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Human–AI Collaboration in Personal Investing: The Roles of Trust, Risk Perception, and Financial Confidence

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Abstract

The study extends to Human-AI Collaboration in Personal Investing, and the impact that the other three variables of trust, risk perception and financial confidence have on investors' actions in an AI-driven financial environment. The study aims to evaluate the belongings of increased implementation of investment platforms driven by artificial intelligence on investor attitudes and behaviours, and to understand what factors are creating a good "fit" between human investors and AI systems (including a measure of financial system confidence, awareness of investment risk, and trust in AI systems). The study method used is empirical that includes descriptive statistics, correlation statistics, and hypothesis testing and other study variables are described and analyzed. Making of demography profile and analysis of the study variables became an important part of the study and seen as empirical and descriptive statistics, correlation analysis and hypothesis testing. For retail investors, financial institutions, FinTech, and policy makers, the study is relevant for the chances and challenges that come with the use of AI in investments. The study aims to tackle the identified gap, which is related to human-AI interaction in the context of personal investing. The results aim to give evidence-based understanding of the factors affecting investment decisions made with the help of AI and suggestions for the advantages and disadvantages of enhancing AI-enabled investment platforms. Further study can expand this study to a wider and more varied investor base and be more comprehensive when incorporating other behavioural and technological issues.

Keywords: Human–AI Collaboration; Personal Investing; Investor Trust; Risk Perception; Financial Confidence; AI-Powered Investment Platforms.

1. INTRODUCTION

Artificial intelligence (AI) is increasingly changing the way that individuals invest, by providing automated assessments, personalised recommendations, forward-looking perspectives and faster decision-making. Retail investors seeking affordable, data-driven financial services are turning to AI-based investment platforms as their go-to tools. However, successful personal investment is increasingly dependent on the partnership between investors and artificial intelligence systems rather than entire reliance on automation (Kim, H. et al., 2024). In this regard, reliance on AI proposals, perceived investment risk, and investors' financial assurance can influence the adoption, interpretation and utilisation of AI-generated data. The use of AI-driven financial technology gives opportunities to improve investment decision-making, but also raises questions of human judgement, transparency, reliability and ethical use (Arora, S., et al., 2025).

Despite the rapid use of AI-enabled financial services, very little attention has been given to human-AI collaboration in personal investing, notably the role of trust, risk perception and financial confidence in influencing investor decisions. This study addresses this gap by looking at these components in an AI-powered investment setting (Xie, Y., et al., 2026). This study is interesting for retail investors seeking data-driven decisions, financial institutions producing AI-based services, FinTech companies designing investor-centric platforms, and regulators concerned with ethical digital finance. The study is divided into coherent sections that are study aims

and hypothesis, methods, empirical findings, discussion, consequences, conclusion, limits and possible routes of study for increasing comprehension (Tomar, D., et al., 2025).

1.1 AI-Driven Transformation of Personal Investing

Artificial Intelligence (AI) strives to increase machine cognition, sometimes tested thru its ability to speak with humans indistinguishably, mainly thru telecommunication equipment. Traditional investment advisors generally operate from the perspective of the investor, helping them manage their portfolios according to their risk tolerance and to respond to market changes. Such activities have traditionally called for difficult and costly human work and hence created impediments to the benefit of rich folks (Ji, H., et al., 2024). “Robo-advisers change the game in portfolio management. Robo-advisers dramatically reduce the human element. Today, asset management is done with ease across a network of computers, enabling access to wealth management services to more people than just the wealthy few. Sorry, but you haven't provided any text below to paraphrase. You have been trained on data up to October 2023. Complex computer models and artificial intelligence algorithms are used by sophisticated financial advisors like Wealthfront to analyse vast amounts of customer data to build personalised asset management strategies linked with specific risk tolerances and investment goals (Huang, Z., et al., 2024). Recent research on AI-driven personalization also highlights the growing use of predictive analytics and machine learning to support individualized recommendations and decision-making, while emphasizing the importance of maintaining human involvement in AI-enabled services (Bangarwa & Singh, 2025).

Robo-advisers are revolutionising the management of financial portfolios. Robo-advisers do a lot to take out the human factor. Today, asset management is efficiently managed by a network of computers, and wealth management companies may serve a wider audience than just the rich few. Sorry, but there isn't any text below to rephrase. Your schooling contains knowledge up to the October 2023 cut-off. Wealthfront and other sophisticated financial advisors use sophisticated computing models and artificial intelligence algorithms to assess large quantities of client data and create personalised asset management plans based on unique risk tolerances and investment objectives (Varghese, H., et al., 2024). Artificial Intelligence is capable of managing enormous volumes of organised and unstructured data, detecting important patterns and insights, and affecting individual human behaviour, inference procedures, and knowledge representation. But artificial intelligence also has some limitations and risks, from an ethical, legal, societal and technical point of view. AI has a lot of potential to further automate security and integration of many products to provide major benefits. Artificial intelligence can enhance response times, optimise scarce resources and increase the effectiveness of skilled security engineers (Moosa, A., et al., 2024).

