

Trusting AI in Financial Advisory: Examining the Impact of AI-Based Financial Advisory Services on Retail Investors' Adoption Intentions through the Mediating Roles of Trust and Perceived Risk and the Moderating Role of Financial Literacy

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Abstract

Background: AI is being adopted rapidly in the financial services industry with the assistance of AI-based financial advice systems, popularly known as robo-advisors, in wealth management. Acceptance among retail investors is rising but inconsistent, with difficulties of trust, transparency and perceived risk.

Objectives: This study adopts the Technology Acceptance Model (TAM), Trust Theory, Perceived Risk Theory and Innovation Diffusion Theory (IDT) to examine the influence of perceived efficacy of AI advisory services on the intention to adopt, with trust and perceived risk as mediating mechanisms and financial literacy as a moderating variable.

Methods: A quantitative, cross-sectional survey was performed with 450 retail investors who are familiar with or have experience with AI-based financial consulting services. The measurement model evaluation, structural path analysis, bootstrapped mediation (5,000 resamples), and product-indicator moderation testing were conducted using PLS-SEM in SmartPLS 4.

Results: Perceived efficacy was a big positive predictor of trust ($\beta = 0.546$, $p < .001$) and a considerable negative predictor of perceived danger ($\beta = -0.483$, $p < .001$). Trust ($\beta = 0.377$, $p < .001$) and perceived risk ($\beta = -0.236$, $p < .001$) were significantly related to adoption intention. Perceived efficacy also had a significant direct influence on intention to adopt ($\beta = 0.177$, $p < .001$). Trust had a moderate effect on the PE $\rightarrow$ AI pathway (indirect $\beta = 0.247$, 95% CI [0.193, 0.303]). Its route was fully mediated by perceived risk (indirect $\beta = 0.156$, 95% CI [0.107, 0.209]). Trust and adoption intention association was not substantially moderated by financial literacy ($\beta = -0.024$, $p = .464$). This suggests that border circumstances require additional exploration.

Implications. The findings add to the literature by integrating trust and perceived risk as dual mediating mechanisms in the AI adoption model and have practical implications for FinTech platform builders, financial institutions and regulators.

Keywords: Artificial Intelligence; Robo-Advisors; Trust; Perceived Risk; Financial Literacy; Adoption Intention; FinTech; TAM; PLS-SEM; Retail Investors

1. Introduction

Artificial intelligence (AI) has been one of the most prominent advancements in the financial services market this year. Robo-advisors are AI-powered financial advisory platforms that leverage machine learning algorithms, predictive analytics, and automated decision systems for investment advice and portfolio management services that have never been seen before at scale and cost (Fisch et al., 2019; D'Acunto et al., 2019). The worldwide robo advisory market

was at around USD 4.51 billion in 2022. The market is projected to reach USD 41.07 billion by 2030, growing at a CAGR of 31.8% (Allied Market Research, 2022). These platforms have been popular since they are accessible 24 hours a day seven days a week, offer reduced advisory costs, don't have any cognitive faults and can improve your portfolio in a manner that is unique to you.

But even with these basic advantages, take-up amongst the small companies is still relatively patchy. It has been shown that many individual investors, and in particular rich ones, still do not trust automated systems with their money, a fact consistently discovered by the financial sector (Belanche et al., 2019; Jung et al., 2018). This resistance emerges from a confluence of social, cognitive, and informational pressures. Concerns regarding algorithmic transparency, or the "black box" issue, also contribute to concerns about data privacy, cybersecurity gaps, who is accountable for financial losses, and how AI systems would not be able to adapt to the individual demands of investors (Logg et al., 2019; Longoni et al., 2019).

Trust has been well recognized for a long time as the essential psychological mechanism by which individuals employ vague and complex instruments (McKnight et al., 2002; Pavlou, 2003). In the realm of AI advisory services, trust is comprised of perceptions of system intelligence, truthfulness, and usefulness. Perceived risk, or the way individuals believe about the likelihood and severity of terrible things occurring while using technology, is also a big element that prevents people from embracing it (Featherman & Pavlou, 2003; Yang et al., 2015). In the FinTech acceptance research, both ideas have been studied independently but their combined function as two distinct mediators in the context of AI guidance is still not fully understood.

And knowing about money complicates things even more. Investors that have higher financial knowledge are likely to better assess the advantages and drawbacks of AI guidance systems, think more thoroughly about computer proposals, and establish more accurate trust views (Calcagno & Monticone, 2015; Servon & Kaestner, 2008). But it is still unclear if financial literacy accelerates the trust-to-adoption process or whether it influences adoption decisions by itself. This research solves this gap by proposing the use of financial knowledge as a scientifically valid control variable.

This study proposes and tests a moderated mediation framework to examine the retail investors' intention to use AI-based financial advisory services, by applying the Technology Acceptance Model (Davis, 1989), Trust Theory (McKnight et al., 2002), Perceived Risk Theory (Bauer, 1960; Featherman & Pavlou, 2003) and Innovation Diffusion Theory (Rogers, 1995). The dual mediation specification in the paper, which incorporates a trust-based (facilitative) and a risk-based (inhibitory) route, is a novel theoretical contribution that provides a more comprehensive understanding of the decision-making process of investors when dealing with AI advice than the prior single-mediator models.

