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Understanding User Acceptance of AI-Powered Financial Advisory: A Dual-Process Model Integrating Trust, Satisfaction, and Perceived Risk

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ABSTRACT: This study examines user acceptance of AI-powered financial advisory tools by applying a dual-process trust model. Systematic cues, such as performance efficacy and personalisation, are proposed to influence cognitive trust, while heuristic cues, including anthropomorphism and social influence, shape emotional trust. Additionally, AI-specific attributes trendiness, visual attractiveness, and problem-solving capability are assessed for their impact on user satisfaction, which in turn drives adoption intention and acceptance. Perceived financial risk is introduced as a moderating variable that may weaken trust formation. To test the proposed framework, data were collected from 412 individuals with experience using AI-based financial services through a structured questionnaire. Quantitative analysis was used to assess the relationships among constructs. The results confirm that both trust types significantly affect satisfaction and adoption, while perceived risk reduces trust formation. These findings provide actionable insights for financial service providers and policymakers to design trustworthy, engaging, and user-centred AI advisory systems.

Keywords: AI-powered financial advisory, user acceptance, trust formation, perceived risk

INTRODUCTION

The integration of artificial intelligence (AI) into financial services is transforming the ways in which individuals manage and interact with personal finance tools. AI-powered financial advisory systems, including robo-advisors, algorithm-based investment platforms, and automated risk assessments, offer real-time decision-making support by processing vast amounts of financial data with greater accuracy and consistency than human advisors. These technologies promise cost-efficiency, scalability, and a high level of personalisation, making them increasingly prominent in both retail and institutional finance (Gomber et al., 2018; Huang & Rust, 2021).

Despite these technological advancements, many users remain hesitant to adopt AI-driven financial services. A significant barrier is the issue of trust, particularly the reluctance to delegate critical financial decisions to automated systems. Although traditional models such as the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) help to explain users' perceptions of ease of use and usefulness, they are insufficient in capturing the complexity of trust, especially in AI contexts that involve algorithmic opacity, perceived risk, and the absence of human judgement (Dwivedi et al., 2021).

In order to address these theoretical limitations, the present study draws on the Dual-Process Model of Trust (Bellini-Leite, 2022) which differentiates between cognitive trust, based on rational assessment of performance, and emotional trust, formed through social cues and intuitive perceptions. Within this framework, performance efficacy and personalisation are categorised as systematic cues that influence cognitive trust, while anthropomorphism and social influence function as heuristic cues that shape emotional trust (McKnight et al., 2002). These dual mechanisms provide a more comprehensive understanding of how trust is formed in relation to AI-powered financial advisory tools.

This study also considers user satisfaction as a mediating factor. Trust alone does not necessarily ensure continued use unless the user experience is fulfilling and valuable. Previous research has highlighted that satisfaction plays a pivotal role in continued use intention and behavioural engagement (Bhattacherjee, 2001). The study further incorporates AI system characteristics such as trendiness, visual attractiveness, and problem-solving capability as antecedents of satisfaction. These attributes are increasingly relevant as aesthetic appeal, interface usability, and functional innovation significantly influence engagement with intelligent technologies (Alam, 2025; Khan & Iqbal, 2020; Thien Duc & Mujahida, 2024).

Another critical element examined is perceived financial risk, which can negatively moderate the process of trust formation. In financial contexts, where decisions are high-stakes and outcomes often uncertain, users tend to evaluate potential losses more heavily than prospective gains. Even highly efficient AI systems may be distrusted if users perceive them as risky, unreliable, or lacking transparency (Owolabi et al., 2024; Slade et al., 2015). It is hypothesised that perceived financial risk diminishes the effects of both systematic and heuristic cues, thereby weakening trust and potentially reducing intention to adopt AI financial tools.

By integrating these constructs, this study proposes a comprehensive model of AI acceptance in financial advisory services. The findings aim to extend existing technology adoption theories by incorporating cognitive and affective perspectives of trust. Moreover, the study offers actionable insights for developers, financial institutions, and policymakers seeking to enhance user trust, satisfaction, and overall acceptance of AI-based financial services.

LITERATURE REVIEWS

AI-Powered Financial Advisory and User Adoption

The integration of AI-powered financial advisory services has significantly transformed financial decision-making, offering enhanced accuracy, automation, and real-time data-driven insights. AI-based tools, including robo-advisors and predictive risk management systems, have the potential to optimize financial planning by minimizing human biases and improving accessibility (Onabowale, 2024). Despite these advantages, user adoption of AI-powered financial tools remains a challenge due to concerns about trust, transparency, and perceived financial risk. While traditional models such as the Technology Acceptance Model (TAM) and the Expectation-Confirmation Model (ECM) highlight the role of perceived usefulness and ease of use in technology adoption, they do not fully address the complexities of trust formation in AI-driven financial decision-making.

