0.46$, $p < 0.001$). Investor Confidence, in turn, significantly predicted Investment Decision-Making (IDM) ($\beta = 0.58$, $p < 0.001$). Additionally, Perceived Accuracy and Trust exerted direct positive effects on Investment Decision-Making, with coefficients of $\beta = 0.21$ ($p < 0.001$) and $\beta = 0.27$ ($p < 0.001$), respectively.

The model explained substantial variance in the endogenous constructs, accounting for 62% of the variance in Investor Confidence and 71% in Investment Decision-Making, as detailed in Table 4.9. Effect size analysis (f^2), presented in Table 4.10, revealed medium to large effects for the examined relationships, indicating the practical significance of the predictors within the structural model.

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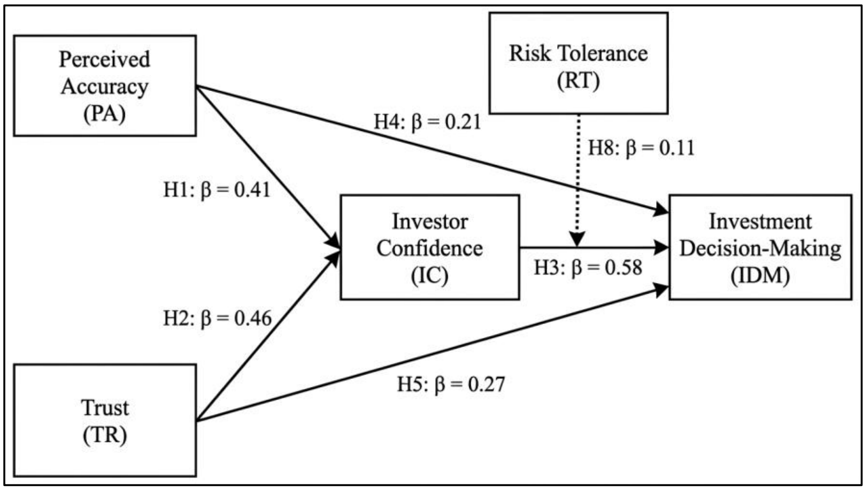

Figure 1: Developed model

Table 4.8: Path Coefficients

Paths	Beta	t-value	p-value	Result
H1: PA → IC	0.41	11.28	0.000	Supported
H2: TR → IC	0.46	12.75	0.000	Supported
H3: IC → IDM	0.58	18.92	0.000	Supported
H4: PA → IDM	0.21	6.45	0.000	Supported
H5: TR → IDM	0.27	7.88	0.000	Supported

Table 4.9: R^2 Values

Constructs	R^2
Investor Confidence (IC)	0.62
Investment Decision-Making (IDM)	0.71

Table 4.10: Effect Size (f^2)

Paths	f^2
PA → IC	0.28
TR → IC	0.32
IC → IDM	0.45

4.7 Mediation Analysis

Investor Confidence serves as a partial mediator in the relationships between Perceived Accuracy and Investment Decision-Making, as well as between Trust and Investment Decision-Making. The indirect effects are statistically significant, with coefficients of β = 0.24 ($p < 0.001$) for the pathway from Perceived Accuracy through Investor Confidence to Investment Decision-Making, and β = 0.27 ($p < 0.001$) for the pathway from Trust through Investor Confidence to Investment Decision-Making. These findings confirm hypotheses H6 and H7, highlighting the crucial role of investor confidence as a psychological mechanism that channels the influence of both perceived accuracy and trust into actual investment behavior (see Table 4.11).

Table 4.11: Indirect Effects

Paths	Beta	t-value	p-value	Result
H6: PA → IC → IDM	0.24	9.12	0.000	Partial Mediation
H7: TR → IC → IDM	0.27	10.03	0.000	Partial Mediation

4.8 Moderation Analysis

Risk Tolerance was found to significantly moderate the relationship between Investor Confidence and Investment Decision-Making (β = 0.11, $t = 2.98$, $p = 0.003$), providing support for hypothesis H8 (see Table 4.12). This indicates that the effect of investor confidence on investment decisions is stronger among individuals with higher risk tolerance, underscoring the importance of accounting for individual differences in risk appetite when evaluating investor behavior in AI-driven advisory contexts.