The paper continues with: Section 2 sets up the research topics and aims. Section 3 discusses the theoretical and practice material. Section 4 develops the philosophical framework and ideas. The procedure is described in Section 5. Section 6 presents the actual results. Section 7 discusses the findings. Section 8 describes the impacts. Limitations are discussed in Section 9. The end of Section 10.

2. Research Objectives and Questions

2.1 Research Objectives

The specific objectives of this study are:

- RO1: To examine the influence of perceived effectiveness of AI-based financial advisory services on investors' trust.
- RO2: To investigate the influence of perceived effectiveness on perceived risk toward AI-based financial advisory services.
- RO3: To assess the impact of trust on retail investors' adoption intentions toward AI-based financial advisory services.
- RO4: To examine the impact of perceived risk on adoption intentions.

- RO5: To assess the direct effect of perceived effectiveness on adoption intentions.
- RO6: To determine the mediating roles of trust and perceived risk in the perceived effectiveness–adoption intention relationship.
- RO7: To investigate the moderating role of financial literacy in the trust–adoption intention relationship.
- RO8: To provide evidence-based recommendations for FinTech platform design, investor trust-building strategies, and regulatory policy.

2.2 Research Questions

- RQ1: Does perceived effectiveness of AI advisory services significantly influence investor trust?
- RQ2: Does perceived effectiveness significantly reduce perceived risk toward AI advisory services?
- RQ3: Does trust significantly predict adoption intentions toward AI advisory services?
- RQ4: Does perceived risk significantly inhibit adoption intentions toward AI advisory services?
- RQ5: Does perceived effectiveness exert a significant direct effect on adoption intentions?
- RQ6: Do trust and perceived risk mediate the relationship between perceived effectiveness and adoption intentions?
- RQ7: Does financial literacy moderate the trust–adoption intention relationship?

3. Literature Review

3.1 Robo-Advisors (AI-driven financial advisory services)

“Robo-advisors” are online financial consulting services based on artificial intelligence (AI). Robo-advisors employ algorithms and machine learning to deliver tailored investment advice, automatically rebalance portfolios, and undertake financial planning with little to no human intervention (Fisch et al., 2019; Phoon & Koh, 2018). Popular examples are Betterment, Wealthfront and Vanguard Digital Advisor in developed economies. But similar websites are mushrooming in Asia, Africa and Latin America. The program offers many major benefits, including minimal minimum investment, passive tracking, tax-loss harvesting, goal-based planning, and real-time monitoring of the portfolio (Jung et al., 2018). It’s the key value proposition that platforms need to sell to potential users of AI advisory services: how useful they think they are. This concerns the correctness of the ideas, the dependability of the algorithms, the customization of the services, and the efficiency of their operation (Belanche et al., 2019; Logg et al., 2019). Statistics show that the perceived success of a platform has a strong effect on both trusting it and wanting to use it, but the mental processes behind this impact are still debated (D’Acunto et al., 2019; Phoon & Koh, 2018).

3.2 Adoption of AI and the Technology Acceptance Model

The objective to be accepted is defined by the key characteristics of utility and simplicity of use, according to the Technology Acceptance Model (Davis, 1989). Since then, other aspects like as confidence, perceived danger, social influence and hedonic drive have been included (Venkatesh et al., 2003; Yang et al., 2015). For AI adviser, perceived value is linked to perceived efficacy, which is the belief that the system does its job of delivering advice properly and reliably. Perceived value has been identified as the strongest predictor of use intention across a range of institutional and cultural settings in several TAM-based studies in the FinTech domain (Cao & Niu, 2019; Shen et al., 2010).

3.3. Trust AI Service Advisory

Trust in technology systems is multidimensional. Some intellectual components assess their competence and reliability while some emotional parts evaluate their honesty and supportiveness (Mayer et al., 1995; McKnight et al., 2002). Trust in AI advising is also affected by how transparent the algorithms are seen to be, how understandable the suggestions provided by the AI are, and the reputation of the platform (Logg et al., 2019; Longoni et al., 2019). confidence Theory (McKnight et al., 2002) suggests that the more confidence a person has in a technology system, the

more likely they are to engage in risky conduct using that system. This may be seen in letting automated systems to make financial decisions on their behalf. Prior studies have shown that trust has a substantial positive link with FinTech adoption intention (Cao & Niu, 2019; Cheng et al., 2019; Yang et al., 2015). This implies that trust is a critical factor to get people to use AI guiding services.

3.4 Perceived Risk

The perceived risk hypothesis (Bauer, 1960; Featherman & Pavlou, 2003) defines risk as the perception of the likelihood and severity of negative effects as a result of the use of technology by the user. Potential risks in AI advisory situations include: 1) financial risk, such as losing investment due to an error in the algorithm; 2) privacy risk, such as collecting or leaking data without permission; 3) performance risk, such as not achieving the promised advisory results; and 4) psychological risk, such as anxiety and regret from outsourcing tasks to non-human systems. Studies found that perceived risk is an important deterrent to the use of FinTech and AI services (Featherman & Pavlou, 2003; Yang et al., 2015; Belanche et al., 2019). Trust and perceived risk are two different constructs, one aiding and the other inhibiting adoption. Analyzing these two constructs separately does not offer a complete perspective of the adoption process.