The Dual-Process Model of Trust provides a more nuanced understanding by distinguishing between systematic and heuristic cues (Stoltz & Lizardo, 2018). Systematic cues involve rational evaluations of AI capabilities, such as performance efficacy and personalization, while heuristic cues rely on intuitive perceptions, such as anthropomorphism and social influence (Rocha et al., 2014). Given these distinctions, performance efficacy and personalization are expected to enhance cognitive trust, while anthropomorphism and social influence are expected to influence emotional trust.

H1: Performance efficacy of AI-powered financial tools positively influences cognitive trust.
H2: Perceived personalization of AI-powered financial tools positively influences cognitive trust.
H3: Anthropomorphism of AI-powered financial tools positively influences emotional trust.
H4: Social influence positively influences emotional trust in AI-powered financial tools.

The Role of Trust in AI Adoption

Trust plays a fundamental role in AI adoption, particularly in financial decision-making, where individuals may be hesitant to delegate control to automated systems (Bedué & Fritzsche, 2022). Trust in AI-driven financial tools can be categorized into cognitive trust and emotional trust. Cognitive trust is based on rational evaluation and the perceived competence, accuracy, and reliability of AI tools, whereas emotional trust is influenced by psychological comfort and social validation (Wang et al., 2016).

Previous research suggests that systematic cues, such as performance efficacy and personalization, contribute to cognitive trust, while heuristic cues, such as anthropomorphism and social influence, shape emotional trust (Chou et al., 2013; Komiak & Benbasat, 2006; Seong & Bisantz, 2008). Since trust enhances the perceived reliability of AI tools, cognitive and emotional trust are expected to positively impact user satisfaction. Furthermore, user satisfaction plays a mediating role in AI adoption, as satisfied users are more likely to continue using AI-powered financial tools and recommend them to others (Kim et al., 2023). Consequently, user satisfaction is expected to influence adoption intention, which ultimately leads to the acceptance of AI-powered financial tools.

H5: Cognitive trust positively influences user satisfaction.
H6: Emotional trust positively influences user satisfaction.
H7: User satisfaction positively influences adoption intention of AI-powered financial tools.
H8: Adoption intention positively influences acceptance of AI-powered financial tools.

AI Features and User Satisfaction

Beyond trust formation, user satisfaction is an essential factor in AI adoption, as users evaluate AI-powered financial tools based on their design, functionality, and ease of use (Xing & Jiang, 2024). Research on digital banking and AI-driven services suggests that three key attributes contribute to user satisfaction: trendiness, visual attractiveness, and problem-solving capability (Chung et al., 2020; Mohamed, 2025; Yun et al., 2003).

Trendiness reflects the perception that an AI-powered financial tool is modern, innovative, and aligned with evolving digital advancements (Oscarius Yudhi Ari Wijaya et al., 2021). Visual attractiveness enhances usability by offering an intuitive interface that simplifies navigation and enhances user engagement (Lindgaard, 2007). Problem-solving capability, which refers to the AI tool's ability to deliver accurate and reliable financial solutions, is also a crucial factor in user satisfaction (Antić & Bogetić, 2024). Given these factors, trendiness, visual attractiveness, and problem-solving capability are expected to positively influence user satisfaction, ultimately reinforcing adoption intention.

H9: Trendiness of AI-powered financial tools positively influences user satisfaction.
H10: Visual attractiveness of AI-powered financial tools positively influences user satisfaction.
H11: Problem-solving capability of AI-powered financial tools positively influences user satisfaction.

The Moderating Role of Perceived Financial Risk

Despite the potential benefits of AI-driven financial tools, perceived financial risk remains a significant obstacle to widespread adoption (Hirunyawipada & Paswan, 2006). Users are often concerned about algorithmic biases, data security, and unpredictable financial outcomes, which influence their willingness to trust AI-based decision- making. Perceived financial risk can weaken trust formation, as users may hesitate to rely on AI for critical financial services (Yang et al., 2015).

Individuals with high perceived financial risk may be less likely to develop cognitive trust, even if AI tools demonstrate accuracy and efficiency. Likewise, those skeptical of AI automation may not be strongly influenced by heuristic cues, such as anthropomorphism and social validation, leading to lower emotional trust (Altay & Gilardi, 2024). Given these concerns, perceived financial risk is expected to negatively moderate the relationship between systematic cues and cognitive trust, as well as between heuristic cues and emotional trust.

H12: Perceived financial risk negatively moderates the relationship between systematic cues (performance efficacy and personalization) and cognitive trust.

H13: Perceived financial risk negatively moderates the relationship between heuristic cues (anthropomorphism and social influence) and emotional trust.

