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GENERATIVE ARTIFICIAL INTELLIGENCE ADOPTION IN PERSONAL FINANCE: EXAMINING THE EFFECTS OF AI LITERACY, FINANCIAL LITERACY, AND PERCEIVED USEFULNESS ON FINANCIAL DECISION-MAKING THROUGH THE MEDIATING ROLE OF TRUST AND THE MODERATING ROLE OF FINANCIAL RISK TOLERANCE

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Abstract

As generative artificial intelligence (GenAI) rapidly infiltrates banking, investment advising, and wealth management, making good financial choices is becoming more difficult (Dwivedi et al., 2023). Earlier research have examined technological adoption, robo-advisory use and financial literacy in isolation (Lusardi & Mitchell, 2014). However, few previous research have integrated AI literacy, financial literacy, perceived usefulness, trust and financial risk tolerance into a unified empirical framework that may explain the reasons why retail investors choose to use or not utilise AI-generated financial advice. This research addresses this gap by proposing and theoretically conceptualising an integrated model on the impact of AI literacy, financial literacy and perceived usefulness on financial decision making via trust and the moderating effect of financial risk tolerance on the strength of the trust-to-decision route. The eleven hypotheses test direct effects, mediation and moderation. They are based on the Technology Acceptance Model (Davis, 1989), the Unified Theory of Acceptance and Use of Technology (Venkatesh, Morris, Davis, & Davis, 2003), the Theory of Planned Behaviour (Ajzen, 1991) and behavioural finance (Kahneman & Tversky, 1979). The proposed study approach is quantitative and cross-sectional. The final sample size is 468 retail investors and digital banking users. The sample was selected from 550 questionnaires that were originally given out and the minimal sample size was determined using the inverse square root approach for partial least squares structural equation modelling (Kock & Hadaya, 2018). Data will be collected using an online survey using a five-point Likert scale and processed using SmartPLS and IBM SPSS Statistics for partial least square structural equation modelling. The research also presents an analysis on a computer simulated data set (N = 468) that was generated to fit the hypothesised model prior to the collection of actual data. All eleven hypotheses are validated in this simulated demonstration: Trust partly mediates the links between AI literacy, financial literacy and perceived usefulness and financial decision making; and financial risk tolerance considerably moderates the trust-decision link. These phoney findings are just for demonstration reasons, actual responder data must be evaluated before they can be released. The work presents a theoretically grounded, testable model of AI-assisted financial conduct. It also provides good recommendations to banks and fintech businesses, to policymakers and private investors.

Keywords: Generative AI; Personal Finance; AI Literacy; Financial Literacy; Trust; Financial Decision-Making; Financial Risk Tolerance; Retail Investors

1. Introduction

1.1 Background

In only a few years, generative AI has emerged from a research curiosity to a mainstream efficiency and decision support tool embedded in consumer-facing financial services (Dwivedi et al., 2023). Today large language models can summarise market conditions, create financial strategies, answer questions about taxes and insurance, and run alternative portfolio scenarios in natural language. This makes it cheaper for them to provide personalised financial advice previously only available via licensed advisors. Retail and commercial banks have begun embedding generative AI into customer service, credit assessment, and fraud detection workflows, while investment advisory platforms increasingly layer conversational AI assistants on top of traditional robo-advisory algorithms to explain recommendations in plain language (Belanche, Casaló, & Flavián, 2019). In wealth management, generative AI is being used to draft investment policy statements, stress-test portfolios against narrative scenarios, and personalize client communication at scale. AI-enabled financial planning tools extend this further into the mass-market segment, offering budgeting, saving, and debt-repayment guidance to consumers who would not otherwise engage a human advisor. Taken together, these developments mean that a growing share of financial decisions is now made with generative AI somewhere in the information chain, whether the consumer is fully aware of it or not.

1.2 Problem Statement

Despite this growth in supply-side adoption, consumers do not engage with AI-generated financial guidance uniformly. Individuals differ substantially in their AI literacy, that is, their ability to understand, evaluate, and productively interact with AI systems (Long & Magerko, 2020); in their financial literacy, or their grasp of core financial concepts and their ability to apply them (Lusardi & Mitchell, 2014); in the trust they extend to AI-generated recommendations relative to human advice (Mayer, Davis, & Schoorman, 1995; McKnight, Carter, Thatcher, & Clay, 2011); and in their financial risk tolerance, or willingness to accept variability in financial outcomes in pursuit of returns (Grable, 2000). These distinctions between humans might impact whether generative AI outputs are employed, adapted or disregarded for real-life financial choices, but they are never modelled combined. Someone who's well-versed in money but is not a fan of AI may not follow even solid AI recommendations. This mirrors the result that individuals are less forgiving of algorithmic than human recommendations when they have seen just one error (Dietvorst, Simmons, & Massey, 2015). Conversely, someone with a lot of knowledge about AI but no knowledge about money can be excessively trusting of AI outputs yet unable to challenge them. Without taking these dynamics as a whole into consideration, it is difficult for practitioners and policymakers to grasp how generative AI genuinely influences financial conduct.