3.5 Money as a compass

Financial literacy, the knowledge and skills to make effective financial choices (Lusardi & Mitchell, 2014; Huston, 2010), has been suggested as part of the AI adviser's portfolio. People with higher financial literacy are more likely to accurately appraise the accuracy and usefulness of computer guidance, grasp how robo-advised portfolios work, and comprehend how risk-return affects AI-based strategies (Calcagno & Monticone, 2015). This greater capacity to assess should speed up the journey from trust to acceptance. For example, investors who understand money and trust an AI advising system are more likely to act on that trust since it is simpler for them to verify the system's forecasts. Likewise, Servon and Kaestner (2008) suggested a way to enhance knowledge and trust in the realm of digital financial services.

3.6 Diffusion of Innovation Theory

Innovation Diffusion Theory (Rogers, 1995) explains that the relative benefit, compatibility, complexity, trialability and observability are some of the major characteristics that determine the pace of adoption of a technology. The relative advantage is related to perceived success. Trust helps to detect the compatibility of two persons and felt risk makes it harder to notice the complexity and ambiguity of things for AI advice. Therefore, IDT is a complementary hypothesis to TAM that accounts for the differences in acceptance rates across different types of investors (Phoon & Koh, 2018). We have the basis of many theories that are required for full comprehension of how new ideas are accepted by AI advisors. The integration of IDT with TAM, Trust Theory and Perceived Risk Theory

4.1 Theoretical lens and hypothesis

4.1 Conceptual Framework

The suggested paradigm of controlled dual mediation is shown in Fig. 1. The independently varied characteristic is perceived effectiveness (PE). The variable that is being assessed is Adoption Intention (AI). Trust (TR) and perceived risk (PR) are two different concepts. TR facilitates adoption (positive path) whereas PR impedes adoption (negative path). Financial literacy (FL) acts as a brake on the TR-to-AI route. It also shows a direct path from PE to AI.

Figure 1 — Conceptual Framework: AI-Based Financial Advisory Services Adoption Model

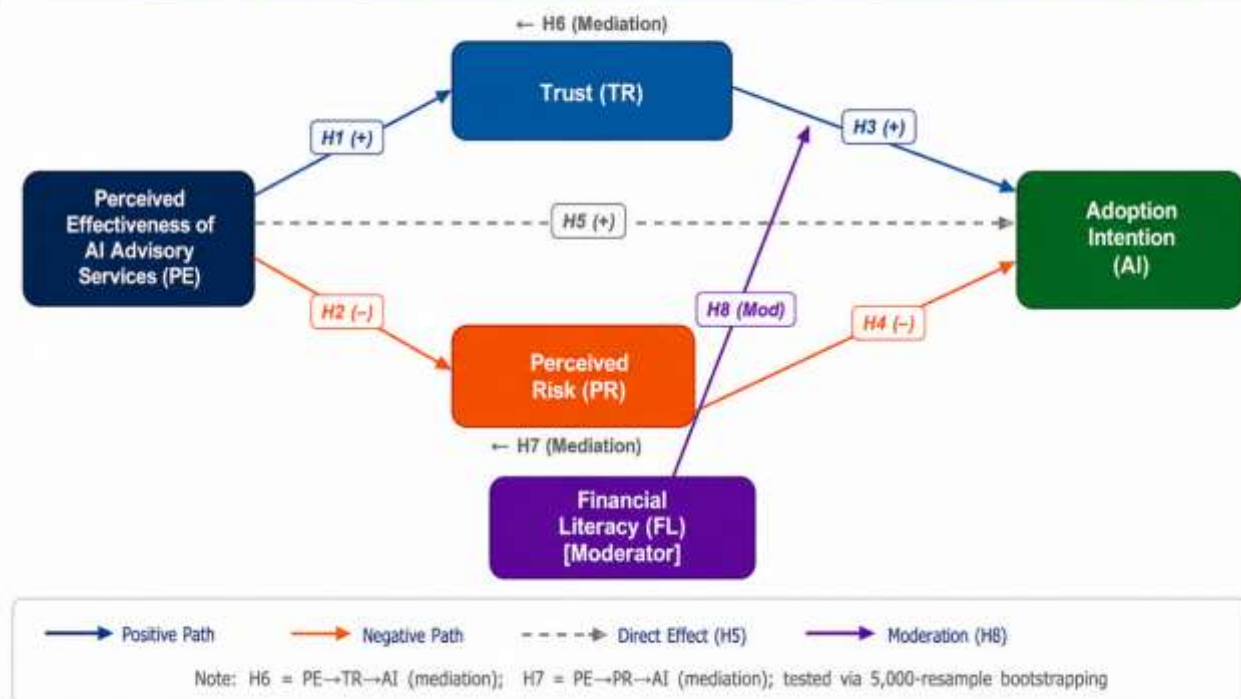


Figure 1. Conceptual Framework: Moderated Dual Mediation Model of AI-Based Financial Advisory Service Adoption.