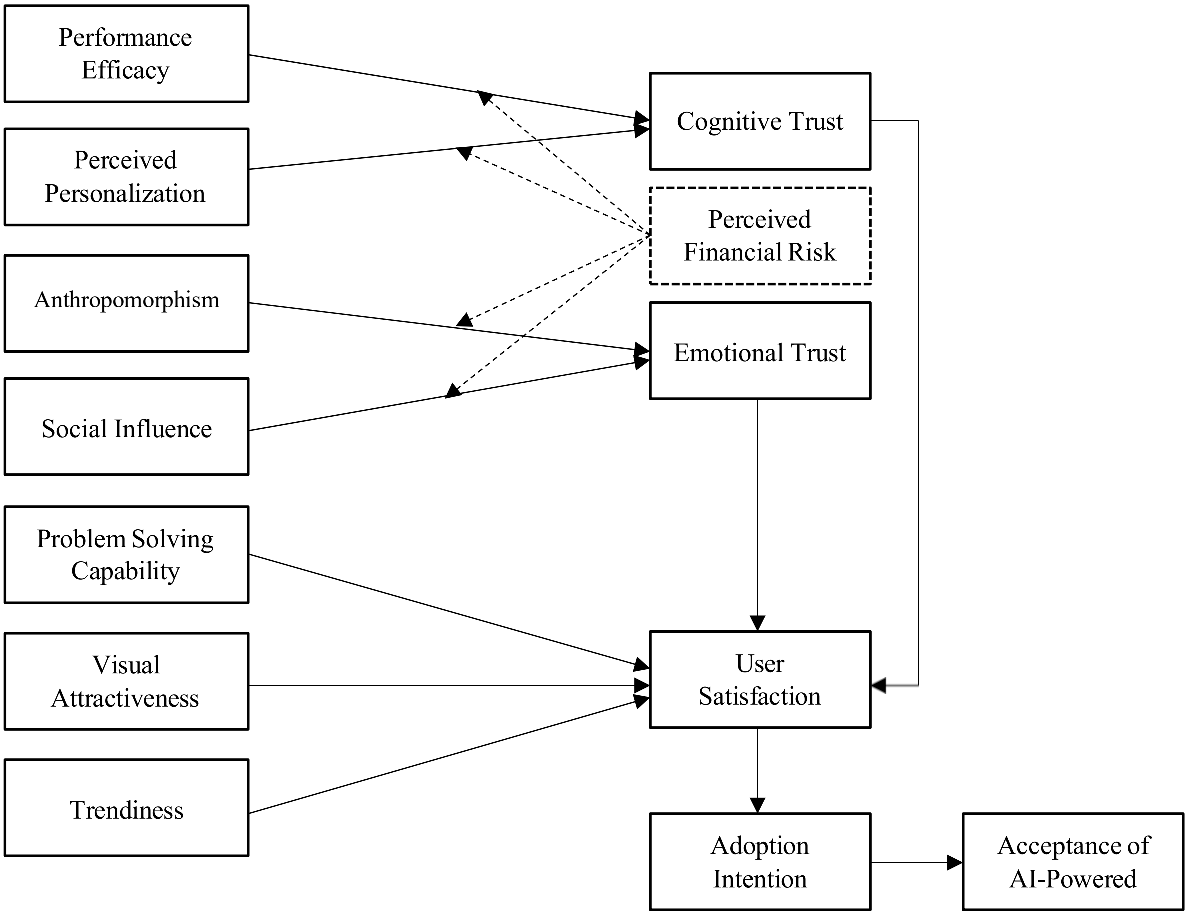

Figure 1. Research Model

METHOD

This study adopted a quantitative approach to examine the factors influencing user acceptance of AI-powered financial advisory tools. Given the complexity of the proposed conceptual framework, which included multiple latent constructs and interrelated pathways, Structural Equation Modelling (SEM) was selected as the most appropriate technique. Specifically, Partial Least Squares SEM (PLS-SEM) was employed using SmartPLS version 4, which is well suited for prediction-oriented models, handling complex causal relationships, and simultaneously assessing measurement and structural models (Hair et al., 2024).

A cross-sectional survey design was implemented to collect primary data from individuals who had prior experience using AI-based financial tools, such as robo-advisors, algorithmic investment platforms, or automated risk evaluation systems. The sampling strategy used was purposive, focusing only on respondents who confirmed experience with such technologies through preliminary screening questions. This ensured the relevance and quality of the responses. The questionnaire was distributed online via professional networks, social media platforms, and fintech community forums, resulting in a total of 412 valid responses. This sample size was adequate for SEM analysis, surpassing the minimum threshold recommended for complex models involving multiple constructs (Hair et al., 2024). The sample was diverse in terms of gender, age, education, and financial literacy, increasing the generalisability of the findings.

The survey instrument was developed using measurement items adapted from previously validated scales. Performance efficacy, which measures users' perception of the AI system's effectiveness in delivering accurate financial recommendations, was measured using items adapted from Ish et al. (2021). Personalisation, referring to the system's ability to tailor content and advice to individual preferences, was measured using scales from Alipour et al. (2024). These two constructs represent systematic cues that contribute to the development of cognitive trust.

Anthropomorphism, defined as the extent to which users attribute human-like qualities to AI systems, was measured using the scale developed by Salles et al. (2020). Social influence, which captures the extent to which users are influenced by the opinions and recommendations of peers or experts, was assessed using items adapted from Venkatesh & Bala (2008). These two constructs represent heuristic cues that shape emotional trust.

