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HUMAN WITH AI IN FINANCIAL DECISION-MAKING: THE ROLE OF AI EXPLAINABILITY, ALGORITHMIC TRUST AND FINANCIAL LITERACY

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Abstract

The rapid development of artificial intelligence (AI) is bringing significant changes to the way financial information is accessed, analyzed and used for decision-making. AI-based financial tools can process large amounts of information and provide recommendations within a short period, but the usefulness of these systems ultimately depends on how people understand and respond to their recommendations. In this context, the present study examines the role of AI explainability, algorithmic trust and financial literacy in human–AI financial decision-making. The study focuses on whether individuals are more willing and able to rely on AI-supported financial decisions when they can understand the basis of AI recommendations, trust the algorithms involved and possess adequate financial knowledge. Primary data were collected from 320 respondents through a structured questionnaire using a five-point Likert scale. The reliability analysis indicated satisfactory internal consistency, with Cronbach's alpha values above the generally accepted threshold of 0.70 for the study constructs. The findings from descriptive and correlation analyses indicated positive associations among AI explainability, algorithmic trust, financial literacy and human–AI financial decision-making. Multiple regression analysis revealed that the three independent variables jointly explained 64.0% of the variation in human–AI financial decision-making ($R^2 = 0.640$; Adjusted $R^2 = 0.636$). Among the predictors, algorithmic trust showed the strongest positive influence ($\beta = 0.38$, $p < 0.001$), followed by AI explainability ($\beta = 0.31$, $p < 0.001$) and financial literacy ($\beta = 0.24$, $p < 0.001$). The overall regression model was statistically significant ($F = 187.42$, $p < 0.001$). These findings suggest that technological capability alone is not sufficient to ensure effective AI-supported financial decision-making. Users need to understand the reasoning behind AI-generated recommendations, have confidence in the reliability and fairness of the algorithms, and possess sufficient financial

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knowledge to evaluate the information provided by AI systems. The study concludes that effective human–AI collaboration in finance requires a balanced approach in which technological innovation is supported by transparency, trust and informed human judgement. The findings provide useful implications for financial institutions, fintech companies, policymakers and AI developers in designing financial technologies that are more understandable, trustworthy and responsive to users' needs.

Keywords: Artificial Intelligence, Human–AI Collaboration, Financial Decision-Making, AI Explainability, Algorithmic Trust, Financial Literacy, FinTech, Explainable AI, Digital Finance, Financial Services

Introduction

Artificial intelligence (AI) has moved from being primarily a technological innovation to becoming an important part of everyday financial activities. Financial institutions, fintech companies and digital platforms increasingly use AI to analyse large volumes of information, identify patterns, assess risks and provide recommendations to customers and investors. Applications such as automated investment platforms, AI-based credit assessment, fraud detection, financial forecasting and personalised financial recommendations have changed the way financial decisions are made. Unlike traditional financial decision-making, where individuals often depend on personal experience, professional advice and publicly available information, AI-supported decision-making can provide rapid and data-driven insights. This development has created a new form of interaction in which human judgement and machine intelligence increasingly operate together.

The growing role of AI in finance, however, does not mean that human judgement has become less important. Financial decisions frequently involve uncertainty, incomplete information and considerable personal or economic consequences. An individual may receive an AI-generated investment recommendation, credit assessment or financial forecast, but the final decision may still depend on whether that individual understands the recommendation and considers it reliable. This makes the relationship between humans and AI particularly important. The question is no longer simply whether AI can produce accurate financial recommendations, but whether individuals are willing and able to use those recommendations appropriately. The effectiveness of AI in financial decision-making therefore depends on a combination of technological capability and human factors.

One of the most important factors in this relationship is AI explainability. Many AI systems, particularly complex machine-learning models, can generate highly sophisticated predictions without providing users with a clear explanation of how the outcome was reached. In financial settings, this lack of transparency can create uncertainty. When individuals are asked to make important financial decisions based on an AI recommendation, they may want to know why a particular recommendation was generated, what factors influenced the result and whether the recommendation is appropriate for their circumstances. Explainable AI attempts to address this issue by making the reasoning, factors or processes behind an AI-generated output more understandable to users. Greater explainability may therefore help individuals evaluate AI recommendations rather than accepting them without question.

Alongside explainability, algorithmic trust represents another important dimension of human–AI interaction. Individuals may hesitate to rely on AI if they are uncertain about the accuracy, reliability, fairness or consistency of an algorithm. On the other hand, excessive trust may also create problems if users accept AI recommendations without applying their own judgement. In financial decision-making, both insufficient trust and excessive reliance can have important consequences. A balanced level of trust

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is therefore necessary for effective human–AI collaboration. Users need sufficient confidence in an AI system to consider its recommendations, while also retaining the ability to question and evaluate those recommendations.

Another factor that can influence the quality of AI-supported financial decisions is financial literacy. Financial literacy enables individuals to understand basic financial concepts, evaluate risk and return, compare financial alternatives and make informed financial choices. As AI increasingly becomes a source of financial information and recommendations, financial literacy may become even more important. An individual with stronger financial knowledge may be better positioned to interpret an AI-generated recommendation, identify potential limitations and determine whether the recommendation is consistent with personal financial objectives and risk preferences. Conversely, individuals with limited financial knowledge may find it difficult to distinguish between useful AI-generated information and recommendations that require further evaluation.

The interaction among these three factors AI explainability, algorithmic trust and financial literacy—provides an important basis for understanding human–AI financial decision-making. Explainability may improve understanding, understanding may contribute to trust, and financial literacy may enable individuals to critically evaluate the information generated by AI. These factors are not necessarily independent in practical decision-making. A person may trust an AI system because its recommendations are understandable, while financial knowledge may determine whether that trust results in a sensible financial decision. Examining these relationships together can therefore provide a more complete understanding of how individuals engage with AI-enabled financial services.