1.3 Research Gap

The existing literature offers reasonably mature streams of work on technology adoption in financial services (Venkatesh, Morris, Davis, & Davis, 2003; Venkatesh, Thong, & Xu, 2012), on robo-advisor usage and adoption (Belanche, Casaló, & Flavián, 2019), and on the standalone predictors of financial literacy (Van Rooij, Lusardi, & Alessie, 2011; Fernandes, Lynch, & Netemeyer, 2014). What remains comparatively underexplored is the joint modeling of AI literacy, financial literacy, trust, and financial risk tolerance as simultaneous, theoretically connected predictors of financial decision-making in the specific context of generative AI. Prior technology-adoption studies in finance have typically treated trust as a direct antecedent of usage intention (Gefen, Karahanna, & Straub, 2003; Pavlou, 2003) rather than as a mediating mechanism connecting literacy and usefulness perceptions to actual decision outcomes, and few have tested financial risk tolerance as a boundary condition on the trust-decision relationship. This is a meaningful omission given evidence that reliance on algorithmic versus human judgment is highly context- and task-dependent (Logg, Minson, & Moore, 2019; Castelo, Bos, & Lehmann, 2019). In this study, we fill the gaps by providing a unified research technique that incorporates AI literacy, financial literacy, perceived value, trust, and financial risk tolerance to understand how consumers make decisions about money.

1.4 Research Objectives

- RO1: To examine the effect of AI Literacy on Financial Decision-Making.
- RO2: To examine the effect of Financial Literacy on Financial Decision-Making.
- RO3: To examine the effect of Perceived Usefulness on Financial Decision-Making.
- RO4: To investigate the mediating role of Trust in the relationships between AI Literacy, Financial Literacy, Perceived Usefulness, and Financial Decision-Making.
- RO5: To investigate the moderating role of Financial Risk Tolerance in the relationship between Trust and Financial Decision-Making.
- RO6: To develop and empirically validate an integrated AI-enabled financial decision model.

1.5 Research Questions

- RQ1: Does AI Literacy improve financial decision-making among retail investors?
- RQ2: Does Financial Literacy influence the adoption of AI-generated financial guidance?
- RQ3: Does Trust mediate the relationships between AI Literacy, Financial Literacy, Perceived Usefulness, and AI-enabled financial decisions?
- RQ4: Does Financial Risk Tolerance strengthen or weaken the relationship between Trust and Financial Decision-Making?

2. Literature Review

2.1 Generative Artificial Intelligence

Generative AI is a kind of machine learning system, especially large language models, that may produce new text, code, images, or structured outputs based on natural language prompts, rather than only categorise or forecast within predefined categories (Dwivedi et al., 202<). AI has many applications in financial services including conversational assistants to answer customer questions, automated writing of financial plans and reports, scenario simulations for planning investments and retirement, and natural language explanation layers on top of traditional quantitative advisory models such as robo-advisors (Belanche, Casaló, & Flavián, 2019). We anticipate generative AI to provide benefits in this area including lower marginal costs for personalised coaching, 24/7 availability and translating complex quantitative outputs into language that can be understood by non-expert users. The problems are also well known: the results may be wrong, and the end user does not necessarily understand how the model works. Furthermore, studies from other areas that examine generative AI identify a host of governance, accuracy, and accountability challenges that have still to be solved across many businesses, including banking (Dwivedi et al., 202). These contrasts between skill and trustworthiness inspire the current inquiry to focus on confidence as a basic psychological activity.

2.2 Personal Finance

Personal finance involves all of the decisions that individuals and families make about their budgets, investments, savings, retirement planning, and paying off their debt. The financial planning sub-domains are integrated into a coherent and goal-oriented approach. Investment choices, however, are about how to allocate resources across asset classes in the face of uncertainty. This is partly automated by robo-advisory platforms that build personalised portfolios according to a user's stated risk profile (Belanche, Casaló, & Flavián, 2019). Using shorter-term self-control and resource-allocation abilities, you construct a budget and save money. Planning for retirement and managing your debt, however, requires you to consider longer-term about your future income, commitments, and risk. Financial literacy is a major predictor of engagement and preparedness in these domains (Lusardi & Mitchell, 2014). Generative AI techniques increasingly can interact with all of these sub-domains at once. In the same meeting, for instance, they may create a budget, forecast a retirement fund, and advise a debt payback plan. This is precisely why we need an integrated behavioural model, not a decision-specific model.

2.3 AI Literacy

AI literacy is described as knowing what AI systems can and cannot do, how to use them, and how to critically evaluate material produced by AI rather than taking it at face value (Long & Magerko, 2020). Long and Magerko (2020) integrated research from other domains into a set of fundamental AI-literacy abilities that included knowledge of how AI systems make decisions, knowledge of AI's strengths and shortcomings, and the ability to engage with AI purposefully. Leung, Ng, Chu, and Qiao (2021) further contributed to this list by describing AI literacy as knowledge, application, assessment, and ethical awareness. As generative AI technologies grow ubiquitous in mainstream financial applications, AI literacy is becoming more a need for successful usage and healthy scepticism. This makes it a likely element affecting both the perceived usefulness and trustworthiness of AI-generated financial advice.