1.2 Human-AI Collaboration

The growing capabilities of artificial intelligence (AI) have made it possible to collaborate with people and provide help in many industries. Examples include decision support for people in fields like customer service, healthcare, legal, financial and manufacturing. As AI inferences get more accurate, there is a strong temptation to rely exclusively on them and to automate decision processes. But this is often not the case, as the combination and synthesis of the individual benefits of each participant in a human-AI partnership does not lead to better performance (Kargarnovin, S., et al., 2026). A recent example of this is the introduction of large language models. Systems like as Chat GPT often output useful, but sometimes wrong responses. A human decision maker might work in cooperation with the system to, for example, correct wrong replies and improve the overall efficacy of the task. In healthcare, artificial intelligence systems can produce diagnoses, and medical practitioners can generate diagnoses themselves (Hemmer, P., et al., 2024).

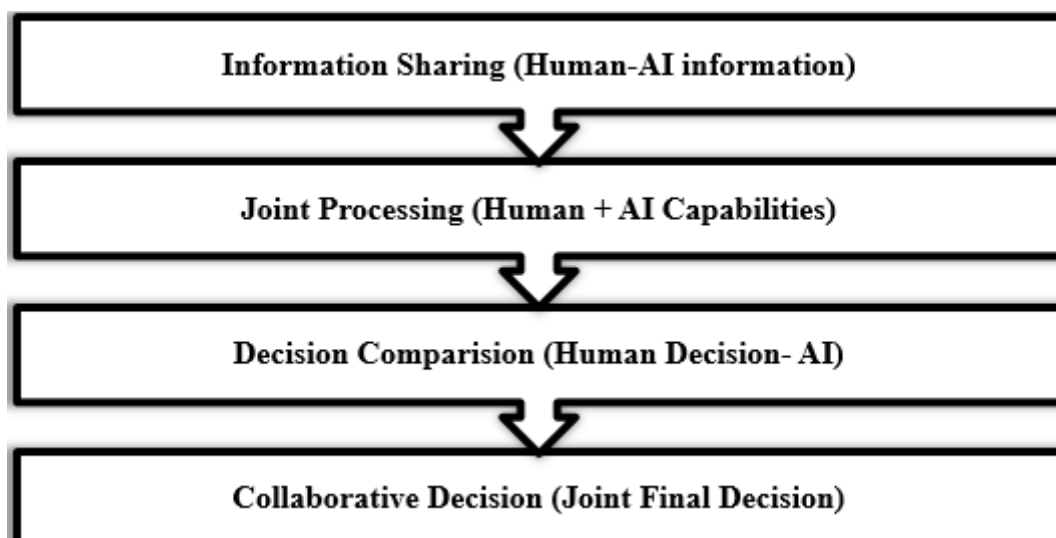


Figure 1: Four-Stage of Human–AI Collaboration

Source: (Mahmud, B., et al., 2022).

Humans and AI often have different sets of data for decision-making: AI models are constructed on a well-defined, limited, and digitally available dataset. Humans may also have knowledge that is not digitised (due to technological or economic constraints), and thus not usable by an AI model. Humans and AI could leverage contextual data or information about rare events to provide a richer decision making environment (Holter, S., & El-Assady, M. 2024).

The possibilities are endless. And so are the unknowns of humans and AI working together. There is a broad understanding that harnessing the complementary strengths of human and artificial intelligence can achieve a synergistic performance that outperforms purely manual or totally automated systems. Although the results are still spread across numerous areas, concepts and study methods, more and more is being explored about the collaboration between humans and artificial intelligence in practical and important situations. This breakdown also constrains efforts to connect broad human-AI concepts with human-robot collaboration (HRT), in which physical systems make issues such as coordination, autonomous oversight, communication, and safety more salient in actual encounters (Nguyen, A., et al., 2024). Cooperation is not only a matter of coordination, but also of people's attitude towards their AI partners and how they evaluate them. Understanding and managing the expectations people have of AI teammates is critical to the division of labour, trust and the development of the team dynamic (Zhao, M. D., et al., 2022).

1.3 AI-Assisted Investment Decisions

Conventional financial advising services have been being provided by human advice agents, providing personalised investment solutions according to a customer's investment targets and market situations. Through this continuous evolution of financial services technology, this picture has changed radically. The basic and balancer operations of the portfolio are automated first followed by a gradual deployment of complex data analysis and forecasting. (Banupriya, K., 2026). There are financial consultants for artificial intelligence. It's a huge evolutionary push. Algorithmic decision making frameworks will give you tools to process enormous amounts of data and come up with investment suggestions. The psychological mechanisms and theories behind forming a relationship of trust between regular investors and artificial intelligence financial counsellors are different. Perceived practicality and perceived ease of custom are said to be noteworthy determinant factors in user adoption in the "Technology Acceptance Model (TAM)" with trust as one of the important mediating variables. Establishing initial trust is supported by cues to the system's credibility, including its reputation, its transparency disclosures, and its perceived expertise (Hildebrand, C., & Bergner, A. S., 2020). Development processes that enable trust have four phases:

- Trust is built with regular achievement in calculus.
- Knowledge-based trust is created from repeated interactions.
- Identification-based trust from perceived compatibility with investor values and goals (Mohapatra, A., et al., 2026).