The issue has become particularly relevant as financial services continue to become more technology-driven. The expansion of digital banking, mobile financial applications, robo-advisory services, algorithmic investment tools and AI-powered personal finance platforms has increased the opportunities for individuals to interact directly with automated financial systems. This shift has also changed the responsibilities of financial institutions and technology providers. It is no longer sufficient to develop systems that are technically efficient; users also need systems that are understandable, dependable and capable of supporting informed decision-making. Building user confidence while preserving human oversight has consequently become an important consideration in the development of AI-enabled financial services.

Despite the growing literature on AI applications in finance, there remains a need to understand the human side of AI-supported financial decision-making. Much of the discussion surrounding AI in finance has concentrated on technological efficiency, predictive performance, automation and operational benefits. While these dimensions are important, they do not fully explain why individuals accept or reject AI-generated financial recommendations. Questions concerning transparency, trust and the user's financial knowledge deserve greater attention, particularly when financial decisions involve personal wealth, investment risk and long-term financial outcomes. The present study addresses this issue by bringing AI explainability, algorithmic trust and financial literacy into a common research framework.

The study is also relevant from a practical perspective. Financial institutions and fintech companies are increasingly investing in AI-based solutions, but adoption of these technologies cannot be assumed merely because the systems are technically advanced. Users need to perceive AI as understandable and reliable, and they must possess sufficient financial knowledge to use its recommendations responsibly. For policymakers and regulators, these issues raise questions about

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transparency, consumer protection, responsible AI and the preservation of human control in financial services. For AI developers, the findings can provide direction for designing systems that communicate recommendations in a manner that ordinary users can understand. Thus, studying human–AI financial decision-making has implications not only for academic research but also for the broader development of responsible digital finance.

Against this background, the present study, titled "Human with AI in Financial Decision-Making: The Role of AI Explainability, Algorithmic Trust and Financial Literacy," seeks to examine how these three factors influence human engagement with AI-supported financial decisions. The study considers AI explainability as a technological and communication-related factor, algorithmic trust as a psychological and behavioural factor, and financial literacy as an individual capability. By examining these dimensions together, the study attempts to move beyond a technology-centred view of AI and place human judgement at the centre of financial decision-making.

The study contributes to the emerging discussion on responsible and human-centred AI in finance by highlighting that successful AI adoption is not determined solely by the sophistication of algorithms. The ability of users to understand AI outputs, develop an appropriate level of trust and apply their financial knowledge may determine whether AI becomes a useful decision-support mechanism or simply another source of financial information. A stronger understanding of these relationships can help create a financial environment in which AI complements rather than replaces human judgement. Ultimately, the future of AI in finance may depend not on choosing between human intelligence and artificial intelligence, but on developing an effective partnership between the two.

Literature Review

Ioannou et al. (2026) examined The Role of Explainability in AI-Driven Financial Decision Making and highlighted those users often depend on explanations when they do not have sufficient expertise to evaluate AI-generated financial advice. Their findings indicate that information quality, usefulness, trust and perceived risk influence users' responses to AI-supported financial decisions. The study is particularly relevant because it directly connects AI explainability with financial decision-making and trust.

Vijayananth and Saravanabhavan (2026) examined Beyond Algorithmic Trust: Human–AI Interaction Competency Strengthens AI-Driven Financial Decision-Making and Financial Resilience. Their study, based on 569 retail investors in major Indian cities, found that AI trading usage and perceived financial uncertainty influenced perceived algorithmic trust, which subsequently supported sustainable investment behaviour and financial resilience. The study further showed that human–AI interaction competency strengthens the relationship between algorithmic trust and financial behaviour, making it highly relevant to human–AI financial decision-making.

Haj Ammar et al. (2026) examined Explainable Artificial Intelligence in Finance: A Bibliometric Review using 586 peer-reviewed Scopus-indexed studies. Their analysis identified interpretability, trust, fairness and regulatory compliance as major themes in XAI-finance research. The authors also highlighted gaps in theoretical integration and the need for stronger frameworks to evaluate explainability, providing a strong basis for further empirical research on how users respond to explainable financial AI.

Haj Ammar et al. (2026) examined Explainable Artificial Intelligence in Finance: Mapping Business Problems and Technological Solutions through a systematic review of 35 studies. The review identified credit risk, market forecasting and fraud detection as major financial applications of XAI and found that SHAP and LIME are among the most frequently used

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explanation techniques. The study concluded that XAI can improve transparency, stakeholder trust and regulatory compliance in financial applications.

Maathuis et al. (2026) examined Designing Effective Explainable AI: A Human-Centered Evaluation of Explanation Formats in Financial Decision-Making and emphasised that explanations should be designed according to users' needs rather than being developed solely from a technical perspective. Their work compared different forms of explanations and reinforced the importance of presenting AI-generated financial recommendations in ways that users can understand and evaluate.

Mirabile et al. (2026) examined Trust in Human–AI Collaboration in Finance: A Bibliometric–Systematic Literature Review and highlighted trust as a central issue in the development of human–AI collaboration in financial services. Their analysis connected algorithmic trust with explainability, transparency, accountability, governance and human oversight. The study suggests that financial AI systems require mechanisms that allow users to understand, monitor and question AI-supported decisions.

Setty et al. (2026) examined Building Trust in AI-Driven Venture Capital Decisions: A Comparative Study of SHAP and GPT Explanations and investigated how different explanation approaches affect trust in AI-generated financial recommendations. Their findings indicated that providing explanations can strengthen users' confidence in AI-supported recommendations and that the quality and contextual relevance of explanations are important for developing appropriate trust.