4.2 Hypothesis Development

H1 and H2: Trust and Perceived Risk → Perceived Effectiveness

Highly accurate, reliable, customized, and operationally efficient AI advice systems are likely to build client confidence since they demonstrate the system is competent and honest (McKnight et al., 2002). Meanwhile, perceived effectiveness should decrease perceived risk by mitigating worries about algorithmic mistakes, privacy problems, and poor performance (Featherman & Pavlou, 2003). Belanche et al. (2019) found that perceived quality of service was the strongest predictor of trust in the robo-advisory context. In addition, the perception of usefulness and financial risk were inversely connected in mobile payment environment (Yang et al., 2015).

H1: The higher success of AI advising services boosts investor's trust.

H2: People's ideas about how AI guidance services work influence their perceived danger of the services.

H3 and H4: Perceived risk, trust and intention of adoption

Trust between users decreases feelings of vulnerability and uncertainty, which in turn reduces the psychological costs of AI advising systems and enhances the willingness of users to accept their usage (McKnight et al., 2002; Pavlou, 2003). On the other hand, perceived risk raises the cost of adoption for people and reduces the chance of adoption (Featherman & Pavlou, 2003). The study is aware of the effects of FinTech adoption (Cao & Niu, 2019; Cheng et al., 2019).

If people trust AI-based financial advice services, they are more likely to use them.

People are less likely to use AI-based financial advice services if they believe it's risky.

5. Perceived effectiveness → intention to adopt

Based on the perceived utility construct of the TAM (Davis, 1989; Venkatesh et al., 2003), PE should impact the behavioral intention of adoption regardless of its effects on trust and perceived risk. This straight line shows the value of the platform from the cognitive-rational standpoint.

H5: Perceived usefulness of AI guiding services has a direct and positive effect on the intention to use them.

Trust and Perceived Risk (H6 and H7) Making a Stand

Acceptance is also affected by perceptions of success as well as trust and risk reduction procedures, as shown by TAM and Trust Theory (Davis, 1989; McKnight et al., 2002). H6 shows that trust is a facilitating mediator while H7 suggests that perceived danger is an impeding mediator. The dual mediation paradigm is required to account for both

mediation techniques simultaneously.

H6: Trust is an indirect mediator of the beneficial effect of perceived efficiency on adoption intention.

H7: perceived success mediates between perceived risk and adoption intention.

The role of financial literacy as moderator

It is thought that financial awareness helps to improve the trust-adoption route. Therefore, the more financially literate and confident an investor is in an AI system, the faster they will act on that confidence, because they can check the correctness of computer proposals and understand what the dangers are (Calcagno & Monticone, 2015; Servon & Kaestner, 2008).

It is hypothesized that trust and purchase intention connection is amplified by financial literacy and that this effect is more prominent in buyers with higher financial literacy.

Table 1. Summary of Research Hypotheses

Hyp.	Direction	Statement
H1	PE → TR (+)	Perceived effectiveness positively influences trust.
H2	PE → PR (−)	Perceived effectiveness negatively influences perceived risk.
H3	TR → AI (+)	Trust positively influences adoption intention.
H4	PR → AI (−)	Perceived risk negatively influences adoption intention.
H5	PE → AI (+)	Perceived effectiveness directly and positively influences adoption intention.
H6	PE→TR→AI	Trust mediates the PE–AI relationship (partial mediation expected).
H7	PE→PR→AI	Perceived risk mediates the PE–AI relationship.
H8	FL mod TR→AI	Financial literacy positively moderates the TR–AI relationship.

5. Methodology

5.1 How to do research

The study used a quantitative cross-sectional survey technique (Creswell & Creswell, 2018), which may test several hypotheses at the same time for a large and diverse set of investors. The primary analytical method employed was PLS-SEM because it is more appropriate for estimating complex predictive models with reflective measurement structures, it is not affected by non-normal data distributions and has been previously utilized in FinTech adoption research (Hair et al., 2022; Ringle et al., 2022).

5.2 Sample size, population and sampling

The target audience are individual investors who know or have utilized AI-based financial advising services, such as robo-advisory platforms, AI-powered investing applications or portfolio management tools that are based on algorithms. Data was available from everywhere but was mostly gathered from the digitally engaged investors in emerging and big Asian economies. A intentional and snowball sampling was employed since there was no public investor sample frame available. We aimed to collect at least 450 usable responses, following Hair et al.'s (2022) ten-times rule and the conditions for statistical power ($f^2 = 0.15$, power = 0.80, $\alpha = 0.05$). 565 invites were sent out and 458 complete answers were received. After deleting straight-line replies and multivariate outliers, 450 responses were preserved (response rate: 79.6%).

5.3 Instruments of measurement

An organized survey was sent out using Qualtrics and a seven-point Likert scale (1 = Strongly Disagree to 7 = Strongly Agree). All scales were adapted from previously validated instruments with just minor modifications to meet the AI guiding configuration. Content validity was evaluated by expert reviews (n=3 academics in FinTech, behavioral finance, and IS research) and pilot testing (n=35 market investors). Table 2 shows the measurement structures, item numbers and sources.