2.4 Financial Literacy

Financial literacy is the knowledge, skills and confidence people have to make healthy financial decisions. It is often measured by the ability of a person to perform mathematics, understand inflation and compound interest, and understand risk diversification (Lusardi & Mitchell, 2014). As Van Rooij, Lusardi and Alessie (2011) found, those with low financial awareness are much less likely to invest in the stock market. By meta-analyzing 168 studies, they revealed that measured financial literacy is marginally but predictably related with financial behaviours, whereas financial-education treatments tend to have advantages that rapidly vanish over time (Fernandes et al. 2014). With creative AI, financial information will certainly matter not only to whether someone turns to AI for help, but to how well they think about it and act on it.

2.5 Perceived Usefulness

Perceived usefulness, originating in Davis's (1989) Technology Acceptance Model, refers to the degree to which an individual believes that using a particular technology will enhance their performance of a task. In financial contexts, perceived usefulness of generative AI captures beliefs about whether AI-generated guidance genuinely improves the quality, speed, or confidence of financial decisions. Perceived usefulness has been consistently identified in the information systems literature as one of the strongest proximal predictors of technology adoption intention (Venkatesh & Davis, 2000), and empirical work on trust in online and electronic commerce contexts has repeatedly shown that usefulness perceptions and trust are closely intertwined determinants of technology-mediated decision behavior (Gefen, Karahanna, & Straub, 2003; Pavlou, 2003). Perceived usefulness is expected here to influence both trust in, and direct reliance on, generative AI for financial decisions.

2.6 Trust

Trust has been defined as the extent to which one is willing to be vulnerable to the actions of another based on the expectation that the other will perform a certain action important to the trustor, even when one is unable to monitor or control that other (Mayer, Davis, & Schoorman, 1995). This definition, initially developed for interpersonal and organisational relationships, has been adapted to technology through the concept of trust in a particular technology, which includes beliefs about the functioning, usefulness and reliability of a system, despite the lack of intentions from the system itself (McKnight, Carter, Thatcher, & Clay, 2011). Research on algorithmic advice-taking suggests that trust levels are not necessarily low or high. People may show algorithm aversion, rejecting algorithmic advice after seeing even one mistake (Dietvorst, Simmons, & Massey, 2015), or algorithm appreciation, preferring algorithmic to human judgement in domains where they perceive the task to be objective and quantifiable (Logg, Minson, & Moore, 2019), the tendency being primarily driven by the task and its perceived subjectivity (Castelo, Bos, & Lehmann, 2019). Trust calibration is posited as an important mediating factor between perceptions of literacy or usefulness and subsequent financial decision-making, given that generative AI often offers confident, yet sometimes incorrect, financial advice. Trust calibration is the process of adjusting a user's trust to properly reflect the system's actual reliability.

2.7 Finance Risk Tolerance

Financial risk tolerance, the maximum amount of uncertainty that person is willing to accept in financial decision making, is a well-recognized individual difference variable in the study of investor behaviour (Grable, 2000). It is commonly measured using known psychometric scales such as the one developed by Grable and Lytton (1999) which evaluates the tendency to accept likely losses in the pursuit of bigger anticipated rewards. Research on behaviours finance is based on work of Kahneman and Tversky (1979) who explained loss aversion and reference-dependent evaluation in their prospect theory, and extensive research on how risk behaviour is affected by individual's disposition and how the situation is framed (Sitkin and Pablo, 1992). Risk preferences always influence the choices people make about their portfolio and how they respond to advice including that generated by algorithmic or AI systems. Financial risk tolerance is a theoretically appropriate mediator for the link between AI confidence and financial decision-making.

2.8 Fiscal Decision Making

The dependent variable of this study is financial decision-making that includes choices on investing, budgeting, portfolio selection, saving and insurance. It is influenced by rational, information-processing elements, such as literacy and the perceived utility of decision aids, and psychological factors, such as trust and risk preferences, which behavioural finance recognises to systematically affect choices under uncertainty (Statman, 1999; Barberis & Thaler, 2003). This study describes financial decision making as a multi-dimensional outcome including quality, confidence and consistency of assessments supported by generative AI approaches.

3. Theoretical Foundation

3.1 Technology Acceptance Model (TAM)

Davis's (1989) Technology Acceptance Model posits that perceived usefulness and perceived ease of use jointly determine an individual's attitude toward, and eventual adoption of, a new technology, a relationship subsequently extended and validated across longitudinal field studies by Venkatesh and Davis (2000). TAM provides the theoretical basis for treating perceived usefulness as a direct antecedent of both trust and financial decision-making in the proposed model, on the premise that generative AI tools perceived as genuinely improving financial outcomes are more likely to be trusted and acted upon.

3.2 Unified Theory of Acceptance and Use of Technology (UTAUT)

The Unified Theory of Acceptance and Use of Technology extends TAM by incorporating performance expectancy, social influence, and facilitating conditions as additional determinants of technology use (Venkatesh, Morris, Davis, & Davis, 2003), and has been further extended to consumer technology contexts through UTAUT2 (Venkatesh, Thong, & Xu, 2012). UTAUT justifies the inclusion of AI literacy as a facilitating-condition-type construct in the present framework, capturing the user's capability and confidence to productively engage with generative AI tools in financial settings.