Ploug et al. (2026) examined Drivers of Trust in AI Across the Domains of Finance, Law, and Healthcare: A Conjoint Study and demonstrated that trust in AI is influenced by several characteristics of the AI system and the decision context. Their findings reinforce the view that algorithmic trust is not a single, simple construct but depends on how users perceive AI when it is used for consequential decisions.

Evite et al. (2026) examined Trade-offs in Financial AI: Explainability in a Trilemma with Accuracy and Compliance and showed that explainability in financial AI cannot be considered independently of accuracy, compliance, cost and speed. Their findings indicated that accuracy and regulatory compliance are fundamental requirements, while explainability can act as a gateway to adoption by influencing whether financial professionals trust, use and defend AI-supported systems.

Zeng et al. (2026) examined When AI Meets Wall Street: A Survey on Trustworthy AI in Fintech and proposed a finance-specific framework for trustworthy and secure AI across the stages of training, deployment and continuous monitoring. Their work highlighted the risks associated with automated financial AI systems and emphasised the importance of robustness, monitoring and governance for maintaining trust in AI-enabled financial services.

Cao et al. (2026) examined AI Trustworthiness in Managerial Decision-Making: Ethics, Transparency, and Explainability as Key Drivers and highlighted that ethical behaviour, transparency and explainability are important foundations for developing trust in AI-supported decisions. Their work suggests that users are more likely to rely responsibly on AI when they can understand and evaluate the basis of AI-generated recommendations.

Pisoni et al. (2023) examined explainable artificial intelligence in financial applications and highlighted the growing importance of transparency when AI is used in areas such as credit assessment, investment decisions and financial risk management. Their work indicates that explainability can help address the black-box problem and improve users' understanding of complex AI-generated financial outcomes.

Černevičienė and Kabašinskas (2024) conducted a systematic review of explainable artificial

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intelligence in finance and identified major applications including credit management, stock-market prediction and fraud detection. Their findings highlighted the importance of interpretability and transparency while also identifying continuing challenges related to trust, fairness and the practical evaluation of explanations in financial AI.

Phan et al. (2025) examined the relationship between AI, trust, risk and the adoption of AI-driven financial investment platforms. Their findings indicated that transparency can strengthen users' trust in AI, while perceived risk can influence users' willingness to adopt AI-based financial services. The study therefore provides direct evidence that transparency and trust are important behavioural mechanisms in AI-supported investment decisions.

Glikson and Woolley (2020) reviewed empirical research on human trust in artificial intelligence and demonstrated that trust is influenced by system performance, transparency and characteristics of both the technology and its users. Although this is an earlier study, it remains an important theoretical foundation for your algorithmic trust variable and helps explain why users may accept, question or reject AI-generated financial recommendations.

Research Gap

Recent research has established that artificial intelligence can improve the speed, efficiency and analytical capability of financial decision-making, but increasing reliance on AI has also raised concerns about transparency, trust and users' ability to understand AI-generated recommendations. Studies such as Ioannou et al. (2026) and Maathuis et al. (2026) highlight the importance of explainability in helping users understand and evaluate AI-supported financial recommendations, while Vijayananth and Saravanabhavan (2026) emphasise the role of algorithmic trust in AI-driven financial decision-making. However, much of the existing literature examines AI explainability, trust, adoption and human–AI interaction as separate areas. Limited empirical research has integrated AI explainability and algorithmic trust within a single framework of human–AI financial decision-making, particularly from the perspective of users who must evaluate AI recommendations rather than simply accept them. This creates a need to examine how understandable AI outputs and appropriate trust together influence the quality and effectiveness of human–AI financial decisions.

A further gap exists in the limited integration of financial literacy into research on AI-supported financial decision-making. Although AI can provide sophisticated financial information and recommendations, individuals still require financial knowledge to understand risk, evaluate alternatives and determine whether an AI recommendation is appropriate for their circumstances. Existing studies have not sufficiently examined how financial literacy operates alongside AI explainability and algorithmic trust in shaping human–AI financial decision-making, particularly in the Indian financial context, where digital finance and AI-enabled financial services are expanding rapidly. The present study therefore addresses this gap by developing an integrated framework combining AI explainability, algorithmic trust and financial literacy to explain human–AI financial decision-making. The study shifts the focus from AI capability alone towards the interaction between technology and human judgement, recognizing that effective financial decisions require understandable AI, appropriately calibrated trust and sufficient financial knowledge.

Research Objectives and Hypotheses

Research Objectives

The present study aims to examine the role of AI-related and individual-level factors in human–AI financial decision-making. The specific objectives are:

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1. To examine the influence of AI explainability on human–AI financial decision-making.
2. To assess the influence of algorithmic trust on human–AI financial decision-making.
3. To examine the influence of financial literacy on human–AI financial decision-making.
4. To analyse the relationship between AI explainability, algorithmic trust and financial literacy.
5. To determine the combined influence of AI explainability, algorithmic trust and financial literacy on human–AI financial decision-making.

Research Questions

Based on the objectives, the study addresses the following research questions:

1. Does AI explainability influence human–AI financial decision-making?
2. Does algorithmic trust influence human–AI financial decision-making?
3. Does financial literacy influence human–AI financial decision-making?
4. What is the relationship between AI explainability, algorithmic trust and financial literacy?
5. To what extent do these factors collectively explain variations in human–AI financial decision-making?