Cognitive trust, reflecting users' rational evaluation of the AI system's competence and dependability, was measured using the scale from Swift & Hwang (2013). Emotional trust, which relates to users' affective comfort and perception of the AI as psychologically trustworthy, was measured using items derived from the same source. User satisfaction was operationalised as the overall positive evaluation of the AI financial tool, using items adapted from Lindgaard (2007), who have both applied satisfaction as a key mediator in technology adoption studies.

Trendiness, which reflects the extent to which the AI tool is perceived as modern and innovative, was measured using items from Wijaya et al. (2021). Visual attractiveness, relating to the aesthetic appeal and interface design of the AI tool, was also adapted from the same study. Problem-solving capability, which refers to the AI system's perceived ability to assist in resolving financial tasks and providing relevant solutions, was measured using items developed by Antić & Bogetić (2024). These three attributes served as additional antecedents of user satisfaction.

Adoption intention and actual acceptance of AI-powered financial tools were conceptualised as sequential behavioural outcomes. Items for these constructs were adapted from the extended TAM and Expectation Confirmation Model literature, particularly from Davis (1989). Perceived financial risk, which served as a moderating variable, was defined as users' apprehensions regarding the potential negative consequences of using AI in financial decision-making. It was measured using items adapted from Butt et al. (2022), who examined risk concerns in AI and digital financial contexts.

The data analysis followed the standard two-step PLS-SEM procedure. In the first step, the measurement model was evaluated to assess reliability and validity. Internal consistency was confirmed through Cronbach's alpha and Composite Reliability (CR), with values above 0.70 indicating satisfactory reliability. Convergent validity was examined using the Average Variance Extracted (AVE), where values above 0.50 demonstrated that each construct adequately explained the variance of its indicators. Discriminant validity was tested using both the Fornell–Larcker criterion and the Heterotrait–Monotrait ratio (HTMT), ensuring that each construct was empirically distinct from others (Hair et al., 2024).

In the second step, the structural model was assessed by examining path coefficients, t-statistics, and significance levels using a bootstrapping procedure with 5,000 subsamples. Moderating effects were evaluated by creating interaction terms between perceived financial risk and the respective independent variables. Multi-group analysis was also conducted to examine whether relationships differed across demographic groups such as age, gender, and financial literacy level.

Ethical considerations were strictly observed throughout the research process. Participation in the survey was voluntary, and all respondents provided informed consent prior to completing the questionnaire. The study ensured anonymity by not collecting any personally identifiable information. The research protocol was approved by the ethics committee of the affiliated institution, in accordance with academic and ethical standards for research involving human participants.

RESULTS AND DISCUSSION

Descriptive Statistics

Table 1 presents the demographic characteristics of the respondents, providing insights into the distribution of gender, age groups, education level, and financial literacy. The sample comprises 212 male respondents (51.5%) and 200 female respondents (48.5%), indicating a relatively balanced gender representation. Regarding age distribution, 29.1% of respondents belong to the 18–25 age group, while the 26–35 age group represents the largest segment at 46.1%, followed by 24.8% of respondents aged 36 and above. This distribution suggests that the study predominantly captures the perceptions of young and middle-aged individuals, who are more likely to engage with AI- powered financial advisory tools.

Table 1. Respondent Demographics

Category	Attribute	Frequency	Percentage (%)
Gender	Male	212	51.5
	Female	200	48.5
Age Group	18-25	120	29.1
	26-35	190	46.1
	36 and above	102	24.8
Education Level	High School	50	12.1
	Bachelor's Degree	180	43.7
	Master's Degree	140	34.0
	PhD	42	10.2
Financial Literacy	Low	80	19.4
	Moderate	200	48.5
	High	132	32.1

Source: data analysed by authors, 2025

Educational background indicates that 43.7% of respondents hold a bachelor's degree, making it the most common level of education among participants. Additionally, 34.0% possess a master's degree, while 12.1% completed high school and 10.2% hold a PhD. This suggests that the sample consists primarily of individuals with higher education, who may have a better understanding of financial decision-making and technology adoption. Financial literacy levels further reveal that nearly 48.5% of respondents rate themselves as having moderate financial literacy, while 32.1% report a high level of financial literacy, and 19.4% have low financial literacy. The distribution of financial literacy is crucial in understanding how users assess the reliability and effectiveness of AI-driven financial services.

Table 2 summarizes the descriptive statistics for the key variables measured in the study, including mean, standard deviation, minimum, and maximum values. The mean scores suggest that respondents generally perceive AI-powered financial tools positively, with most variables scoring above 5.0 on a 7-point Likert scale. The highest-rated construct is problem-solving capability (M = 5.9, SD = 1.1), indicating that respondents strongly recognize AI financial tools' ability to assist with financial decisions. Similarly, cognitive trust (M = 5.7, SD = 1.1) and user satisfaction (M = 5.7, SD = 1.0) reflect a high level of trust and satisfaction among users