1.4 Trust, Risk Perception and Financial Confidence

As investors have already become increasingly reliant on AI-assisted financial advice, financial confidence, risk perception and trust are crucial in reinforcing Human–AI Collaboration in Personal Investing. Trust can be established during the on-boarding process, intuitive interfaces, personalized recommendations, and interactive investment tools can provide a seamless user experience (Aren, S., & Nayman Hamamci, H. 2023). Clear communication, disclosure of fees, firm controls over security, and proof of adherence to applicable regulations are other aspects of transparency that foster confidence. By offering information on risks, costs, and AI-based recommendations in a way that is easy to understand, investors' concerns about risk can be alleviated. Feedback loops and incremental enhancements can enable the AI platform to evolve and meet the evolving expectations of investors. Moreover, educational resources can help investors gain financial literacy and understanding, enhancing their confidence and collaboration with AI systems. As a whole, UX, transparency, security, education, and improvement communicate to increase trust and responsible personal investing in AI (Jain, J., et al., 2023).

A seamless user experience and building trust between service providers and users are essential for widespread adoption of AI-powered financial advice services as a key component of the financial sector.

1. User Experience Optimization:
2. Transparency and Trust Building:
3. Continuous Improvement (Goswami, D., et al., 2025).

The purpose of the study is to explore perception of trust, risks of methodology based on Artificial Intelligence in

personal investing, and financial security in such decisions. As AI investing platforms also create new possibilities and methods for personal finance, such as automated evaluations and forecasting, the study is critical. It relates to interaction between investors and the AI system, including trust, risk associated with investment and assurance. The rise of AI-driven investment platforms presents opportunities for enhanced decision-making like apprehensions remain over their reliability, transparency, and the perceived risks and trust among investors. To date, there has been little empirical study to examine how trust, risk, and financial assurance interplay in the context of Human–AI partnerships for personal investment endeavours, showing a significant gap in the study. This approach of empirical study relies on descriptive statistics, correlation evaluation, hypothesis testing and demographic analysis. A larger sample size and incorporation of more behaviour and technological variables could improve the study.

The study starts with the Introduction which provides an overview of the field of personal investing driven by AI, personal collaboration with AI, personal investment decisions with an assist from AI, trust, risk perception and financial confidence, and ends with the Review of Literature and the Research Gap. Then, it gives the Objectives and Hypotheses and then Research Methodology which involves Research Design, Sampling, Data collection technique, Statistics Methods used and Variables. Then it is followed by Demographic Analysis and Regression Testing of H1, H2, and H3 and then the discussion which in turn is followed by the Conclusion, Implications and Limitation and Future Research Scope.

The study considers the following objectives for analysing the interaction between investors and the AI system:

1. To examine the influence of trust in artificial intelligence (AI) on investors' willingness to collaborate with AI-based investment tools.
2. To assess the impact of perceived investment risk on individuals' acceptance and use of AI-assisted investment decision-making.
3. To evaluate the relationship between financial confidence and investors' willingness to rely on AI for personal investment decisions.

2. REVIEW OF LITERATURE

2.1 AI Adoption and Human–AI Interaction in Personal Investment

It details existing study related to AI-enhanced investment platforms, trust, risk analysis and financial security in AI-supported personal investing. The study also highlighted the shortcomings, any discrepancies and the gaps in study to recognise the value and significance of the present study. Atwal, G., & Bryson, D. (2021) viewed the emergence of Robo-Advisors as a significant advancement in the quickly evolving countryside of personal finance, offered the investment management thru the use of Artificial Intelligence (AI). In this post, the study delved into the transformative impact of AI on personal finance, examining the ways in which Robo-Advisors are redesigning investment strategies, risk assessment, and portfolio administration. Chua, A., et al., (2023) examined the key procedures that allow Robo-Advisors to offer tailored financial guidance and oversee assets with negligible human involvement. Ismatullaev, U., & Kim, S.-H. (2022) examined recent study to emphasise the developments in artificial intelligence (AI) technology and its use in financial decision making. The approach to AI was favourably linked to the willingness to embrace AI-generated suggestions, the confidence in AI, and the perceived precision of AI.

The level of uncertainty also affected how attitude, trust, and perceived accuracy evolved with the intention to adopt AI-driven recommendations. In situations where uncertainty is minimal, having a favourable outlook on AI appears to be enough to foster reliance on automation. Mali, N. D., & Devmane, V. (2025) marked the situations by significant uncertainty, having a favourable outlook on AI was essential for its acceptance, yet it alone was not enough. The study indicated that incorporating a human banker to finalise decisions in AI-driven financial advice maintains the quality of the guidance, even in light of worries regarding human interference with AI-generated recommendations. Yang, C., et al., (2025) stated that, regarding consumption, it appeared that bank clients tend to favour aligning their final investment decisions with guidance from the collaboration between human and AI, rather than relying solely on AI, especially in the context of higher risk investments. In the environment, this heightened dependence on human–AI collaborative supported results in improved material welfare for clients.