Research Hypotheses

- **H01:** AI Explainability and Human–AI Financial Decision-Making
- **H01:** AI explainability has no significant influence on human–AI financial decision-making.
- **H1:** AI explainability has a significant positive influence on human–AI financial decision-making.
- **H02**: Algorithmic Trust and Human–AI Financial Decision-Making
- **H02:** Algorithmic trust has no significant influence on human–AI financial decision-making.
- **H2:** Algorithmic trust has a significant positive influence on human–AI financial decision-making.
- H03: Financial Literacy and Human–AI Financial Decision-Making
- **H03:** Financial literacy has no significant influence on human–AI financial decision-making.
- **H3:** Financial literacy has a significant positive influence on human–AI financial decision-making.
- **H04**: Relationship Among the Independent Variables
- **H04:** There is no significant relationship among AI explainability, algorithmic trust and financial literacy.
- **H4:** There is a significant relationship among AI explainability, algorithmic trust and financial literacy.
- **H05**: Combined Influence on Human–AI Financial Decision-Making
- **H05:** AI explainability, algorithmic trust and financial literacy do not collectively have a significant influence on human–AI financial decision-making.
- **H5:** AI explainability, algorithmic trust and financial literacy collectively have a significant influence on human–AI financial decision-making.

Research Methodology

Research Design

The study adopts a quantitative, descriptive and analytical research design to examine the influence of AI explainability, algorithmic trust and financial literacy on human–AI financial decision-making. Primary data are collected through a structured questionnaire, and statistical techniques are used to examine the relationships and influence among the study variables.

Population and Sample

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The population comprises individuals who have experience with digital financial services, AI-enabled financial applications or AI-supported financial information. A proposed sample of 320 respondents is considered adequate for analysing the relationships among the study variables using correlation and multiple regression techniques.

Sampling Technique

The study uses purposive sampling supported by convenience sampling. Respondents are selected based on their familiarity with digital financial services and AI-enabled financial information. Only respondents capable of providing meaningful responses regarding AI-supported financial decision-making are included in the study.

Data Collection and Research Instrument

Primary data are collected using a structured questionnaire. The questionnaire consists of demographic information and statements measuring four major constructs: AI Explainability, Algorithmic Trust, Financial Literacy and Human–AI Financial Decision-Making. A five-point Likert scale, ranging from 1 = Strongly Disagree to 5 = Strongly Agree, is used to measure respondents' perceptions.

Measurement of Variables

- AI Explainability measures the extent to which users can understand the reasoning and factors behind AI-generated financial recommendations.
- Algorithmic Trust measures users' perceptions of the reliability, accuracy, consistency and dependability of AI systems.
- Financial Literacy measures individuals' understanding of financial concepts such as risk, return, interest, inflation, diversification and financial planning.
- Human–AI Financial Decision-Making measures the extent to which individuals use AI-generated financial information along with their own judgement when making financial decisions.

Reliability and Validity

The reliability of the measurement instrument is assessed using Cronbach's Alpha, with a value of 0.70 or above considered generally acceptable. Content validity is established through a review of relevant literature and expert evaluation. Construct validity may be assessed using appropriate factor-analysis procedures.

Data Analysis

The collected data are analysed using SPSS. Descriptive statistics such as frequency, percentage, mean and standard deviation are used to describe the respondents and study variables. Pearson correlation analysis is employed to determine the strength and direction of relationships among the variables. Multiple regression analysis is used to examine the individual and combined influence of AI explainability, algorithmic trust and financial literacy on human–AI financial decision-making. The proposed regression model is:

$$\mathbf{HAIFDM = \beta_0 + \beta_1(AIE) + \beta_2(AT) + \beta_3(FL) + \varepsilon}$$

Where:

HAIFDM = Human–AI Financial Decision-Making

AIE = AI Explainability

AT = Algorithmic Trust

FL = Financial Literacy

$\boldsymbol{\beta_0}$ = Constant

$\boldsymbol{\beta_1, \beta_2, \beta_3}$ = Regression coefficients

$\boldsymbol{\varepsilon}$ = Error term

Hypothesis Testing

The hypotheses are tested at a 5% level of significance ($p < 0.05$). The null hypothesis is rejected when the obtained p-value is less than 0.05. The findings are interpreted based on statistical significance, direction and magnitude of the relationships.

Ethical Considerations

Participation in the study is voluntary, and respondents are informed about the general purpose of the research. The confidentiality and anonymity of responses are maintained, and the

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collected information is used exclusively for academic and research purposes.

Data Analysis and Results

This section presents the analysis and interpretation of the data collected for the study titled "Human with AI in Financial Decision-Making: The Role of AI Explainability, Algorithmic Trust and Financial Literacy." The analysis focuses on understanding respondents' perceptions and examining whether AI explainability, algorithmic trust and financial literacy significantly influence human–AI financial decision-making.

The analysis is organised into several stages. First, the demographic characteristics of the respondents are examined. Second, the reliability of the measurement scales is assessed using Cronbach's Alpha. Third, descriptive statistics are used to understand the overall level of the study variables. Pearson's correlation analysis is then employed to examine the relationships among the variables. Finally, multiple regression analysis is used to determine the individual and combined contribution of AI explainability, algorithmic trust and financial literacy to human–AI financial decision-making.

Demographic Profile of Respondents

The demographic profile provides an understanding of the characteristics of the respondents included in the study. The variables considered include age, gender, educational qualification, occupation, income and experience with digital or AI-enabled financial services.

Demographic Variable	Category	Frequency	Percentage
Age	Below 25 years	72	22.5
	25–34 years	118	36.9
	35–44 years	76	23.8
	45 years and above	54	16.9
Gender	Male	176	55.0
	Female	144	45.0
Education	Undergraduate	68	21.3
	Postgraduate	184	57.5
	Professional/ Other	68	21.3
AI/Financial Technology Experience	Less than 2 years	82	25.6
	2–5 years	137	42.8
	More than 5 years	101	31.6
Total		**320**	**100.0**

The demographic profile indicates that the respondents represent different age groups and levels of educational and technological experience. The largest proportion of respondents falls within the 25–34 years age group. A considerable proportion also has postgraduate qualifications and several years of experience with digital or technology-enabled financial services.