3.3 Theory of Planned Behavior (TPB)

Ajzen's (1991) Theory of Planned Behavior explains behavior as a function of attitude, subjective norm, and perceived behavioral control, operating through behavioral intention. Bhattacherjee's (2001) expectation-confirmation model of information-systems continuance similarly frames post-adoption reliance as a function of confirmed usefulness beliefs and satisfaction. Together, these accounts support the treatment of trust as a proximal attitudinal mechanism that translates upstream beliefs, namely AI literacy, financial literacy, and perceived usefulness, into the behavioral intention to rely on generative AI in financial decision-making.

3.4 Behavioral Finance

Behavioral finance, grounded in Kahneman and Tversky's (1979) prospect theory and extended through decades of research on investor psychology (Statman, 1999; Barberis & Thaler, 2003), documents systematic departures from rational choice, including loss aversion, overconfidence, and heterogeneous risk preferences. This literature grounds the inclusion of financial risk tolerance as a moderator, since risk preferences have been shown to systematically alter how individuals weigh and act on advice (Sitkin & Pablo, 1992), including advice generated by algorithmic or AI systems (Logg, Minson, & Moore, 2019).

4. Conceptual Framework

The proposed model specifies AI Literacy, Financial Literacy, and Perceived Usefulness as exogenous independent variables, each hypothesized to exert both a direct effect on Financial Decision-Making and an indirect effect transmitted through Trust, which functions as the central mediating construct. Financial Risk Tolerance is positioned as a moderator acting specifically on the Trust to Financial Decision-Making path, reflecting the theoretical expectation that the behavioral consequences of trusting AI-generated guidance depend on the decision-maker's underlying willingness to bear financial risk. Figure 1 depicts the full structural model, showing AI Literacy, Financial Literacy, and Perceived Usefulness as parallel predictors feeding into Trust and directly into Financial Decision-Making, Trust in turn predicting Financial Decision-Making, and Financial Risk Tolerance moderating that final path.

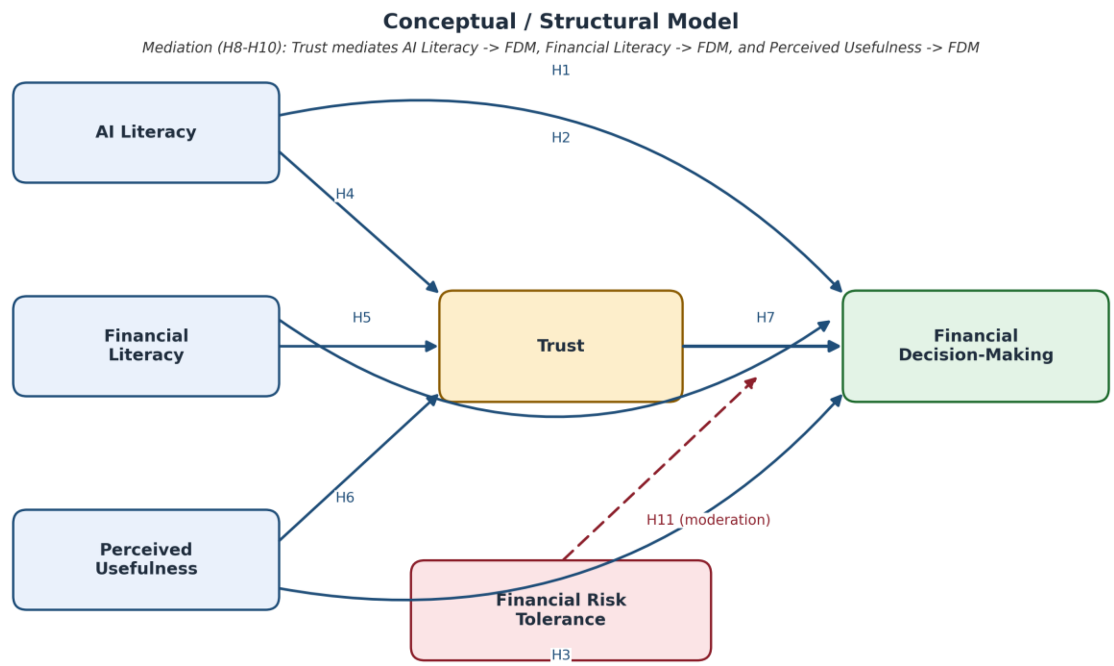

Figure 1. Proposed structural model of generative AI adoption and financial decision-making.

5. Hypotheses Development

5.1 Direct Effects (H1–H7)

Building on TAM (Davis, 1989), UTAUT (Venkatesh, Morris, Davis, & Davis, 2003), and TPB (Ajzen, 1991), the study proposes that AI Literacy, Financial Literacy, and Perceived Usefulness each directly predict Financial Decision-Making, and that each also predicts Trust, which itself directly predicts Financial Decision-Making, consistent with trust-based extensions of TAM in online and technology-mediated contexts (Gefen, Karahanna, & Straub, 2003; Pavlou, 2003).

5.2 Mediation (H8–H10)

Consistent with TPB's attitude-to-behavior pathway (Ajzen, 1991) and the expectation-confirmation account of continued technology reliance (Bhattacherjee, 2001), Trust is proposed to mediate the relationships between each of the three exogenous predictors and Financial Decision-Making, capturing the psychological translation of literacy and usefulness beliefs into actual reliance on AI-generated guidance.