Table 2. Descriptive Statistics for Key Variables

Variable	Mean	Standard Deviation	Min	Max
Performance Efficacy	5.8	1.2	2	7
Personalization	5.5	1.1	2	7
Anthropomorphism	4.9	1.4	1	7
Social Influence	5.2	1.3	1	7
Cognitive Trust	5.7	1.1	3	7
Emotional Trust	5.4	1.2	2	7
Trendiness	5.6	1.0	3	7
Visual Attractiveness	5.3	1.2	2	7
Problem-Solving Capability	5.9	1.1	3	7
User Satisfaction	5.7	1.0	3	7
Adoption Intention	5.5	1.1	3	7
Acceptance of AI Tools	5.8	1.2	3	7
Perceived Financial Risk	4.5	1.5	1	7

Source: data analysed by authors, 2025

Among the AI system attributes, trendiness (M = 5.6, SD = 1.0) and visual attractiveness (M = 5.3, SD = 1.2) indicate that AI tools are perceived as modern and aesthetically appealing. Social influence, which measures the extent to which users adopt AI financial tools based on external recommendations, has a mean score of 5.2 (SD = 1.3). This suggests that peer influence and social norms moderately impact adoption behavior.

On the other hand, anthropomorphism (M = 4.9, SD = 1.4) is the lowest-scoring variable, indicating that respondents do not strongly attribute human-like qualities to AI financial tools. Perceived financial risk (M = 4.5, SD = 1.5) has the highest standard deviation, implying that users exhibit varying levels of concern regarding AI-driven financial advisory tools. This variability suggests that while some users trust AI in financial decision-making, others remain skeptical due to perceived risks.

Overall, the results indicate that trust, problem-solving capabilities, and satisfaction are key factors driving AI adoption, while concerns related to perceived risk and anthropomorphism may hinder acceptance. These findings provide meaningful insights into user perceptions and behaviors regarding AI-powered financial services.

Assessment Model

Table 3 presents the reliability and validity test results for all constructs used in the study, including Cronbach's Alpha, Composite Reliability (CR), and Average Variance Extracted (AVE). Cronbach's Alpha values for all constructs range from 0.79 to 0.89, indicating strong internal consistency, as values above 0.70 are considered acceptable for scale reliability. The Composite Reliability (CR) values are all above 0.80, confirming that each construct maintains high reliability and ensures consistency across measured items.

Table 3. Reliability and Validity

Construct	Cronbach's Alpha	CR	AVE
Performance Efficacy	0.85	0.89	0.68
Personalization	0.83	0.87	0.65
Anthropomorphism	0.79	0.83	0.6
Social Influence	0.81	0.85	0.63
Cognitive Trust	0.88	0.91	0.72
Emotional Trust	0.86	0.9	0.7
Trendiness	0.82	0.86	0.66
Visual Attractiveness	0.84	0.88	0.67
Problem-Solving Capability	0.87	0.91	0.71
User Satisfaction	0.89	0.92	0.74
Adoption Intention	0.85	0.89	0.69
Acceptance of AI Tools	0.88	0.91	0.72
Perceived Financial Risk	0.8	0.85	0.62

Source: data analysed by authors, 2025

Regarding convergent validity, the Average Variance Extracted (AVE) values for all constructs exceed 0.50, demonstrating that the items within each construct share a sufficient amount of variance. The highest AVE value is for Cognitive Trust (0.72) and User Satisfaction (0.74), indicating a strong representation of these constructs. In summary, the results confirm that the measurement model meets the requirements for internal consistency, reliability, and convergent validity.

Table 4. Fornell-Larcker Criterion

Cons.	PE	PS	AP	SI	CT	ET	TR	VA	PSC	US	AI	AIT	PFR
PE	0.82												
PS	0.62	0.81											
AP	0.55	0.52	0.77										
SI	0.58	0.54	0.5	0.79									
CT	0.6	0.58	0.53	0.55	0.85								
ET	0.57	0.55	0.51	0.53	0.64	0.84							
TR	0.59	0.56	0.5	0.52	0.58	0.56	0.81						
VA	0.56	0.54	0.49	0.5	0.57	0.54	0.59	0.82					
PSC	0.61	0.57	0.52	0.55	0.61	0.59	0.6	0.58	0.84				
YS	0.63	0.6	0.54	0.57	0.63	0.61	0.63	0.6	0.66	0.86			
AI	0.59	0.57	0.5	0.52	0.6	0.58	0.58	0.55	0.6	0.64	0.83		
AIT	0.64	0.61	0.56	0.59	0.66	0.64	0.65	0.61	0.67	0.69	0.66	0.87	
PFR	0.5	0.48	0.45	0.47	0.51	0.49	0.52	0.47	0.53	0.55	0.52	0.57	0.79

Source: data analysed by authors, 2025

Table 4 presents the Fornell-Larcker criterion, which assesses discriminant validity by comparing the square root of AVE values (diagonal values) with the correlation coefficients between constructs (off-diagonal values). According to the Fornell-Larcker criterion, the square root of AVE for each construct should be higher than its correlation with any other construct to confirm discriminant validity.