The diversity of respondents provides a useful basis for examining how users with different levels of exposure to financial technology perceive AI-based financial decision-making.

Reliability Analysis (Reliability Statistics)

Reliability analysis was conducted to determine the internal consistency of the measurement scales. Cronbach's Alpha was calculated for each construct included in the study.

Construct	Number of Items	Cronbach's Alpha	Construct
AI Explainability	5	0.884	AI Explainability
Algorithmic Trust	5	0.901	Algorithmic Trust
Financial Literacy	5	0.862	Financial Literacy
Human–AI Financial Decision-Making	5	0.914	Human–AI Financial Decision-Making

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Overall Scale	20	0.927	Overall Scale

The results indicate satisfactory internal consistency across all four constructs. The Cronbach's Alpha values are above the commonly accepted threshold of 0.70, suggesting that the items included under each construct consistently measure the underlying concept.

The reliability coefficient for Human–AI Financial Decision-Making is particularly strong, while the values for AI Explainability, Algorithmic Trust and Financial Literacy also indicate good internal consistency. Therefore, the measurement instrument can be considered suitable for further statistical analysis.

Descriptive Statistics (Descriptive Statistics of Study Variables)

Descriptive statistics were calculated to determine the mean scores and standard deviations of the major study variables.

Variable	Mean	Standard Deviation
AI Explainability	3.78	0.71
Algorithmic Trust	3.69	0.76
Financial Literacy	3.74	0.68
Human–AI Financial Decision-Making	3.81	0.70

The results show that all four variables have mean values above the midpoint of the five-point scale. Human–AI Financial Decision-Making records the highest mean value, followed by AI Explainability, Financial Literacy and Algorithmic Trust.

The findings suggest that respondents generally demonstrate a positive orientation towards using AI as a support mechanism in financial decision-making. At the same time, the relatively lower mean score for algorithmic trust indicates that users may remain somewhat cautious about completely relying on AI-generated financial recommendations.

Correlation Analysis (Pearson Correlation Matrix)

Pearson's correlation coefficient was used to examine the relationship between the independent variables and Human–AI Financial Decision-Making.

Variables	AIE	AT	FL	HAIFDM
AI Explainability (AIE)	1			
Algorithmic Trust (AT)	0.62**	1		
Financial Literacy (FL)	0.48**	0.51**	1	
Human–AI Financial Decision-Making (HAIFDM)	0.71**	0.74**	0.63**	1

Note: p < 0.01.

The correlation results indicate positive relationships between all three independent variables and Human–AI Financial Decision-Making. AI Explainability shows a strong positive association with Human–AI Financial Decision-Making ($r = 0.71$, $p < 0.01$). Algorithmic Trust demonstrates an even stronger positive relationship ($r = 0.74$, $p < 0.01$), while Financial Literacy also shows a substantial positive relationship ($r = 0.63$, $p < 0.01$).

These findings suggest that respondents who perceive AI systems as more understandable and transparent are more likely to use AI effectively in financial decision-making. Similarly, greater confidence in the reliability and accuracy of AI systems is associated with stronger human–AI decision-making behaviour. Financial literacy also appears to contribute positively by helping individuals evaluate and use AI-generated financial information more effectively.

Multiple Regression Analysis

Multiple regression analysis was conducted to examine the combined influence of AI

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Explainability, Algorithmic Trust and Financial Literacy on Human–AI Financial Decision-Making.

The regression model is specified as:

$$\textbf{HAIFDM} = \beta_0 + \beta_1(\textbf{AIE}) + \beta_2(\textbf{AT}) + \beta_3(\textbf{FL}) + \varepsilon$$

Model	R	R^2	Adjusted R^2	Std. Error
1	0.800	0.640	0.636	0.430

The model produces an R^2 value of 0.640, indicating that approximately 64.0% of the variation in Human–AI Financial Decision-Making is explained collectively by AI Explainability, Algorithmic Trust and Financial Literacy.

The adjusted R^2 value of 0.636 indicates that the explanatory power of the model remains strong after adjusting for the number of predictors included in the analysis. The remaining variation may be associated with other factors not included in the present model.

ANOVA Results

Model	Sum of Squares	df	Mean Square	F	Sig.
Regression	103.85	3	34.62	187.42	<0.001
Residual	58.42	316	0.185		
Total	162.27	319			

The ANOVA results indicate that the regression model is statistically significant, $F(3,316) = 187.42$, $p < 0.001$. This indicates that AI Explainability, Algorithmic Trust and Financial Literacy, when considered together, significantly predict Human–AI Financial Decision-Making.

Regression Coefficients

Predictor	Beta (β)	t-value	Sig.
AI Explainability	0.31	6.84	<0.001
Algorithmic Trust	0.38	8.21	<0.001
Financial Literacy	0.24	5.17	<0.001

The regression coefficients show that all three independent variables have a positive and statistically significant influence on Human–AI Financial Decision-Making.

Algorithmic Trust has the strongest standardized coefficient ($\beta = 0.38$, $p < 0.001$), suggesting that trust in the reliability and competence of AI systems plays an important role in users' willingness to incorporate AI into financial decisions.

AI Explainability also demonstrates a significant positive effect ($\beta = 0.31$, $p < 0.001$). This indicates that users are more likely to make effective AI-assisted financial decisions when they can understand the reasoning behind AI-generated recommendations.

Financial Literacy has a positive and significant influence ($\beta = 0.24$, $p < 0.001$). Although its coefficient is comparatively smaller, the finding indicates that financial knowledge remains important even when individuals have access to sophisticated AI-based financial tools.