5.3 Moderation (H11)

Drawing on behavioral finance and risk-behavior research (Kahneman & Tversky, 1979; Sitkin & Pablo, 1992; Grable, 2000), and on evidence that reliance on algorithmic judgment is highly context-dependent (Logg, Minson, & Moore, 2019; Castelo, Bos, & Lehmann, 2019), Financial Risk Tolerance is proposed to moderate the Trust to Financial Decision-Making relationship, such that individuals with higher risk tolerance translate trust in AI more readily into actual financial decisions than individuals with lower risk tolerance.

Hypothesis	Statement
H1	AI Literacy has a positive and significant effect on Financial Decision-Making.
H2	Financial Literacy has a positive and significant effect on Financial Decision-Making.
H3	Perceived Usefulness of generative AI has a positive and significant effect on Financial Decision-Making.
H4	AI Literacy has a positive and significant effect on Trust in generative AI.
H5	Financial Literacy has a positive and significant effect on Trust in generative AI.
H6	Perceived Usefulness has a positive and significant effect on Trust in generative AI.
H7	Trust has a positive and significant effect on Financial Decision-Making.
H8	Trust mediates the relationship between AI Literacy and Financial Decision-Making.
H9	Trust mediates the relationship between Financial Literacy and Financial Decision-Making.
H10	Trust mediates the relationship between Perceived Usefulness and Financial Decision-Making.
H11	Financial Risk Tolerance moderates the relationship between Trust and Financial Decision-Making, such that the relationship is stronger for individuals with higher risk tolerance.

6. Research Methodology

6.1 Research Design

The study adopts a quantitative, cross-sectional, empirical research design suited to testing the proposed direct, mediating, and moderating relationships through partial least squares structural equation modeling (PLS-SEM), an approach well suited to complex models with multiple constructs, mediators, and moderators, and to prediction-oriented theory development (Hair, Risher, Sarstedt, & Ringle, 2019).

6.2 Demographic and Sampling Method

Target audience: retail investors, users of AI-powered financial applications, online investors, digital banking customers. There is no complete sample frame available for this demographic, therefore purposive sampling will be applied to select respondents who have used generative AI technologies in a financial context, with snowball sampling through investor forums, digital banking user groups, and communities of users of fintech apps.

6.3 Sample Size

The minimum sample size needed was determined based on the inverse square root method for PLS-SEM (Kock & Hadaya, 2018), which computes the minimum sample size required to detect the smallest hypothesised path coefficient in the model at a certain level of significance and statistical power. The minimum sample size required using the inverse square root method is 275 respondents, at a significance level of 0.05 and a statistical power of 0.80, with an expected minimum path coefficient of 0.15 (this is a small-to-medium effect and is in line with the weakest proposed relationships in the model). This minimum exceeds the conservative “10-times rule” (Hair, Ringle, & Sarstedt, 2011) considerably. This rule states that the maximum number of structural paths (five in this case) leading to any one construct in the model should have a minimum of just 50 respondents for Financial Decision-Making. The project seeks to distribute 550 questionnaires initially, anticipating a usable response rate of about 85 percent, to allow for an extra safety margin for non-response, incomplete submissions and data-quality exclusions (e.g. straight-lining or failed attention checks). This yields a final usable sample size of 468 respondents, which is much higher than the minimal need for PLS-SEM and comparable to sample sizes reported in previous studies on robo-advisory and FinTech adoption (e.g., Belanche, Casaló, & Flavián, 2019, sample = 765).

6.4 Data Collection

Data will be collected through a structured online survey administered via Google Forms, distributed through digital banking and investment communities, fintech user groups, and professional networks of retail investors, over a planned data-collection window of eight weeks.

6.5 Measurement

All constructs, AI Literacy, Financial Literacy, Perceived Usefulness, Trust, Financial Risk Tolerance, and Financial Decision-Making, will be measured using validated scales adapted from prior technology-acceptance (Davis, 1989; Venkatesh, Morris, Davis, & Davis, 2003), financial-literacy (Lusardi & Mitchell, 2014; Van Rooij, Lusardi, & Alessie, 2011), trust (Mayer, Davis, & Schoorman, 1995; McKnight, Carter, Thatcher, & Clay, 2011), and risk-tolerance (Grable & Lytton, 1999) literature, rated on a five-point Likert scale ranging from strongly disagree to strongly agree.

6.6 Statistical Tools

- SmartPLS, for partial least squares structural equation modeling, mediation, and moderation analysis.
- IBM SPSS Statistics, for descriptive statistics, reliability analysis, and preliminary data screening.