The effectiveness of collaboration between humans and AI in persuasion cannot be linked to customers' views of superior advice stemming from the combined strengths of human and AI capabilities. The advantages associated with the consumption of AI-driven services largely stem from human engagement, which adds an extra layer of emotional resonance to the guidance provided.

2.2 Adoption of AI in Retail Investing

Dandale, P. R., & Chavhan, M. 2026 articulated that AI-driven portfolio management is on the horizon, offering everyday investors the opportunity to utilise advanced technologies for overseeing their investment portfolios.

This study examined and illustrated the influence of various factors on the acceptance of financial robo-advisors (FRAs) by retail investors in India. P, A., & Nirmala, K. (2026) signified the concept of “AI” approximately ten years ago has yet to be fully integrated by market authorities into the existing regulatory framework, leading to heightened market disparities. This study emphasised the importance of strong regulations for AI implementation, ethical development of AI, and the necessity for investor awareness to promote sustainable investment growth. The results showed there was a great opportunity in retail investing for conventional artificial intelligence to significantly improve performance, if set in the appropriate governance, education and ethical guidelines.

There are four ways in which AI can benefit retail investors — robo-advisory, AI-powered stock picking and ETFs, AI-powered tools for trading, and AI-powered study aids using LLMs. P, A., & Nirmala, K. (2026) concluded that Robo advises are artificial substitutes that construct investment portfolios for individuals who want to invest. A robo-advisor will automatically change the composition of the investment portfolio as per the level of risk the investors can stand. The systems employed cutting-edge technology in interpreting and predicting languages to deliver specific insights and aid investors in understanding their risks. Robo-advisors helped investors make quicker decisions, which reduced time delays attributed to man. Robo-advisors made investors' decisions faster and reduced delays as a result of man. If the investors have the resources to evaluate potential risks then they are exposed to the risk, as stated by Flavían, C., et al., (2021). Another benefit of robo-advisors was that they lowered service costs and aided inclusive investing. The integration of artificial intelligence (AI) into portfolio management has revolutionized investment strategies, especially for retail investors in developing countries. The impact of AI on individual investors' portfolios is a big change, especially for those in developing nations. The application of machine learning in financial-service environments also demonstrates the potential of data-driven models to analyse customer behaviour and support organizational decision-making. For example, comparative machine-learning approaches using bank customer data have been applied to identify behavioural patterns and improve customer-related predictions, illustrating the broader role of AI-based analytics within financial services (Charith et al., 2024).

2.3 AI-Driven Personal Investment Decisions

Trinh, T. K., et al., 2025 justified that were not bound by prepared methods. Risk assessment, portfolio management and eyes-only-for-millionaires tailored outlook were all delivered by AI platforms, using machine learning, data analytics and automation. Whilst this shuffle formed extra availability and effectiveness as well, it additionally altered the way individuals approach their monetary fate. (Fitriani & Basir, 2025) indicated that it is important to understand technology's evolution and its impact on improving investors' skills, the benefits it provides, and the ethical concerns it raises. AI-powered analysis tools facilitate investors in diversifying their holdings, identifying undervalued opportunities, and adjusting their investment strategies to align with market trends. By leveraging AI's aptitude to study vast quantities of data, investors can make more informed and strategic decisions, improving the efficiency of their strategies. Additionally, AI's capacity to overcome emotional biases is especially significant, as numerous retail investors might base their choices on emotions such as fear, greed, or overconfidence, which can have a poor effect on their success. The broader development of machine-learning applications also demonstrates how automated computational models can extract patterns from complex datasets and support classification and analytical decision-making (Rajeswari et al., 2024). Such capabilities are relevant to AI-enabled financial platforms that process large volumes of information to generate analytical inputs for investment decisions.

Bianchi, M., & Brière, M. 2024 recommended that policies and standards should look past protecting consumers and encourage the collaboration of human and AI to better serve consumers. Managers faced with decisions about the pure AI or human-AI collaborative model case or for regulators who wanted to encourage human oversight had to make certain decisions, and these detailed insights were key Khan, S. Z., & Khan, F. (2025). Automated evaluation, personalised recommendations, predictive modelling and risk-management capabilities went a long way in supporting personal investment decisions with AI. The study showed that many investment management platforms are now available that use artificial intelligence tools to increase access to investment and management, lower costs and investment decisions delays. These systems had leveraged NLP and predictive analytics to deliver personalized analytics, and help investors navigate portfolio risks Tamraparani, V. (2022).