Overall, the findings suggest that effective human–AI financial decision-making does not depend on AI capability alone. Rather, it is influenced by whether individuals understand the AI's recommendations, trust the system appropriately and possess sufficient financial knowledge to evaluate the information provided.

Hypothesis Testing

Hypothesis	Statement	Result
H1	AI Explainability has a significant positive influence on Human–AI Financial Decision-Making.	Supported
H2	Algorithmic Trust has a significant positive influence	Supported

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	on Human–AI Financial Decision-Making.	
H3	Financial Literacy has a significant positive influence on Human–AI Financial Decision-Making.	Supported
H4	AI Explainability, Algorithmic Trust and Financial Literacy are significantly related to one another.	Supported
H5	AI Explainability, Algorithmic Trust and Financial Literacy jointly have a significant influence on Human–AI Financial Decision-Making.	Supported

The hypothesis-testing results indicate that all proposed relationships are statistically significant in the analysis. The findings provide empirical support for the argument that human–AI financial decision-making is shaped by both technology-related factors and individual-level capabilities.

Overall Interpretation of Results

The results present an important perspective on the growing role of AI in financial decision-making. AI explainability emerges as an important factor because users may be reluctant to rely on recommendations that they cannot understand. When AI systems provide clear and meaningful explanations, individuals are better positioned to assess whether an AI-generated recommendation is appropriate for their financial circumstances.

Algorithmic trust demonstrates the strongest predictive influence in the proposed model. This suggests that users' willingness to incorporate AI into financial decisions depends substantially on their confidence in the reliability, accuracy and consistency of AI systems. However, trust should not be interpreted as unconditional acceptance. Appropriate human oversight remains important, particularly when financial decisions involve uncertainty or significant personal consequences.

Financial literacy also contributes significantly to human–AI financial decision-making. This finding reinforces the view that AI should function as a decision-support mechanism rather than a complete substitute for human judgement. Individuals with stronger financial knowledge may be better equipped to question AI recommendations, compare alternatives, understand risk and make informed final decisions.

Taken together, the findings support a human-centred approach to AI in finance. The effectiveness of AI-assisted financial decision-making depends not only on the sophistication of the technology but also on the user's ability to understand the system, develop appropriate trust and apply financial knowledge when evaluating AI-generated information.

Important: The numerical values in Tables 1–8 above are illustrative/model values, not actual findings. They should not be reported as your empirical results unless they match your actual SPSS output.

Discussion of Findings

The present study examined the role of AI Explainability, Algorithmic Trust and Financial Literacy in Human–AI Financial Decision-Making. The findings indicate that all three factors have a positive and significant relationship with the way individuals use AI-supported information when making financial decisions. The results also suggest that these factors should not be considered separately because effective human–AI decision-making depends on the interaction between technological transparency, user confidence and financial capability.

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The discussion below interprets the findings in relation to the existing literature and explains their implications for the growing use of artificial intelligence in financial services.

AI Explainability and Human–AI Financial Decision-Making

The findings indicate that AI Explainability has a positive and statistically significant influence on Human–AI Financial Decision-Making. The illustrative regression result shows a standardized coefficient of $\beta = 0.31$ with $p < 0.001$. This suggests that respondents are more likely to use AI-generated financial information when they can understand the reasons behind the recommendations.

The finding is consistent with the recent work of Ioannou et al. (2026), titled The Role of Explainability in AI-Driven Financial Decision Making. Their study demonstrated that the quality of explanations provided by AI can influence how users evaluate financial recommendations. The authors also showed that factors such as information quality, usefulness, trust and perceived risk shape users' responses to AI-supported financial advice.

The result is also in line with Maathuis et al. (2026), who examined explanation formats in financial decision-making from a human-centred perspective. Their findings indicated that end users tend to value explanations that are concise, understandable and relevant to the decision context. This is particularly important in finance because users may not possess the technical knowledge required to understand complex AI models.

The present finding therefore suggests that explainability is not merely a technical feature of an AI system. It is also a communication mechanism between the AI system and the human decision-maker. When users understand why an AI system has produced a particular recommendation, they may be better positioned to question the recommendation, compare alternatives and retain responsibility for the final decision.

Algorithmic Trust and Human–AI Financial Decision-Making

Among the three explanatory variables, Algorithmic Trust demonstrates the strongest positive influence on Human–AI Financial Decision-Making in the illustrative regression model ($\beta = 0.38$, $p < 0.001$). This finding indicates that users' confidence in the reliability, accuracy and consistency of AI systems plays an important role in determining whether they incorporate AI-generated information into their financial decisions.

The result is consistent with Vijayananth and Saravanabhavan (2026), who examined algorithmic trust in AI-driven financial decision-making among retail investors in India. Their findings showed that AI usage and perceptions of financial uncertainty were associated with algorithmic trust, while trust was linked with more sustainable investment behaviour and financial resilience. Their study also highlighted the importance of human–AI interaction competency in strengthening the relationship between trust and financial outcomes.

Similarly, Mirabile et al. (2026) emphasised that trust in human–AI collaboration in finance is closely connected with explainability, transparency, accountability, auditability, governance and human oversight. This supports the present finding that trust should not be understood simply as users' willingness to accept AI recommendations. Rather, appropriate trust requires confidence that the system is reliable while still allowing users to exercise their own judgement.

The strong influence of algorithmic trust also has practical significance. A technically sophisticated financial AI system may have limited value if users do not believe that its recommendations are dependable. Conversely, excessive trust could create the risk of over-reliance on automated recommendations. Therefore, financial AI

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systems should aim for appropriate or calibrated trust rather than blind trust.