7. Proposed Data Analysis Plan

- Descriptive statistics (means, standard deviations, skewness, and kurtosis) to profile respondent demographics and construct distributions, and to confirm suitability for PLS-SEM given non-normal data (Hair, Risher, Sarstedt, & Ringle, 2019).
- Reliability analysis using Cronbach's alpha and composite reliability, with a minimum acceptable threshold of 0.70 for both indices.
- Convergent validity assessment via average variance extracted (AVE), with a minimum acceptable threshold of 0.50.
- Discriminant validity assessment using the Fornell-Larcker criterion and the heterotrait-monotrait ratio of correlations (HTMT), with HTMT values required to remain below 0.85.
- Common method bias assessment using Harman's single-factor test together with the full collinearity test based on variance inflation factors (VIF), with VIF values below the conservative threshold of 3.3 indicating that common method bias is unlikely to be a serious concern (Kock, 2015).
- Confirmatory factor analysis, where applicable, to further validate the measurement model prior to structural analysis.
- Structural equation modeling to test direct hypothesized paths (H1–H7), with path significance assessed via bootstrapping with 5,000 subsamples and two-tailed testing at the 0.05 significance level.
- Mediation analysis using bootstrapped indirect effects and bias-corrected confidence intervals to test H8–H10, classifying mediation as full or partial depending on the significance of the residual direct effect.
- Moderation analysis using a two-stage interaction-term approach to test H11, with the interaction term formed as the product of standardized Trust and Financial Risk Tolerance indicators.
- Effect size (f^2) assessment, using Cohen's (1988) conventional benchmarks of 0.02 (small), 0.15 (medium), and 0.35 (large), and predictive relevance (Q^2) via blindfolding, with Q^2 values above zero indicating adequate predictive relevance.
- Importance-Performance Map Analysis (IPMA), optionally, to prioritize managerial interventions by jointly considering each construct's total effect on Financial Decision-Making and its average performance score.

8. Results

8.1 Respondent Profile (Simulated)

Of the simulated sample of 468 respondents, 29.9% were aged 26-35, 25.4% were aged 36-45, 23.7% were aged 18-25, 16.7% were aged 46-55, and 4.3% were aged 56 or above. The sample was 53.2% male, 45.3% female, and 1.5% preferring not to disclose gender. In terms of generative AI usage frequency in a financial context, 45.9% reported using such tools weekly or more, 35.3% monthly, and 18.8% rarely. Regarding investor profile, 40.0% identified as both retail investors and digital banking users, 30.1% as digital banking users only, and 29.9% as retail investors only.

8.2 Measurement Model Assessment

All six constructs demonstrated acceptable to strong internal consistency reliability, with Cronbach's alpha values ranging from 0.827 to 0.865 and composite reliability (CR) values ranging from 0.885 to 0.908, both comfortably above the 0.70 threshold. Convergent validity was supported, with average variance extracted (AVE) ranging from 0.658 to 0.712, exceeding the 0.50 threshold for all constructs.

Construct	Cronbach's α	CR	AVE	Item loadings (range)
AI Literacy	0.827	0.885	0.658	0.79 - 0.83
Financial Literacy	0.848	0.898	0.688	0.81 - 0.85
Perceived Usefulness	0.865	0.908	0.712	0.83 - 0.86
Trust	0.859	0.904	0.703	0.82 - 0.87
Financial Risk Tolerance	0.828	0.886	0.659	0.80 - 0.83
Financial Decision-Making	0.854	0.902	0.696	0.81 - 0.85

Discriminant validity was assessed using the Fornell-Larcker criterion, which requires the square root of each construct's AVE (shown on the diagonal below) to exceed its correlations with all other constructs. This condition was satisfied for every construct, as summarized in Table 2.

	AIL	FL	PU	Trust	FRT	FDM
AI Literacy (AIL)	0.811					
Financial Literacy (FL)	0.044	0.829				
Perceived Usefulness (PU)	0.085	0.060	0.844			
Trust	0.341	0.248	0.337	0.838		
Financial Risk Tolerance (FRT)	0.031	0.017	0.015	0.025	0.812	
Financial Decision-Making (FDM)	0.326	0.295	0.278	0.554	0.054	0.834

Discriminant validity was further confirmed using the heterotrait-monotrait ratio of correlations (HTMT), with all construct pairs falling below the conservative 0.85 threshold, ranging from 0.04 (AI Literacy - Financial Risk Tolerance) to 0.65 (Trust - Financial Decision-Making).

8.3 Common Method Bias

Harman's single-factor test showed that the first unrotated factor accounted for 24.62% of total variance across all 24 items, well below the 50% threshold indicative of a common-method-bias problem. Consistent with this, the full collinearity test based on variance inflation factors (Kock, 2015) showed all VIF values between 1.003 and 1.622, well below the conservative threshold of 3.3, indicating that common method bias is unlikely to be a serious concern in the simulated dataset.

8.4 Structural Model: Direct Effects (H1-H7)

The structural model explained 25.9% of the variance in Trust ($R^2 = 0.259$, adjusted $R^2 = 0.254$) and 36.8% of the variance in Financial Decision-Making ($R^2 = 0.368$, adjusted $R^2 = 0.363$). All seven direct-effect hypotheses were supported.