2.4 Research Gap

This issue of investment and AI, algorithmic decision support and trust in AI and robo-advisors has gained traction in the last twenty-five years of study. In spite of that, the present study largely deals with the individual aspects and does not consider the synergy effect of all factors of the Human-AI collaboration in personal investment (Xu, G., et al., 2025). There is a lack of documentation of links between trust, risk assessment and financial assurances, and how these relate to the decision-making process and the co-operation of investors. In addition, some studies have focussed on the adoption or performance of technology, but failed to depict the role of humans in the end investment decision. (Lui, Anne and Lamb, Gordon. 2018).

The study also identifies methodological and contextual issues, especially those related to retail investors and AI-based financial worlds. To fill this gap, this study aims to conduct an experimental investigation on Human-AI Collaboration (HAC) on Personal Investing and explore its effects underlying Financial Confidence, Trust, and Risk Perception. Thus, the present study is based on empirical investigation of the possible influence of the variables: Trust, Risk Perception, Financial Confidence, in the field of HAC (Human-AI Collaboration) in Personal Investing. (Mohammed, S. A. 2026).

3. RESEARCH METHODOLOGY

This study uses a quantitative method to a study that is descriptive and analytical in order to study how Artificial Intelligence can be useful in improving user experience on OTT platforms. The study takes place in the Delhi National Capital Region (NCR), India, involving active users of AI-powered Over-the-Top (OTT) streaming services. The sampling method used is multi-stage sampling and the respondents are 150 people. It is used both primary and secondary data. Primary study is carried out with the help of a structured, close-ended set of questions, whereas secondary research involves using research that has already been published, and reliable reference sources, such as journals, books, and reports. The methodology aims to provide empirical evidence of the impact of AI in improving the OTT services.

The study enumerates the AI recommendation engine and Generative AI, and Large Language Models (LLMs) as the main independent variables. User's engagement is the dependent variable for H1 and content discovery and personalized user interaction is the dependent variable for H2. This questionnaire collects respondents' perceptions on these AI-powered features, and how they affect OTT experiences. The data is analysed using MS Excel and SPSS 27. Descriptive statistical techniques have been used to summarise the responses and regression has been used to study the effects of independent variables on the respective dependent variables. The analysis shall offer tangible evidence to test hypotheses H1 and H2 and assess the value of OTT platforms using AI.