Financial Literacy and Human–AI Financial Decision-Making

The findings further show that Financial Literacy has a positive and significant influence on Human–AI Financial Decision-Making ($\beta = 0.24$, $p < 0.001$). Although the coefficient is lower than those of algorithmic trust and AI explainability, financial literacy remains an important predictor. This finding is theoretically important because access to AI does not automatically result in better financial decisions. Individuals need sufficient financial knowledge to interpret recommendations relating to investment risk, returns, interest rates, inflation, diversification and financial planning.

Financially literate individuals may be more capable of asking whether an AI recommendation is appropriate for their personal circumstances rather than accepting the recommendation without further evaluation. They may also be better equipped to recognise unrealistic returns, excessive risk or inappropriate financial products. The finding therefore supports a complementary view of human intelligence and artificial intelligence. AI can process large volumes of financial information rapidly, but human financial knowledge remains necessary for interpreting the output and making the final decision.

Combined Influence of AI Explainability, Algorithmic Trust and Financial Literacy

The regression analysis indicates that the three independent variables collectively explain a substantial proportion of the variation in Human–AI Financial Decision-Making. The illustrative model produces an R^2 value of 0.640, suggesting that the three factors together explain approximately 64% of the variation in the dependent variable.

This finding provides an important insight into the nature of AI-assisted financial decision-making. The effectiveness of AI cannot be explained solely by technological performance. Instead, successful human–AI financial decision-making requires a combination of understandable AI, appropriate trust and financially capable users.

AI explainability helps users understand the recommendation. Algorithmic trust determines whether they are willing to rely on the system. Financial literacy enables them to critically evaluate the recommendation before making the final decision. These three elements therefore represent complementary dimensions of responsible human–AI financial decision-making.

Human Oversight as an Important Element

An important implication emerging from the findings is the continuing importance of human oversight. The results do not suggest that AI should replace human financial judgement. Instead, they support the idea that AI should act as a decision-support mechanism.

This perspective is particularly relevant when financial decisions involve uncertainty, substantial financial consequences or changing market conditions. An individual may use AI to identify investment alternatives, analyse market information or assess financial risks, but the final decision should remain subject to human evaluation.

Recent research on human–AI collaboration in finance similarly emphasises the importance of governance, transparency and human oversight. This indicates a shift from viewing AI as an autonomous decision-maker towards viewing it as part of a broader human–AI decision system.

Theoretical Implications

The findings contribute to the literature in several ways.

First, the study brings together AI explainability, algorithmic trust and financial literacy within a single empirical framework. Existing research often examines these factors independently, whereas the present study considers their

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combined contribution to financial decision-making.

Second, the findings strengthen the argument that explainability can influence users' interaction with AI systems. Understanding an AI recommendation can reduce uncertainty and provide users with greater confidence when evaluating financial information.

Third, the findings demonstrate that trust is an important bridge between technological capability and actual human use. Users may recognise the potential benefits of AI but still hesitate to rely on it when they question its accuracy or reliability.

Finally, the inclusion of financial literacy highlights the importance of the human side of AI adoption. Technology alone cannot guarantee informed financial decisions. Users require sufficient financial knowledge to interpret and critically assess AI-generated information.

Practical Implications

The findings provide several implications for financial institutions, FinTech companies, investment platforms and AI developers.

For financial institutions, AI-based financial services should provide understandable explanations alongside recommendations. Users should not be expected to accept a financial recommendation without knowing the major factors that influenced the result.

For FinTech companies, building trust should involve more than improving prediction accuracy. Systems should demonstrate reliability, transparency, consistency and appropriate communication of uncertainty.

For financial educators, the increasing use of AI creates a need to integrate AI-related financial literacy into existing financial education programmes. Users should learn not only traditional financial concepts but also how to evaluate AI-generated financial recommendations.

For regulators, appropriate standards for transparency, explainability, accountability and human oversight may become increasingly important as AI becomes more deeply integrated into financial Services.

Conclusion and Implications

The study titled "Human with AI in Financial Decision-Making: The Role of AI Explainability, Algorithmic Trust and Financial Literacy" examines an increasingly important issue in the changing financial environment. Artificial intelligence is becoming an important part of financial services, investment analysis, financial planning and digital decision-support systems. However, the usefulness of AI in finance cannot be evaluated only in terms of technological capability. The way people understand, trust and use AI-generated information is equally important.

The findings of the study indicate that AI Explainability, Algorithmic Trust and Financial Literacy are positively associated with Human–AI Financial Decision-Making. The results suggest that individuals are more likely to use AI as a financial decision-support tool when they understand the reasons behind AI recommendations, have confidence in the reliability of the system and possess sufficient financial knowledge to evaluate the information provided by AI.

Among the three explanatory factors, Algorithmic Trust demonstrates the strongest influence in the proposed model. This highlights the importance of confidence in the accuracy, reliability and consistency of AI systems. At the same time, the result should not be interpreted as support for unquestioned dependence on AI. Excessive trust may encourage users to accept recommendations without adequate evaluation. The objective should therefore be to develop appropriate and calibrated trust.

AI Explainability also emerges as an important determinant of human–AI financial decision-making. Financial decisions can involve uncertainty, risk and significant personal consequences. When AI systems operate as

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unexplained black boxes, users may find it difficult to assess whether their recommendations are appropriate. Providing meaningful explanations can improve users' understanding and enable them to exercise better judgement.

Financial Literacy provides the third important dimension of the model. The findings indicate that human financial capability remains relevant even in an increasingly automated financial environment. AI may provide information and recommendations, but financially literate users are better positioned to question those recommendations, understand financial risks and make decisions that reflect their own circumstances.

Overall, the study concludes that AI should complement human financial intelligence rather than replace it. The strongest approach to financial decision-making is one in which AI provides analytical support while human users retain the ability and responsibility to evaluate information and make the final decision.

Theoretical Implications

The study contributes to the existing literature by bringing together three important dimensions of AI-supported financial decision-making: technological transparency, user trust and individual financial capability.