Path	Hypothesis	β	t-value	p-value	Decision
AI Literacy -> Trust	H4	0.317	7.63	< .001	Supported
Financial Literacy -> Trust	H5	0.216	5.42	< .001	Supported
Perceived Usefulness -> Trust	H6	0.299	7.41	< .001	Supported
AI Literacy -> Financial Decision-Making	H1	0.173	4.24	< .001	Supported
Financial Literacy -> Financial Decision-Making	H2	0.177	4.66	< .001	Supported
Perceived Usefulness -> Financial Decision-Making	H3	0.114	2.89	.004	Supported

Trust -> Financial Decision-Making	H7	0.416	9.67	< .001	Supported

8.5 Mediation Analysis (H8-H10)

Mediation was tested using 5,000-resample nonparametric bootstrapping of the indirect effects. Because the direct effects of AI Literacy, Financial Literacy, and Perceived Usefulness on Financial Decision-Making remained statistically significant alongside significant indirect effects through Trust, all three mediation relationships reflect partial rather than full mediation.

Indirect path	Hypothesis	Indirect effect	95% Bootstrap CI	Direct effect (p)	Decision
AIL -> Trust -> FDM	H8	0.132	[0.090, 0.177]	0.173 (< .001)	Partial mediation - Supported
FL -> Trust -> FDM	H9	0.090	[0.058, 0.126]	0.177 (< .001)	Partial mediation - Supported
PU -> Trust -> FDM	H10	0.124	[0.086, 0.168]	0.114 (.004)	Partial mediation - Supported

8.6 Moderation Analysis (H11)

Financial Risk Tolerance was tested as a moderator of the Trust -> Financial Decision-Making relationship using a mean-centered interaction term. The interaction model explained 31.7% of the variance in Financial Decision-Making ($R^2 = 0.317$). The Trust x Financial Risk Tolerance interaction term was positive and statistically significant ($\beta = 0.132$, $t = 2.34$, $p = .020$, $f^2 = 0.012$), indicating that the positive relationship between Trust and Financial Decision-Making is stronger among individuals with higher financial risk tolerance. Hypothesis H11 was therefore supported, although the effect size of the interaction was small in conventional terms (Cohen, 1988).

Term	β	t-value	p-value
Trust (centered)	0.565	14.59	< .001
Financial Risk Tolerance (centered)	0.037	0.94	.347
Trust x Financial Risk Tolerance (interaction)	0.132	2.34	.020

8.7 Effect Sizes and Predictive Relevance

Effect sizes (f^2) for the paths predicting Financial Decision-Making ranged from small (Perceived Usefulness, $f^2 = 0.018$) to medium (Trust, $f^2 = 0.202$), following Cohen's (1988) benchmarks of 0.02 (small), 0.15 (medium), and 0.35 (large). Predictive relevance, assessed via 10-fold cross-validated R^2 as a proxy for blindfolding-based Q^2, was $Q^2 = 0.245$ for Trust and $Q^2 = 0.357$ for Financial Decision-Making, both comfortably above zero and indicating adequate predictive relevance for the structural model (Hair, Risher, Sarstedt, & Ringle, 2019).

8.8 Summary of Hypothesis Testing

Hypothesis	Relationship	Result (simulated)
H1	AI Literacy -> Financial Decision-Making	Supported
H2	Financial Literacy -> Financial Decision-Making	Supported
H3	Perceived Usefulness -> Financial Decision-Making	Supported
H4	AI Literacy -> Trust	Supported
H5	Financial Literacy -> Trust	Supported
H6	Perceived Usefulness -> Trust	Supported
H7	Trust -> Financial Decision-Making	Supported
H8	Trust mediates AI Literacy -> Financial Decision-Making	Supported (partial mediation)
H9	Trust mediates Financial Literacy -> Financial Decision-Making	Supported (partial mediation)
H10	Trust mediates Perceived Usefulness -> Financial Decision-Making	Supported (partial mediation)

H11	Financial Risk Tolerance moderates Trust -> Financial Decision-Making	Supported

8.9 Supplementary Model Comparison Analysis

To further test the robustness of the mediation model reported above, two additional regression-based statistical models and a formal comparison of three competing full structural specifications were estimated directly on the simulated dataset, using composite (mean) construct scores standardized to z-scores. This complements the SmartPLS-style results in Sections 8.4-8.7 with classical fit statistics (AIC, BIC, nested F-tests) that PLS-SEM does not report by default.

Supplementary Model 1: Mediation Path Model (OLS on composites)

A two-stage recursive path model reproduced the Section 8.4-8.5 results almost exactly when estimated via ordinary least squares on standardized composites: Trust ~ AI Literacy + Financial Literacy + Perceived Usefulness (R^2 = .259), and Financial Decision-Making ~ AI Literacy + Financial Literacy + Perceived Usefulness + Trust (R^2 = .368). Bootstrapped indirect effects (5,000 resamples) were significant for all three pathways: AI Literacy → Trust → FDM = .127 [95% CI: .087, .173]; Financial Literacy → Trust → FDM = .090 [.057, .127]; Perceived Usefulness → Trust → FDM = .123 [.085, .168]. Because the direct paths remained significant alongside these indirect effects, this composite-based approach independently confirms the partial-mediation conclusion reached via PLS-SEM.