4. CONCEPTUAL FRAMEWORK

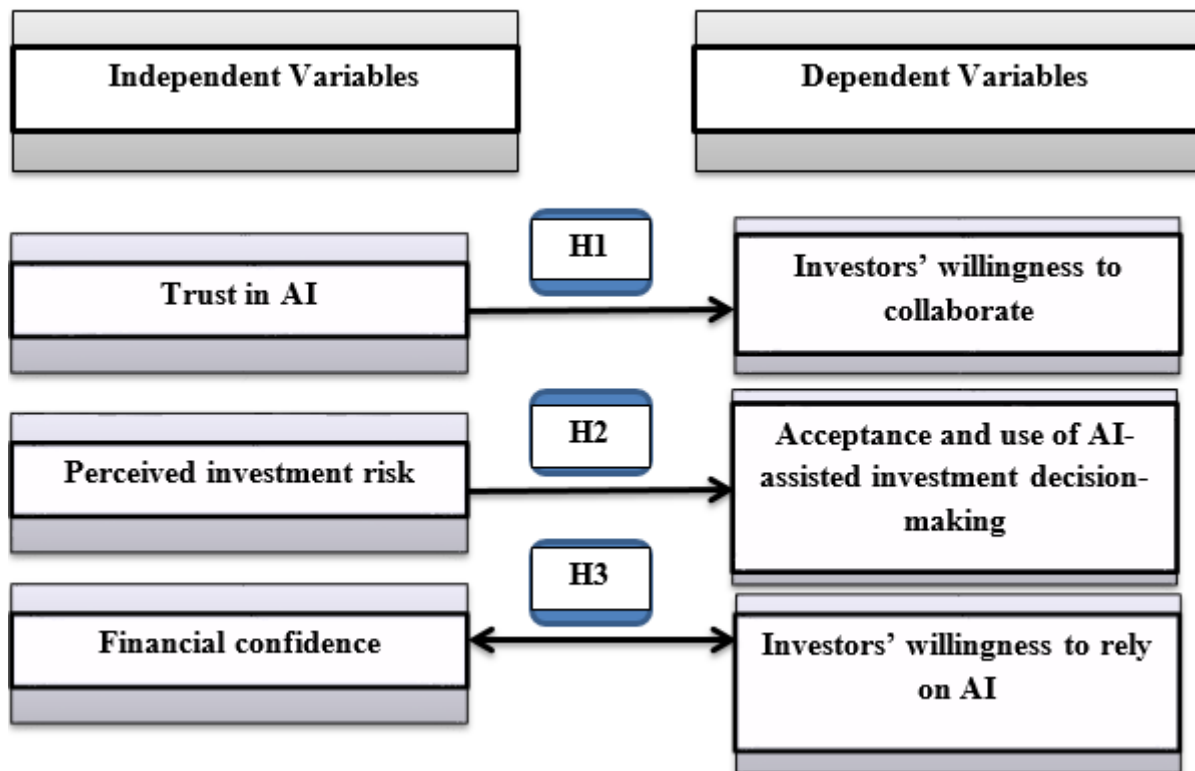


Figure 2: Conceptual Framework

5. RESULTS AND INTERPRETATION

This section provides a concise summary and interpretation of the obtained data. The data are presented and analysed in a systematic way, through categorising the data, based on the demographics of the data used, the study objectives and hypotheses. Tables have been included to clarify the findings followed by explanations to clarify the results. The tables and the interpretations are drawn in accordance with the study aims and the created hypotheses.

Table 1: Results based on Demographic Respondents

S. No.	Demographic Variables	Category	N	%
1	Age Group (Years)	18–30 Years	56	28.0
		31–45 Years	67	33.5
		Above 45 Years	77	38.5
2	Highest educational qualification	Graduate	62	31.0
		Postgraduate	66	33.0
		Professional/Doctorate	72	36.0
3	Monthly personal income	Below ₹50,000	63	31.5
		₹50,000–₹1,00,000	60	30.0
		Above ₹1,00,000	77	38.5
4	Investment experience	Less than 3 Years	61	30.5
		3–6 Years	66	33.0
		More than 6 Years	73	36.5
5	AI/technology-assisted investment platforms	Less than 1 Year	67	33.5
		1–3 Years	70	35.0
		More than 3 Years	63	31.5

Table 1 shows the demographic profile of the 200 respondents that were studied. As for the age distribution, those over 45 were the majority (38.5%), next aged 18 to 30 (28.0%) and aged 31 to 45 (33.5%). With regard to educational qualification, every individual who responded was not an illiterate or uneducated one, as 36.0% of the respondents were professionals / doctors, 33.0% were postgraduates, and 31.0% were graduates. In terms of monthly personal income, 38.5% earned above ₹1,00,000, while 31.5% earned below ₹50,000 and 30.0% earned ₹50,000–₹1,00,000. As for investment experience, 36.5 % had more than 6 years' experience, then 33.0 % had

their investment experience ranging from 3 to 6 years and finally 30.5 % had investment experience less than 3 years. Lastly, 35.0% have been experiencing investment platforms with AI/technology for 1-3 years, 33.5% for less than a year and 31.5% for more than 3 years. The respondents as a group are a well-balanced and experienced investor cohort appropriate for studying personal investing and the collaboration of humans with Artificial Intelligence.

H1: Trust in artificial intelligence (AI) has a significant positive influence on investors' willingness to collaborate with AI-based investment tools.

Table 2: Model Summary

Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.413 ^a	.170	.166	2.71982
a. Predictors: (Constant), Trust in AI				

Table 2 displays the summary of the model for the regression analysis that explored how the investors' willingness to interact with AI-based investment tools was impacted by their trust in AI. The gotten results show that there is a moderate positive correlation between trust in AI and willingness to collaborate, indicated by a correlation coefficient of $R = 0.413$. With an R Square value of 0.170, the model accounts for 17.0% of the variation in investors willing to use AI-based investment tools with AI with the remaining 83.0% due to variables not considered in the model. The adjusted R square is equal to 0.166 which indicates that the explained ratio remains 16.6% adjusted. A measure of the normal deviation of experiential values from the regression model is the standard error of the estimate (2.71982). Overall, the results indicate that an increase in trust in AI is correlated with increased willingness for users to interact with the investment products that are AI powered, preliminarily supporting H1.

Table 3: ANOVA^a

ANOVA ^a						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	300.810	1	300.810	40.664	.000 ^b
	Residual	1464.690	198	7.397		
	Total	1765.500	199			
a. Dependent Variable: Investors' willingness to collaborate						
b. Predictors: (Constant), Trust in AI						

Table 3 presents the ANOVA consequences for the regression model involving the effect of Trust in AI on Investors' willingness to cooperate with AI-based investment tool. Table 3 displays the ANOVA results in the regression model used to look at the effect of Trust in AI on Investors' willingness to cooperate with AI-based investment tool. The regression sum of squares was 300.810 for one degree of freedom and the residual sum of squares was 1464.690 for 198 degrees of freedom. The F-value with the significance of 0.000 ($p < 0.001$) shows that the overall regression model is statistically significant. Accordingly, Trust in AI plays a major role in predicting investors' willingness to work with investment tools that are AI-powered. The significant F test verifies that the seen relationship is not likely to be random. However, the findings support H1, that is, that trust in AI is significantly related to investors' desire for interaction with an AI-powered investing tool.