First, the study extends research on explainable AI by demonstrating its relevance beyond technical model interpretation. Explainability has practical value because it influences how ordinary users understand and evaluate financial recommendations.

Second, the study contributes to the literature on algorithmic trust by highlighting that trust is an important condition for meaningful human–AI collaboration. However, the findings also support the distinction between appropriate trust and excessive reliance.

Third, incorporating financial literacy into the human–AI framework highlights the importance of individual capability. The effectiveness of AI-based financial services depends partly on the ability of users to understand financial concepts and critically evaluate AI-generated information. The proposed framework therefore provides a more comprehensive perspective than models that examine technology adoption alone.

Managerial Implications

The findings provide useful guidance for financial institutions, banks, FinTech companies, investment platforms and developers of AI-based financial applications.

Financial institutions should design AI systems that provide clear and meaningful explanations rather than presenting users with unexplained recommendations. Explanations should be presented in language that ordinary users can understand without requiring advanced technical knowledge.

FinTech organisations should also focus on trustworthy system design. Accuracy, reliability, consistency, data protection and transparency are important for developing appropriate user confidence. Systems should also communicate uncertainty rather than presenting every AI prediction as certain.

Financial service providers can further support users by integrating financial education features into AI-enabled platforms. For example, applications could explain concepts such as risk, diversification, interest rates and investment horizons while providing recommendations.

Managers should also maintain appropriate human oversight for important financial decisions. AI should support users by analysing information and identifying alternatives, while individuals retain control over decisions that may significantly affect their financial well-being.

Implications for Financial Education

The increasing use of AI creates a need to redefine financial literacy. Traditional financial literacy focuses mainly on concepts such as saving, borrowing, investment, interest and risk. In an AI-enabled financial environment, users also need to understand how automated

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recommendations are generated and how such recommendations should be evaluated.

Therefore, future financial education programmes should include basic AI literacy, algorithmic awareness and responsible use of AI-generated financial information. Individuals should learn to distinguish between useful decision support and inappropriate dependence on automated recommendations.

Implications for Policy and Regulation

The findings also have implications for policymakers and financial regulators. As AI becomes increasingly embedded in financial services, regulatory frameworks need to consider issues such as transparency, explainability, accountability, consumer protection and human oversight.

Users should have sufficient information to understand when they are interacting with an AI system and how AI-generated recommendations may influence their financial choices. Financial AI systems should also provide appropriate mechanisms for human review, particularly where decisions have significant consequences.

The policy objective should not be to restrict financial innovation but to ensure that AI develops within a framework that promotes trust, transparency, accountability and responsible human control.

Overall Implication

The central implication of the study is that successful AI adoption in finance is not simply a technological issue. It is a human–technology relationship.

The effectiveness of AI-supported financial decision-making depends on three complementary conditions:

Understand the AI → Trust the AI appropriately → Evaluate the AI using financial knowledge → Make the final human decision

This perspective places the human decision-maker at the centre of the financial AI ecosystem and provides a foundation for responsible and sustainable AI adoption.

Limitations and Future Research

Although the study provides useful insights into human–AI financial decision-making, several limitations should be acknowledged.

First, the study relies on cross-sectional data. Information collected at a particular point in time can identify relationships among variables but may not fully capture how attitudes towards AI change over time. User trust, technological familiarity and perceptions of explainability may change as individuals gain more experience with AI systems.

Second, the proposed study uses a self-reported questionnaire. Respondents' answers may therefore be influenced by their personal perceptions, experiences and willingness to report their actual behaviour accurately. Perceived use of AI may not always correspond exactly with actual behaviour.

Third, the use of purposive and convenience sampling may limit the generalisability of the findings. Although these approaches can help reach respondents with relevant experience, the resulting sample may not perfectly represent the wider population of financial-service users.

Fourth, the study concentrates on three major explanatory variables—AI Explainability, Algorithmic Trust and Financial Literacy. Other factors may also influence human–AI financial decision-making, including perceived risk, privacy concerns, AI experience, technological readiness, digital literacy, financial self-efficacy and perceived usefulness.

Finally, AI technology is developing rapidly. New forms of generative AI, financial large language models and autonomous financial agents may influence users' perceptions differently from the AI applications available during the period of data collection.

Future Research Directions

Future studies can extend the present research in several directions.

Longitudinal research could examine how trust and financial decision-making change as users

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gain greater experience with AI. Such research would provide stronger evidence about whether initial uncertainty gradually develops into confidence or whether negative experiences lead to reduced trust.

Future researchers could also examine perceived risk and privacy concerns as additional variables. Financial information is highly sensitive, and concerns about data security may influence whether users are willing to rely on AI-enabled financial services.

Another important direction would be to examine AI literacy and digital literacy separately from financial literacy. An individual may possess strong financial knowledge but still have difficulty understanding how AI systems operate. Conversely, technically skilled users may understand AI systems but lack sufficient financial knowledge to evaluate financial recommendations.

Future research could also investigate whether human–AI interaction competency moderates the relationship between algorithmic trust and financial decision-making. Users who are better at questioning, interpreting and supervising AI outputs may be less vulnerable to both algorithmic aversion and excessive reliance.

Comparative studies across different groups would also be valuable. Researchers could compare retail investors, financial professionals, students, salaried employees and entrepreneurs to determine whether the importance of explainability, trust and financial literacy varies across user groups.

Cross-country studies could further determine whether cultural, regulatory and financial-system differences influence human–AI financial decision-making. Such research would help establish whether the proposed framework is applicable beyond the Indian context.

Finally, future research could examine generative AI and autonomous financial agents. As AI systems become capable of producing personalised financial explanations and performing increasingly complex financial tasks, the relationship between human judgement and machine autonomy will become even more important.

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