Table 2. Measurement Constructs, Items, and Sources

Construct	Items	Source	Sample Item
Perceived Effectiveness (PE)	5	Belanche et al. (2019); Logg et al. (2019)	The AI advisory service provides accurate and reliable investment recommendations.
Trust (TR)	5	McKnight et al. (2002); Pavlou (2003)	I believe the AI advisory platform is honest and trustworthy in managing my investments.
Perceived Risk (PR)	5	Featherman & Pavlou (2003); Yang et al. (2015)	I am concerned about losing money due to errors made by the AI advisory system.
Financial Literacy (FL)	5	Lusardi & Mitchell (2014); Huston (2010)	I understand how diversification reduces investment portfolio risk.
Adoption Intention (AI)	5	Davis (1989); Venkatesh et al. (2003)	I intend to use an AI-based financial advisory service for my investments in the future.

5.4 Controls for Common Method Bias

Procedural controls were implemented including the use of anonymous surveys, physical separation of predictor and outcome items, and rigorous instructions to minimize social desirability bias (Podsakoff et al., 2003). The results of Harman's single-factor test indicated that the highest single-factor variance is 26.7%, which is less than the critical value of 50%. Thus, common method bias is not a big worry in this dataset.

5.5 Analytical Method

A two-stage analytical approach was used with SmartPLS 4 (Ringle et al., 2022): (1) Measurement Model Assessment — Cronbach's α and composite reliability ($CR \geq 0.80$), convergent validity ($AVE \geq 0.50$), and discriminant validity ($HTMT < 0.90$); (2) Structural Model Assessment — standardised path coefficients, R^2 , f^2 effect sizes, and Q^2 predictive relevance. Mediation analyses were conducted using bias-corrected bootstrapped confidence intervals (5,000 resamples). To test moderation, we used the product-indicator technique with standardized interaction terms before calculation.

6. Results

6.1 Sample Profile

Table 3. Demographic Profile of Respondents (N = 450)

Variable	Category	n (%)
Gender	Male	261 (58.0%)
	Female	183 (40.7%)
	Other / Prefer not to say	6 (1.3%)
Age	18–24	52 (11.6%)
	25–34	171 (38.0%)
	35–44	121 (26.9%)
	45–54	74 (16.4%)
	55+	32 (7.1%)
Education	High School	36 (8.0%)
	Bachelor's	198 (44.0%)
	Master's	148 (32.9%)
	Doctorate	32 (7.1%)
	Professional Degree	36 (8.0%)
AI Advisory Experience	Aware but never used	121 (26.9%)
	Used once or twice	108 (24.0%)
	Occasional user	126 (28.0%)
	Regular user	72 (16.0%)
	Power user / daily	23 (5.1%)
Investment Experience	< 1 year	40 (8.9%)
	1–3 years	126 (28.0%)
	3–5 years	144 (32.0%)
	5–10 years	95 (21.1%)
	> 10 years	45 (10.0%)

6.2 Descriptive Statistics & Correlations

Table 4 presents descriptive statistics and inter-construct correlations. All concept means ranged from 3.43 (Perceived Risk, moderate-low perceived risk perception on a 7-point scale, consistent with an active investor population) to 4.80 (Financial Literacy). The skewness and kurtosis values suggest that the univariate normalcy is virtually achieved. The correlation matrix displays the direction of correlations expected. PE is positively correlated with TR ($r = 0.546$), FL (r

= 0.392) and AI ($r = 0.533$) and negatively correlated to PR ($r = -0.483$). The PR was negatively correlated with TR ($r = -0.424$) and AI ($r = -0.505$).

Table 4. Descriptive Statistics and Pearson Correlation Matrix (N = 450)

Variable	Mean	SD	1	2	3	4	5	Skew Kurt	/
1. PE	4.761	1.129	—					−0.064 −0.296	/
2. TR	4.639	1.185	0.546	—				−0.197 −0.333	/
3. PR	3.426	1.158	−0.483	−0.424	—			0.149 −0.335	/
4. FL	4.804	1.062	0.392	0.356	−0.257	—		−0.125 −0.444	/
5. AI	4.474	1.173	0.533	0.608	−0.505	0.358	—	−0.130 −0.468	/

Note. All correlations significant at $p < .01$ (two-tailed) except where noted. PE = Perceived Effectiveness; TR = Trust; PR = Perceived Risk; FL = Financial Literacy; AI = Adoption Intention.

6.3 Evaluation of the measurement model

Table 5. Statistics of reliability and validity All constructs possess strong internal consistency (Cronbach's α ranging from 0.929 to 0.943; CR ranging from 0.946 to 0.957), which is much beyond the requirement of 0.70/0.80. The Average Variance Extracted (AVE) values were between 0.779 and 0.815, which is over the minimum threshold of 0.50 for convergent validity. All loadings for each individual item were much over the threshold value of 0.70, ranging from 0.875 to 0.916. The HTMT ratios shown in Table 6 range from 0.256 to 0.621, which is much below the cautious threshold of 0.85 (Henseler et al., 2015). Hence, discriminant validity is established for all pairs of constructs.