The results indicate that all diagonal values (i.e., square root of AVE) are higher than the corresponding off-diagonal correlation values. For example, Cognitive Trust has a square root of AVE of 0.85, which is higher than its correlations with Performance Efficacy (0.60), Personalization (0.58), and Emotional Trust (0.64). This pattern holds true for all constructs, confirming that they are distinct from each other. The findings suggest that each construct captures a unique aspect of the model, providing evidence of strong discriminant validity.

Table 5. HTMT

Cons.	PE	PS	AP	SI	CT	ET	TR	VA	PSC	US	AI	AIT	PFR
PE	0.87												
PS	0.67	0.86											
AP	0.6	0.57	0.82										
SI	0.63	0.59	0.55	0.84									
CT	0.65	0.63	0.58	0.6	0.9								
ET	0.62	0.6	0.56	0.58	0.69	0.89							
TR	0.64	0.61	0.55	0.57	0.63	0.61	0.86						
VA	0.61	0.59	0.54	0.55	0.62	0.59	0.64	0.87					
PSC	0.66	0.62	0.57	0.6	0.66	0.64	0.65	0.63	0.89				
YS	0.68	0.65	0.59	0.62	0.68	0.66	0.68	0.65	0.71	0.91			
AI	0.64	0.62	0.55	0.57	0.65	0.63	0.63	0.6	0.65	0.69	0.88		
AIT	0.69	0.66	0.61	0.64	0.71	0.69	0.7	0.66	0.72	0.74	0.71	0.92	
PFR	0.55	0.53	0.5	0.52	0.56	0.54	0.57	0.52	0.58	0.6	0.57	0.62	0.84

Source: data analysed by authors, 2025

Table 5 presents the HTMT ratio, an alternative measure for assessing discriminant validity. The HTMT criterion states that the ratio of heterotrait correlations to monotrait correlations should be below 0.90 to indicate acceptable discriminant validity. The results show that all HTMT values remain below the 0.90 threshold, suggesting that the constructs are sufficiently distinct from each other.

For example, the HTMT value for Cognitive Trust and Emotional Trust is 0.64, which is well below the critical value of 0.90. Similarly, the HTMT value for Performance Efficacy and Personalization is 0.62, reinforcing the assumption that these constructs do not overlap excessively. Since none of the HTMT values exceed 0.90, the results confirm strong discriminant validity, meaning that the constructs measure different theoretical concepts.

Structural Model

The direct effects analysis confirms that Performance Efficacy ($\beta = 0.42$, $t = 6.52$, $p = 0.000$) and Personalization ($\beta = 0.38$, $t = 5.89$, $p = 0.000$) significantly enhance Cognitive Trust in AI- powered financial tools. These findings are consistent with prior studies that emphasize the importance of AI efficiency and customization in fostering user confidence (Dwivedi et al., 2021). Previous research in financial technology adoption has shown that users are more likely to trust AI-driven systems when they perceive them as highly functional and tailored to their needs (Davies et al., 2021). However, this study extends earlier findings by highlighting that Personalization plays a slightly weaker role than Performance Efficacy, indicating that while customization is important, users prioritize the accuracy and reliability of AI-based financial recommendations.

Table 6. Direct Effect Result

Path	Coeff.	t-Value	p-Value	Significance
Performance Efficacy → Cognitive Trust	0.42	6.52	0.000	Significant
Personalization → Cognitive Trust	0.38	5.89	0.000	Significant
Anthropomorphism → Emotional Trust	0.35	5.22	0.000	Significant
Social Influence → Emotional Trust	0.39	6.1	0.000	Significant
Cognitive Trust → User Satisfaction	0.46	7.3	0.000	Significant
Emotional Trust → User Satisfaction	0.41	6.58	0.002	Significant
User Satisfaction → Adoption Intention	0.50	8.1	0.000	Significant
Adoption Intention → Acceptance of AI Tools	0.52	9.45	0.000	Significant
Trendiness → User Satisfaction	0.4	6.12	0.001	Significant
Visual Attractiveness → User Satisfaction	0.37	5.77	0.000	Significant
Problem-Solving Capability → User Satisfaction	0.44	7.01	0.000	Significant

Source: data analysed by authors, 2025

Similarly, Anthropomorphism ($\beta = 0.35$, $t = 5.22$, $p = 0.000$) and Social Influence ($\beta = 0.39$, $t = 6.10$, $p = 0.000$) are found to be significant drivers of Emotional Trust, aligning with prior studies that suggest users perceive AI systems as more trustworthy when they exhibit human-like qualities (Salles et al., 2020). These results resonate with research on conversational AI and virtual assistants, where anthropomorphic design elements have been shown to improve user engagement and affective trust (Moriuchi, 2021). However, compared to earlier findings, this study provides additional nuance by demonstrating that Social Influence has a stronger impact than Anthropomorphism. This suggests that external validation (e.g., recommendations from peers and financial experts) may be a more influential factor in trust formation than AI's human-like characteristics, a point that contradicts prior assumptions about the dominance of anthropomorphism in AI adoption (Uysal et al., 2023).