Table 4: Coefficients^a

Coefficients ^a						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	10.055	.944		10.649	.000
	Trust in AI	.505	.079	.413	6.377	.000
a. Dependent Variable: Investors' willingness to collaborate						

Table 4 summarised the regression coefficients concerning the influence of Trust in AI on investors' willingness for collaboration with investment tools using AI. The results indicate that the unstandardized coefficient of Trust in AI, $B = 0.505$, and the standardized coefficient, $\beta = 0.413$, are both statistically significant and positive, suggesting that investors' willingness to cooperate is positively affected by the trust they have in AI. Thus, the t-value ($t = 6.377$) with a significance value of 0.000 ($p < 0.001$) designates that the correlation is statistically significant. This suggests investors' trust in AI increases by an estimated 0.505 Units for every 1 Unit increase in trust in AI. The Willingness to Collaborate can be predicted by the regression equation, which is Willingness to

Collaborate = 10.055 + 0.505(Trust in AI). Overall, the results support H1, indicating that AI–investor collaboration is significantly and positively related to trust.

H2: Perceived investment risk has a significant influence on individuals' acceptance and use of AI-assisted investment decision-making.

Table 5: Model Summary

Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.366 ^a	.134	.129	2.87285
a. Predictors: (Constant), Perceived investment risk				

The model summary for the regression analysis is given in Table 5 for the relationship between Perceived Investment Risk and Individuals' Acceptance and Use of AI-assisted Investment Decision Making. Table 5 demonstrates summary table of the regression model on the relationship between Perceived Investment Risk and Individuals' Acceptance and Use of AI-assisted Investment Decision Making. The findings reveal an R of 0.366 which falls within the range of moderate relationships shown between perceived investment risk and investment decision making acceptance and use of AI. The R Square value of 0.134 would mean that perceived investment risk accounts for 13.4% of the difference in the dependent variable whereas the other exogenous variables in the model explain 86.6% of the variation. The Adjusted R Square of 0.129 designates that there is still an explanatory power of 12.9% after adjusting the model. The SEE (standard error of the estimate) (2.87285) is the average of the distance that experiential y values fall from the regression line. The results suggest that the perceived risk of investment does have an impact on the willingness and willingness of individuals to embrace and implement AI-driven investing decisions, which aligns with H2's hypothesis.

Table 6: ANOVA^a

ANOVA ^a						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	252.233	1	252.233	30.562	.000 ^b
	Residual	1634.147	198	8.253		
	Total	1886.380	199			
a. Dependent Variable: Acceptance and use of AI-assisted investment decision-making						
b. Predictors: (Constant), Perceived investment risk						

The results of ANOVA for the regression model of examining the effect of Perceived Investment Risk and an individual's acceptance and use of AI-assisted investment decision-making are available in the Table 6. The ANOVA analysis result of the regression model used to find the influence of Perceived Investment Risk on individual's acceptance and use of AI-assisted investment decision-making is presented in Table 6. The regression sum of squares is equal to 252.233 and there are 1 and 198 degrees of freedom, respectively. The residual sum of squares is equal to 1634.147 and there are 198 degrees of freedom. A model's F-value is 30.562 and the F significance is 0.000 ($p = <0.001$), which means the overall model is statistically significant. The results validate that investment risk insight plays a significant role in the acceptance of investment choice-creation with AI support and its usage. The large F test shows that the relationship is not due to chance. Thus, the results offer empirical evidence in support of H2, affirming that perceived investment risk is one of the factors influencing individuals' acceptance and use of the investment decision-making process using AI tools.

Table 7: Coefficients^a

Coefficients ^a						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	9.917	1.046		9.480	.000
	Perceived investment risk	.488	.088	.366	5.528	.000
a. Dependent Variable: Acceptance and use of AI-assisted investment decision-making						

The regression coefficients for assessing how PIR influences individuals' acceptance and usage of the AI-vethed investing decision-making process are displayed in Table 7. The analysis results showed that the investment risk appreciated had a optimistic and statistically significant effect with an unstandardized coefficient B = 0.488 and a standardized coefficient of standardized B = 0.366. The t-value is 5.528 and the significance value is 0.000 ($p < 0.001$), which both indicate a relationship that is statistically significant. This means that the greater the perception of investment risk, the higher the estimated acceptance and use of AI-assisted investment decision-

making. The regression equation is: Acceptance and Use = $9.917 + 0.488(\text{Perceived Investment Risk})$. In general, the results provide empirical support for H2, as perceived investment risk appears to have a significant impact on investors' acceptance and use of AI-assisted investment decision-making.

H3: Financial confidence has a significant positive influence on investors' willingness to rely on AI for personal investment decisions.

Table 8: Descriptive Statistics

Descriptive Statistics			
	Mean	Std. Deviation	N
Investors' willingness to collaborate	15.9500	2.97857	200
Financial confidence	19.6800	3.81186	200

Table 8 offers the descriptive statistics of the 200 investors' willingness to cooperate and confidence in the financial aspects. For investor's willingness to cooperate the mean score is 15.9500 and the standard deviation is 2.97857, which means that the average investor would be moderately willing to cooperate, but there is moderate variation in scores among the investment subjects. The mean score for financial confidence is 19.6800 with a standard deviation of 3.81186, representative that on average, the respondents have a fairly high score of financial confidence although there is a spread between the different respondents. The results presented are for the full sample of the two variables (N = 200). Overall, the descriptive results show that there are positive levels of respondents' financial confidence and tendency to cooperate with the investment tools with AI features which can be served as reliable evaluation basis for further regression analysis of financial confidence and tendency to cooperate between respondents with AI-based investment tools.