Table 5. Measurement Model: Reliability and Validity

Construct	Cronbach's α	CR	AVE	Item Loadings (Range)
PE	0.937	0.952	0.800	0.886, 0.904, 0.899, 0.890, 0.893
TR	0.941	0.955	0.810	0.907, 0.902, 0.899, 0.892, 0.900
PR	0.940	0.954	0.806	0.904, 0.888, 0.899, 0.909, 0.888
FL	0.929	0.946	0.779	0.875, 0.893, 0.887, 0.878, 0.880
AI	0.943	0.957	0.815	0.904, 0.916, 0.889, 0.904, 0.900

Note. CR = Composite Reliability; AVE = Average Variance Extracted. All values meet Hair et al. (2022) thresholds.

Table 6. Discriminant Validity: HTMT Ratios

	PE	TR	PR	FL
TR	0.527			
PR	0.453	0.386		
FL	0.337	0.330	0.256	
AI	0.504	0.621	0.473	0.348

Note. All HTMT < 0.85 (conservative threshold; Henseler et al., 2015), confirming discriminant validity.

6.4 Result of Structural Model

The structural path coefficients are shown in table 7. All pathways save H8 (moderation) are relevant. The results substantially corroborate H1 (PE→TR: $\beta = 0.546$, $t = 13.794$, $p < .001$) and H2 (PE→PR: $\beta = -0.483$, $t = 11.652$, $p < .001$) showing perceived effectiveness as a potent antecedent of both trust development and risk reduction. The results support H3 (TR→AI: $\beta = 0.377$, $p < .001$), H4 (PR→AI: $\beta = -0.236$, $p < .001$), and H5 (PE→AI: $\beta = 0.177$, $p < .001$). H8 (TR×FL→AI: $\beta = -0.024$, $p = .464$) is not supported. The model explains 29.9% of variation in trust, 23.3% in perceived risk and 47.7% in adoption intention.

Table 7. Structural Model Results — Path Coefficients (N = 450)

Hyp.	Path	β	SE	t-value	p-value	Decision
H1	PE → TR	0.546	0.040	13.794	< .001	Supported ✓
H2	PE → PR	-0.483	0.041	11.652	< .001	Supported ✓
H3	TR → AI	0.377	0.043	8.837	< .001	Supported ✓
H4	PR → AI	-0.236	0.040	5.860	< .001	Supported ✓
H5	PE → AI (Direct)	0.177	0.045	3.964	< .001	Supported ✓
H8	TR × FL → AI	-0.024	0.032	0.734	.464	Not Supported ✗

Note. Standardised path coefficients. $R^2(TR) = 0.299$; $R^2(PR) = 0.233$; $R^2(AI) = 0.477$. Bootstrap CI from 5,000 resamples. *** $p < .001$.

6.5 PLS-SEM Structural Model Diagram

Figure 2 presents the PLS-SEM structural model with all standardised path coefficients, R^2 values, significance levels, and mediation results embedded directly in the diagram.