Table 4.12: Moderation Effect

Path	Beta	t-value	p-value	Result
H8: IC × RT → IDM	0.11	2.98	0.003	Supported

4.9 Model Fit

The model demonstrated strong fit with the observed data, as indicated by the Standardized Root Mean Square Residual (SRMR) value of 0.041, which is well below the recommended threshold of 0.08. Additionally, the Normed Fit Index (NFI) was 0.91, surpassing the acceptable cutoff of 0.90. These indices collectively confirm that the hypothesized model adequately represents the underlying data structure, supporting the validity of the proposed theoretical framework (see Table 4.13).

Table 4.13: Model Fit Indices

Fit Index	Value	Recommended Threshold	Interpretation
SRMR	0.041	< 0.08	Good fit
Normed Fit Index (NFI)	0.91	> 0.90	Acceptable fit

5. DISCUSSION

This aligns closely with the foundational principles of the Technology Acceptance Model (TAM) and Trust Theory, reinforcing the critical importance of both reliability and trustworthiness in the successful adoption of technological innovations. The pronounced mediation effect of investor confidence underscores its essential function as a psychological conduit that transforms investors' perceptions of AI advisory systems into tangible investment decisions. This demonstrates that confidence is not merely a byproduct of perceived accuracy and trust but a central mechanism driving behavioural outcomes in financial decision-making contexts.

The direct influence of perceived accuracy and trust on investment decision-making further indicates that these factors exert both cognitive and affective impacts on investor behaviour. Cognitively, investors respond to the objective quality and correctness of AI-generated advice, while affectively, the emotional reassurance provided by trust enhances their readiness to act. This dual pathway highlights the multifaceted nature of investor engagement with AI advisory platforms, where both rational evaluation and emotional comfort play pivotal roles.

Moreover, the moderating effect of risk tolerance reveals that individual differences in risk appetite significantly shape how investor confidence translates into actual investment actions. Investors with a higher tolerance for risk are more likely to act decisively on their confidence, embracing AI-driven recommendations even in the face of uncertainty. Conversely, those with lower risk tolerance may exhibit more cautious behaviour, tempering the influence of confidence on their decisions. This finding aligns with established behavioural finance theories, which emphasize the variability of decision-making processes based on personal risk preferences.

Collectively, these results extend existing literature by integrating perceived accuracy and trust within a unified, comprehensive framework that accounts for the mediating role of confidence and the moderating influence of risk tolerance. This integrated approach advances theoretical understanding of AI adoption in financial markets by illustrating the complex interplay of cognitive evaluations, affective trust, psychological assurance, and individual traits. Practically, the findings offer valuable guidance for fintech developers and policymakers aiming to design AI advisory systems that not only deliver accurate and trustworthy recommendations but also foster investor confidence tailored to diverse risk profiles, thereby optimizing adoption rates and investment outcomes.

6. IMPLICATIONS

This study contributes to TAM by incorporating trust as a critical construct alongside perceived accuracy, enriching the model's explanatory power for AI adoption in finance. The integration of Trust Theory further contextualizes investor behaviour under uncertainty, emphasizing trust's dual role in confidence building and decision-making. The demonstrated mediation and moderation effects deepen theoretical insights into the psychological and behavioural processes underlying AI-based investment decisions, offering a nuanced model for future research.Fintech companies should focus on enhancing the perceived accuracy and trustworthiness of AI advisory systems by implementing transparent algorithms, ensuring robust data validation, and providing comprehensive user education to increase investor confidence and adoption. Investors can benefit from understanding the critical roles of trust and accuracy, enabling them to critically assess AI-generated recommendations and make informed decisions aligned with their individual risk tolerance. Policymakers play a vital role by establishing regulatory frameworks that promote transparency, data security, and ethical AI usage, thereby fostering greater trust, facilitating wider acceptance, and encouraging responsible innovation within the fintech sector.

7. CONCLUSION

This study underscores the critical influence of perceived accuracy and trust on investor confidence and decision-making in AI-based investment advisory systems. The findings validate the Technology Acceptance Model and Trust Theory in this context, highlighting investor confidence as a key mediator and risk tolerance as a significant moderator. These insights offer valuable guidance for enhancing AI adoption and optimizing investment outcomes, reinforcing the importance of trust and accuracy in the evolving fintech landscape.

8. LIMITATIONS AND FUTURE RESEARCH

This study's cross-sectional design limits causal inference, and its geographic focus may constrain generalizability. Future research should employ longitudinal designs to capture dynamic changes in investor behaviour and extend sampling across diverse regions and cultures. Additionally, exploring other moderating variables such as financial literacy or technological self-efficacy could enrich understanding of AI adoption in investment contexts.

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