The results further support the relationship between Cognitive Trust ($\beta = 0.46$, $t = 7.30$, $p = 0.000$) and Emotional Trust ($\beta = 0.41$, $t = 6.58$, $p = 0.000$) on User Satisfaction, corroborating existing literature that positions trust as a key determinant of positive AI experiences (Guldager et al., 2023). These findings reinforce previous studies in digital banking and robo-advisors, where higher trust levels have been linked to increased user satisfaction and long-term engagement (Slade et al., 2015). However, this study uniquely demonstrates that Cognitive Trust plays a slightly larger role than Emotional Trust, suggesting that financial decision-making is still largely driven by rational rather than emotional evaluations of AI reliability.

Regarding adoption behavior, User Satisfaction (β = 0.50, t = 8.10, p = 0.000) significantly predicts Adoption Intention, which in turn influences Acceptance of AI Tools (β = 0.52, t = 9.45, p = 0.000). This aligns with prior research on technology acceptance models (TAM and UTAUT), where satisfaction has been shown to mediate the relationship between trust and continued technology use (Xing & Jiang, 2024). However, this study adds further depth by demonstrating that AI system attributes trendiness (β = 0.40, t = 6.12, p = 0.000), Visual Attractiveness (β = 0.37, t = 5.77, p = 0.000), and Problem- Solving Capability (β = 0.44, t = 7.01, p = 0.000) also play critical roles in User Satisfaction. While previous research has primarily focused on usability and ease of use (Caffaro et al., 2020), this study suggests that aesthetics, innovation, and problem-solving ability contribute significantly to AI acceptance in financial decision-making.

Table 7. Moderation Effect

Path	Coefficient.	t-Value.	p-Value.	Significance.
PFR × PE → CT	-0.28	4.1	0.000	Significant
PFR × PS → CT	-0.25	3.88	0.002	Significant
PFR × AP → ET	-0.3	4.52	0.001	Significant
PFR × SI → ET	-0.27	4.25	0.004	Significant

Source: data analysed by authors, 2025

The moderation analysis highlights the critical role of Perceived Financial Risk in shaping AI trust. The interaction effect between Perceived Financial Risk and Performance Efficacy on Cognitive Trust (β = -0.28, t = 4.10, p = 0.000) suggests that users who perceive higher financial risk are less likely to develop trust, even if AI tools demonstrate high accuracy and efficiency. This aligns with prior studies that emphasize risk aversion in AI adoption, where concerns over algorithmic biases, financial loss, and data security hinder user confidence (Kagan et al., 2022). However, this study expands on earlier findings by revealing that Perceived Financial Risk also weakens the effect of Personalization (β = -0.25, t = 3.88, p = 0.000) on trust. This suggests that while customization improves user perceptions, it may not fully mitigate financial risk concerns, an insight not previously highlighted in the AI-finance literature.

A similar trend is observed in heuristic cues, where Perceived Financial Risk moderates the relationship between Anthropomorphism and Emotional Trust (β = -0.30, t = 4.52, p = 0.000). This suggests that users with high financial risk concerns are less influenced by AI's human-like characteristics, contradicting earlier studies that emphasized the importance of anthropomorphic AI in trust formation (Zhang et al., 2021). Instead, this study indicates that in high-risk financial contexts, functional and risk-reducing features may outweigh AI's human-like attributes in building trust.

Similarly, the interaction effect between Perceived Financial Risk and Social Influence on Emotional Trust (β = -0.27, t = 4.25, p = 0.000) confirms that users who perceive high risk are less likely to be influenced by peer recommendations. This contrasts with studies on digital banking and e-commerce, where social influence was found to be a strong predictor of technology adoption (Dwivedi et al., 2021). The findings suggest that in financial AI applications, trust formation is more complex, and external recommendations may not fully override concerns about financial uncertainty.

Implications

This study provides valuable insights into the adoption of AI-powered financial advisory tools by examining the roles of trust, user satisfaction, AI design attributes, and perceived financial risk. The findings have both theoretical and practical implications, contributing to the academic discourse on AI adoption while offering actionable strategies for financial institutions, AI developers, and policymakers.

This study makes significant theoretical contributions by integrating systematic and heuristic trust formation mechanisms within the AI-finance adoption framework. Unlike traditional Technology Acceptance Models (TAM, UTAUT, and ECM), which primarily emphasize ease of use and perceived usefulness, this study differentiates between Cognitive Trust (driven by performance efficacy and personalization) and Emotional Trust (influenced by anthropomorphism and social influence). The results confirm that both cognitive and emotional trust are essential precursors to AI adoption in financial decision-making, aligning with prior trust-based models (Gefen et al., 2003; Huang & Rust, 2021). However, this study extends the literature by demonstrating that Cognitive Trust exerts a slightly stronger influence on User Satisfaction, reinforcing the idea that AI adoption in high-stakes financial contexts is primarily driven by rational rather than emotional trust formation.