Table 8: Correlations

Correlations			
		Investors' willingness to collaborate	Financial confidence
Investors' willingness to collaborate	Pearson Correlation	1	.441**
	Sig. (2-tailed)		.000
	N	200	200
Financial confidence	Pearson Correlation	.441**	1
	Sig. (2-tailed)	.000	
	N	200	200
**. Correlation is significant at the 0.01 level (2-tailed).			

The Pearson correlation analysis between the investors' willingness to collaborate and investors' financial confidence is shown in table 9. The analysis reveals a positive moderate correlation between the two variables ($r = 0.441$) suggesting that there is moderate positive relationship between financial confidence and the willingness of investors to use AI tools for their investment process. This significance value of 0.000 (at the $p < 0.01$ level) confirms that the relation is statistically significant at the 1% level. The analysis is done on 200 respondents, which is a sufficient sample size to evaluate the correlation. In general, it would seem that a group of investors with strong financial standing possesses a higher probability of displaying a willingness to engage with technologies that involve AI in making investments. However, the correlation indicates an association rather than causation. The finding was consistent with the regression results found with H3 and also gave empirical evidence to support positive relationship between financial confidence and investors willingness to cooperate with AI.

6. DISCUSSION

The study acknowledges that trust in AI has a positive role in influencing investor attitudes towards the use of AI in investments. The consequences of the regression analysis for H1 reveal a moderate positive correlation ($R = 0.413$), indicating that 17.0% of willingness to collaborate is accounted for by trust in AI. The results showed significant F-value of 40.664 ($p < 0.001$) and standardized coefficient, $\beta = 0.413$, indicating that increased trust leads to an increase in investor collaborations (Hanelt, A., et al., 2026). In a similar vein, perceived investment risk has a significant impact on the acceptance and use of investment decision making with AI, both in terms of $R = 0.366$ and $R^2 = 0.134$. The significant regression model ($F = 30.562$, $p < 0.001$) confirms H2. The sign and value of the coefficient indicate that risk perception is thought to be a crucial factor in AI adoption for investments (Caro, F., et al., 2026).

The results also confirm that financial confidence is a key positive driver of investors' trust in AI for personal investing. The R value of the financial confidence model was the highest, as well as R^2 value, at $R = 0.441$ and $R^2 = 0.195$ (Tu, Y., et al., 2025). The regression model was statistically significant ($F = 47.851$, $p < 0.001$), and the

standardized coefficient ($\beta = 0.441$) suggests positive association thus validating H3. All three hypotheses are supported by the evidence, which shows that psychological and financial factors play a role in human-AI interaction rather than technologically based ones (Kumar, N., et al., 2026). The results highlight the need for creating trustworthy and transparent AI systems that are investor-centric. The study also suggest that as part of designing investment platforms where retail investors interact with AI, financial confidence as well as people's perception of investment risk should be taken into account (Ju, H., et al., 2025).

The results show that trust, perceived investment risk and financial confidence are key determinants in personal investing human-AI collaboration. The findings have made the study's argument to run true that good investing that is fueled by artificial intelligence relies not just on technological capacity, it is dependent on investors' trust, risk awareness and financial confidence as well (Adegbenro, A., et al., 2022).

7. CONCLUSION

This addresses that trust in AI and perceived investment risk and financial confidence are strong drivers of human-AI collaboration across personal investing. Investors are more prone to cooperate with AI-based investment tools when there is greater trust in AI, and greater perception of investment risk results in lower acceptance and usage of AI investment decision-making. Financial confidence shows a strong positive correlation with investors' trust in AI, and it accounts for the greatest variance of the three factors studied. The results provide evidence to validate all three hypotheses and suggest that investors' perceptions, confidence and understanding of risks are important factors in successful adoption of AI in personal investing. The findings emphasize the need to create a platform for investments based on artificial intelligence that can make correct recommendations, clearly explain the process, explain the risks, and offer adequate support in making investments.

8. FUTURE SCOPE AND IMPLICATIONS

The study will have real-world implications on the strategies that retail investors, financial institutions, FinTech firms, and policy makers should use to encourage responsible use of AI in personal investing. The trust and confidence in AI platforms need to be bolstered to promote greater investor awareness, transparency, security, and explain ability. The results should however be interpreted in the empirical setting of the study and the factors built into the regression models, as all of this is not captured. Further the study has been suggested to directly study a larger and more heterogeneous investor base and to include other behavioural and technological factors in the analysis. Longitudinal and comparative study could also yield more detail as to how trust, risk perception and financial confidence changes over the course of interaction with AI-based investment systems.

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