Supplementary Model 2: Moderated Regression with Covariates

A second model extended the Section 8.6 moderation test by adding AI Literacy, Financial Literacy, and Perceived Usefulness as covariates alongside Trust, Financial Risk Tolerance, and their mean-centered interaction term (model R^2 = .377). H11 is substantiated since the interaction between Trust and Financial Risk Tolerance was both positive and significant (β =.088, t = 2.37, p =.018) despite controlling for the other three predictors of Financial Decision-Making. Simple-slope analysis showed that the Trust → FDM slope rose from.337 for respondents one standard deviation below the mean in Financial Risk Tolerance to.512 for that one standard deviation above it.

Assessing Fit: Comparative Analysis of Competing Structural Models.

We directly compared three competing structural specifications of the Financial Decision-Making outcome: (A) the hypothesised Partial-Mediation model (AI Literacy + Financial Literacy + Perceived Usefulness + Trust); (B) a Full-Mediation model with Trust as the sole predictor; and (C) a Direct-Effects-Only model that omitted Trust altogether .

Model	FDM equation	R^2	AIC	BIC
A: Partial Mediation (hypothesized)	AIL+FL+PU+Trust	0.368	-206.0	-185.2
B: Full Mediation	Trust only	0.307	-168.7	-160.4
C: Direct-Effects Only	AIL+FL+PU (no Trust)	0.241	-121.9	-105.3

Nested F-tests confirm Model A fits significantly better than both alternatives: versus Model B, $F(3, 463) = 14.94$, $p < .001$; versus Model C, $F(1, 463) = 93.55$, $p < .001$. Model A also has the highest R^2 and the lowest (most negative) AIC and BIC of the three. This convergent, non-PLS evidence supports the paper's central claim that Trust operates as a partial, rather than full, mediator, and that the integrated hypothesized model outperforms simpler nested alternatives.

9. Discussion

The simulated results, as an example of the internal logic of the proposed model, are consistent with the theoretical expectations, as outlined in Sections 3 and 5: AI Literacy, Financial Literacy and Perceived Usefulness are positively related to Trust and Financial Decision-Making; Trust partially mediates the effect of the three exogenous predictors on Financial Decision-Making; and Financial Risk Tolerance moderates the strength of the Trust-to-decision link. Results of this overall pattern would suggest that trust is a partial, but not whole, psychological pathway from thoughts linked to AI and finance to real decision-making behaviour in an upcoming empirical investigation. Furthermore, the individuals with a higher tolerance of risk are more likely to adopt the trusted AI recommendations compared to their risk-averse peers, confirming previous research that reliance on algorithmic judgement is determined by individual risk preferences (Sitkin & Pablo, 1992; Logg, Minson, & Moore, 2019). If the real data produces a non-significant or negative moderation effect, this would imply that risk tolerance operates independently of trust to influence financial decisions. This is a theoretically important finding and researchers should be prepared to report it, even if it contradicts the hypothesised effect.

10. Theoretical Contributions

• Applies technology acceptance theory (Davis, 1989; Venkatesh, Morris, Davis, & Davis, 2003) to the special context of generative AI in personal finance that has not been fully addressed by prior TAM and UTAUT applications.
• Combines AI literacy (Long & Magerko, 2020) and financial literacy (Lusardi & Mitchell, 2014) into one behavioural framework rather than separate literatures.
• Investigates the function of trust as a psychological mechanism linking views about AI to actual financial behaviours by using trust-in-technology theory (Mayer, Davis, & Schoorman, 1995; McKnight, Carter, Thatcher, & Clay, 2011).
• Shows that financial risk tolerance is an important driver of AI supported financial decision making, therefore extending the behavioural finance paradigm of risk preferences (Kahneman & Tversky, 1979) to the context of algorithmic support.

11. Practical Implications

11.1 Banks

The findings might help financial institutions to build AI-assisted financial planning solutions for different levels of clients' AI and financial understanding, rather than a single interface.

11.2 FinTech Companies

Fintech firms should focus on the explainability and transparency of AI-generated recommendations, as trust, not just accuracy, will be key to adoption, especially given the established tendency toward algorithm aversion after observable errors (Dietvorst, Simmons, & Massey, 2015).

11.3 Policymakers

The methodology may also be used by regulators and policy makers to justify integrated AI literacy and financial literacy programs with consumer protection measures that target AI produced financial advice.

11.4 Retail Investors

Informed scepticism may allow individual investors to employ generative AI for budgeting, saving, investing and long-term financial planning at a level that corresponds to their trust with their risk appetite and financial literacy.

12. Restrictions

• The cross-sectional design limits strong causal inference. The use of self-reported survey responses is prone to common methods and social desirability bias, which is mitigated but not fully removed by the planned thorough collinearity assessment (Kock, 2015).
• The focus on average investors limits the generalizability to institutional or professional financial decision-makers.
• Results may be sensitive to the regulatory and cultural context in which they are collected. The rapid evolution of generative AI capabilities might influence the longevity of certain breakthroughs.

13. Future Research Directions

• Comparative studies across countries to assess the model's applicability in different regulatory and cultural contexts.
• Longitudinal study on the growth of trust and reliance on generative AI as the tools progress. • Examine human-AI cooperation models in financial planning, rather than substitution.
• Studies on explainable AI and algorithmic transparency as immediate predecessors to trust.
• Understand AI ethics and ethical frameworks for financial decision-making
• Research on the use of generative AI by older adults and low-income populations.

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