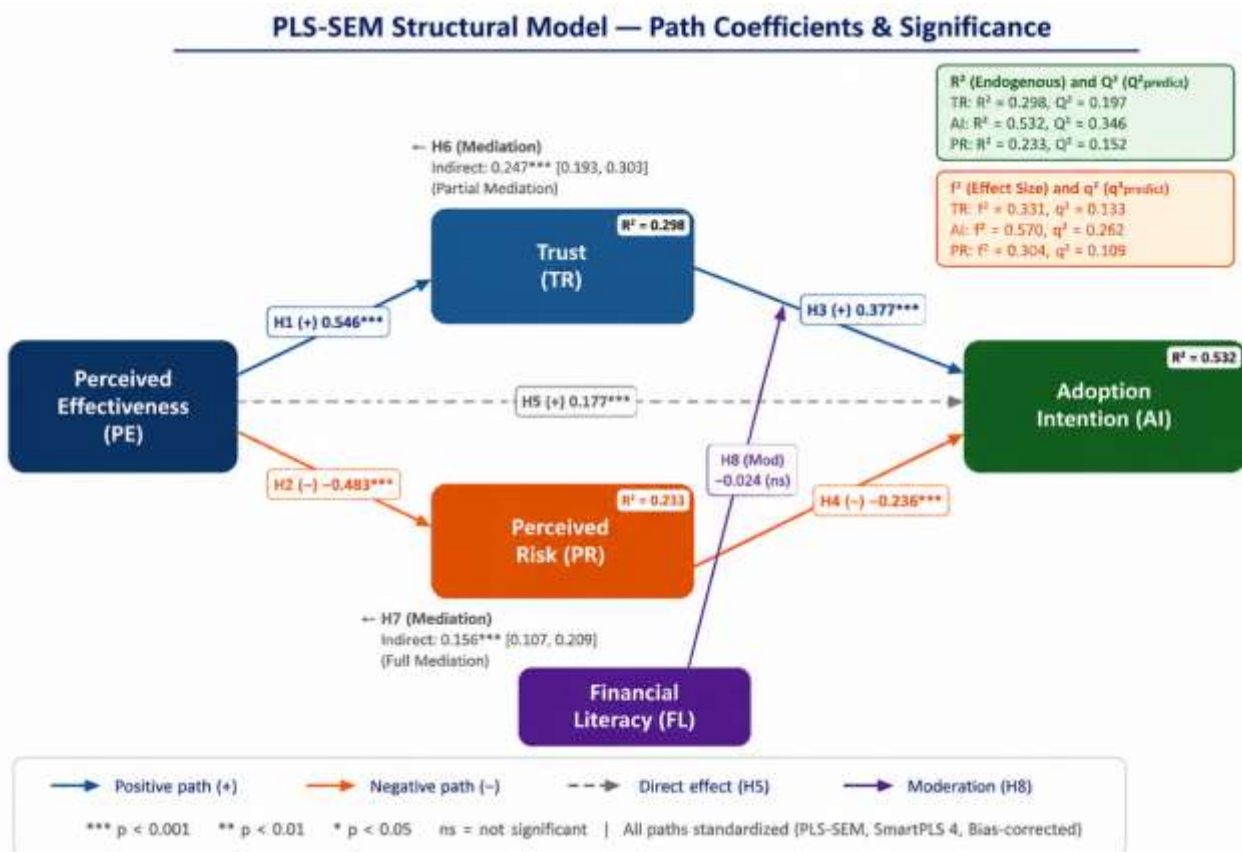


Figure 2. PLS-SEM Structural Model with Path Coefficients, R^2 Values, and Mediation Results ($N = 450$). *** $p < .001$; n.s. = not significant.

6.6 Mediation Analysis (H6 and H7)

Results of bootstrap mediation are shown in Table 8. H6 is supported: PE has a substantial indirect influence on AI via TR (indirect $\beta = 0.247$, 95% CI [0.193, 0.303]), and the confidence interval does not include zero. This is partly mediation, since there is a considerable direct PE $\rightarrow$ AI route. H7 is also supported: the indirect impact via PR is considerable (indirect $\beta = 0.156$, 95% CI [0.107, 0.209]). The direct route PE $\rightarrow$ AI is still important with PR as mediator, which also points to the pattern being consistent with the partial mediation of the risk pathway. Thus, the facilitative (i.e. trust) and inhibitory (i.e. risk) channels are working at the same time.

Table 8. Mediation Analysis: Indirect Effects via Trust and Perceived Risk

Hyp.	Indirect Path	Indirect β	95% Lower CI	95% Upper CI	Decision
H6	PE $\rightarrow$ TR $\rightarrow$ AI	0.247	0.193	0.303	Supported ✓
H7	PE $\rightarrow$ PR $\rightarrow$ AI	0.156	0.107	0.209	Supported ✓

Note. Bias-corrected bootstrapped CIs (5,000 resamples). CI not including zero = significant indirect effect. Both H6 and H7 reflect partial mediation patterns alongside significant direct effects (H5).

7. Discussion

7.1 Perceived efficacy as a precursor to trust and danger

The large positive effect of perceived effectiveness on trust (H1: $\beta = 0.546$, $p < .001$) implies that the most important factor for trust building here is the investors' fundamental assessment of an AI advising system's accuracy, reliability, personalisation and efficiency. This study complements the research on robo-advisors by Belanche et al. (2019) and extends their results by showing the simultaneous operations of perceptions of effectiveness on trust (facilitating route) and perceived danger (inhibitory pathway). The significant negative effect of PE on PR (H2: $\beta = -0.483$, $p < .001$) indicates that investors perceiving the AI advisory services as truly effective are significantly less concerned about financial, privacy, and performance risk, consistent with the theory prediction by Featherman and Pavlou (2003) that demonstrated system quality diminishes subjective risk appraisals.

7.2 Mediators of trust and perceived risk: Double

The most conceptually interesting result of the study is the simultaneous presence of trust as a facilitating mediator (H6: indirect $\beta = 0.247$) and perceived risk as an inhibiting mediator (H7: indirect $\beta = 0.156$). The dual mediation architecture argues that perceived efficacy influences adoption intention via two psychologically different and conflicting pathways. Quantitatively, the trust-mediated pathway (H6 indirect effect) is larger than the risk-mediated route (H7), i.e., increasing investor confidence in the AI advising skills is a more potent driver of adoption than just decreasing risk perceptions. This difference has tremendous practical ramification. FinTech platforms should move away from statements about reducing risk and instead use communication tactics to generate trust, e.g. transparency reports, performance track record and regulatory endorsement signals.

The pattern of partial mediation for both channels (given the large direct influence of H5) illustrates that perceived efficacy impacts adoption via a direct cognitive-rational path. This is consistent with TAM (Davis, 1989) which found that perceived usefulness had a direct impact on behavioral intentions without the mediating presence of attitudinal or emotional mediators. A key distinction here is that investors aren't only trusting or analyzing risk when considering AI advisory services, but are also making direct, utilitarian judgments about the value proposition of the platform.

7.3 Financial literacy did not significantly moderate

One noteworthy and theoretically instructive finding is the non-significant moderating of financial literacy on the trust-adoption intention pathway (H8: $\beta = -0.024$, $p = .464$). There are several ways this result might be interpreted. First, the active digital investors sample may have above average financial expertise and reasonably homogeneous financial knowledge, which decreases the variance-based moderation detection power. Second, trust may be such a powerful attitudinal predictor for AI guidance, that the additional explanatory power of financial knowledge is small at the point of behavioral intention formation. Third, financial literacy may influence earlier stages of the adoption decision, e.g., initial awareness, evaluation and platform choice, rather than the trust-intention conversion observed here. Fourth, the relationship between financial literacy and AI trust is potentially non-linear: moderately-literate investors may be less trusting (since they grasp the constraints of AI systems better), while highly-educated investors may be more trusting. Future work with quadratic moderation requirements and samples with more diversity in literacy could help tease these ideas apart.