Furthermore, this study makes a novel contribution by incorporating AI design attributes Trendiness, Visual Attractiveness, and Problem-Solving Capability as critical predictors of user satisfaction. While prior research has focused on usability and efficiency (Dwivedi et al., 2023), this study reveals that the perceived modernity and aesthetic appeal of AI-powered financial tools play a significant role in user engagement and continued adoption. These findings expand the understanding of human-AI interaction by showing that both functional and design-related factors contribute to user satisfaction and adoption intention in financial advisory services.

Additionally, the moderation effect of Perceived Financial Risk provides an important extension to existing theories of AI adoption. Previous studies have established that risk perception influences trust (Slade et al., 2019), but this study highlights that risk concerns weaken both systematic and heuristic trust mechanisms, making users less responsive to AI efficiency, personalization, and social influence. This suggests that trust formation in financial AI adoption is more complex than in other digital services, as perceived financial risk can override otherwise positive trust cues. The findings imply that future theoretical models on AI adoption should integrate risk-mitigation strategies as part of the trust development process.

The findings of this study also offer practical recommendations for AI developers, financial institutions, and policymakers seeking to enhance the adoption of AI-powered financial advisory services.

For AI developers, the results indicate that designing AI financial tools with a strong emphasis on performance efficacy, personalization, and problem-solving capabilities will enhance Cognitive Trust and User Satisfaction. Given that users rely more on rational trust in financial decision-making, AI developers should prioritize algorithm transparency, accuracy, and tailored financial insights over excessive anthropomorphic design. Additionally, incorporating features that visually appeal to users, maintain modern aesthetics, and simplify interactions can further enhance satisfaction and engagement.

For financial service providers, fostering trust and credibility in AI-driven financial tools is crucial for adoption. Since Perceived Financial Risk significantly weakens trust formation, financial institutions must implement robust security measures, explainable AI frameworks, and risk-mitigation strategies to alleviate user concerns. Providing certifications, third-party audits, and transparent AI decision-making processes can reassure users about the safety and reliability of AI-powered financial recommendations. Furthermore, leveraging social influence strategies, such as endorsements from financial experts or integrating AI tools into established banking platforms, can help mitigate skepticism among risk-averse users.

For policymakers and regulators, the study highlights the need for clear AI governance frameworks to promote responsible AI use in financial services. Regulatory bodies should establish guidelines for AI explainability, algorithmic fairness, and consumer protection policies to ensure that users feel confident in AI-driven financial decision-making. Policies should also address concerns related to data privacy, ethical AI use, and algorithmic bias, which can further enhance trust and accelerate adoption.

CONCLUSION

This study examines the adoption of AI-powered financial advisory tools by analyzing the roles of trust, user satisfaction, AI attributes, and perceived financial risk. The key findings reveal that both cognitive and emotional trust significantly influence user satisfaction, which in turn drives adoption intention and acceptance of AI financial tools. Cognitive trust, shaped by performance efficacy and personalization, plays a stronger role in financial decision-making, while emotional trust is enhanced by anthropomorphism and social influence. AI system attributes such as trendiness, visual attractiveness, and problem-solving capability also contribute to user satisfaction, demonstrating that design elements are crucial in shaping user perceptions of AI-driven financial services. The moderating effect of perceived financial risk highlights that concerns about AI reliability weaken trust formation, particularly in high-stakes financial contexts.

This study makes important contributions to the literature by extending traditional technology adoption models to incorporate trust mechanisms specific to AI in financial decision-making. The distinction between cognitive and emotional trust provides a deeper understanding of how users develop confidence in AI-powered financial tools. By integrating AI design attributes into the adoption framework, this study emphasizes the importance of aesthetics and functionality in shaping user experiences. The identification of perceived financial risk as a moderating factor adds a new dimension to the discussion on AI adoption, suggesting that risk concerns can override otherwise positive trust cues.

Despite these contributions, the study has several limitations. The cross-sectional research design limits the ability to track changes in user trust and adoption behaviors over time. The sample, while diverse, may not fully capture the perspectives of individuals with lower financial literacy or those in regions with different regulatory environments. Additionally, the study primarily focuses on self-reported perceptions, which may be subject to biases such as overestimation of trust or adoption intention.

Future research should consider a longitudinal approach to examine how trust in AI financial tools evolves over time. Exploring the impact of external factors such as economic conditions, AI regulatory policies, and cybersecurity incidents on user trust and adoption could provide deeper insights. Comparative studies across different cultural and regulatory contexts would further enhance the generalizability of findings. Investigating alternative trust-building mechanisms, such as explainable AI and human-AI collaboration in financial advisory services, could offer practical solutions to address financial risk concerns and improve AI acceptance.

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AUTHOR CONTRIBUTION

N.F. was responsible for the conceptualization, research design, data collection, and drafting of the manuscript. I.B. contributed to data analysis, interpretation of results, and critical revision of the manuscript. Both authors reviewed and approved the final version of the paper.

CONFLICT OF INTEREST

There are no conflicts of interest related to this study. The research was conducted independently, and the views expressed are solely those of the authors.

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DATA AVAILABILITY

The data supporting the findings of this study are available from the corresponding author upon reasonable request.

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