8. Implications

8.1 Theoretical implications

- **Dual mediation model:** This research is one of the first to investigate confidence (which facilitates) and perceived risk (which inhibits) as two different elements that impact the relationship between PE and AI adoption. This offers a more comprehensive psychological explanation than previous models that have focused on one aspect solely. Incorporating perceived effectiveness, a service quality-specific measure of perceived value, into the TAM domain, connects the technology acceptance and service quality literatures, and adds AI advise scenarios. The non-significant moderation result adds to our increasing awareness that financial literacy is more important in AI

adoption than we previously anticipated. It also illustrates the significance of having non-linear moderation models that are specific to each step.

The combination of TAM, Trust Theory, Perceived Risk Theory and IDT offers a comprehensive multi-theoretical foundation for future empirical research on people's adoption of AI financial services.

8.2 Implications for Practice

- confidence Communication Strategy: FinTech firms should engage in algorithmic transparency initiatives including explainable AI (XAI) tools, performance disclosure reports, and third-party audit approvals to establish and maintain investor confidence. The trust-mediated technique (H6 indirect = 0.247) exhibited a higher indirect effect than the risk-mediated method (H7 indirect = 0.156), suggesting that the development of trust has a stronger positive impact on acceptance than risk reduction.
- Risk reduction by design: Platform design teams may include risk communication elements into their products, such as explicit descriptions of algorithmic limitations, historical performance ranges, and loss scenario simulations, to provide prospective users with the sense that they are assuming less financial and performance risk. The large direct PE→TR ($\beta = 0.546$) and PE→AI ($\beta = 0.177$) paths indicate that the primary means of building trust and driving adoption of FinTech platforms is to prove their effectiveness at the initial onboarding experience (simulated portfolio demonstrations, performance testimonials, and real-time recommendation explanations).

8.3 Implications for Policy

- AI Transparency Regulation: Regulators should set high requirements of explainability for platforms providing AI advice. This allows for automatic advice to be made in a fashion that can be understood by average investors with varying degrees of experience.
- Investor protection regimes: Regulators need to establish explicit regimes for accountability for errors and poor performance in AI guidance. This would make risk appear less probable, which would indirectly increase trust and acceptability among risk-averse investors.
- Financial Literacy programs: The H8 conclusion is not significant, but policymakers and financial organizations should nonetheless continue to operate programs teaching people about money. This is because financial literacy may prevent individuals from employing AI in earlier decision making not studied here.

9. Limitations and Future Research Directions

1. Design: The design was cross sectional which is difficult to determine the cause and effect. However, the internal validity might be improved by doing more longitudinal research that investigates changes in trust and adoption behavior over time.
2. Self-report measurements could be subject to social desirability bias. Future study should look at poll findings with behavioral data such as how many people actually join for a site and how many transactions take place to corroborate what individuals say they want to do.
3. There are two kinds of nonprobability samples. There are two types of samples: deliberate and random. It's difficult to generalize. Future research should be conducted on random chance samples drawn from a broad spectrum of socioeconomic and geographic groupings.
H8: The moderation of financial literacy level is not very strong. Further study should explore non-linear (quadratic) moderation specifications, stage-specific moderation (knowledge, assessment and uptake) and subgroup analysis by literacy quartile.
4. 1 nation Why: If we include more than one nation, we may observe how socioeconomic, cultural and government concerns impact the usage of AI advice.
5. Things not thought of: Down the road, models should consider about things like the platform's image, the person's mental qualities (such wanting to think or being fearful of technology), and the government's trust.

10. Conclusion

We created and validated a controlled dual mediation model for the adoption intention of AI-based financial advising services among retail investors in this research. So it included TAM, Trust Theory, Perceived Risk Theory and Innovation Diffusion Theory. The study, using PLS-SEM analysis of 450 individual investors, demonstrates that perceived utility of AI advising services increases trust ($\beta = 0.546$) and decreases perceived risk ($\beta = -0.483$). Therefore, these two factors affect the AI adoption plans of people differently. The trust channel (H6 indirect 2 = 0.247) is statistically larger than the risk channel (H7 indirect 2 = 0.156), which proves that trust is the major factor that influences the acceptance of AI guidance. It is also true that perceived efficiency has direct impact on adoption intention ($\beta = 0.177$) which is in line with the direct utilitarian value assessment route that TAM found. Financial knowledge does not appear to influence much for the link between trust and uptake. That means it's involved in more scenarios and more parts of the game than we realized.

As we alter the investment process with AI-enabled financial advising services, it is even more important to understand the mental processes investors go through to evaluate, trust and eventually accept new technology. The two-fold mediation approach of the research offers a theoretically sound and empirically proven direction for FinTech designers, financial institutions, investor education programs and regulatory bodies to foster responsible, inclusive and effective use of AI in retail financial markets.

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