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AI-DRIVEN PORTFOLIO SIMULATIONS:

ENHANCING INVESTMENT DECISION-MAKING WITHOUT FINANCIAL COMMITMENT

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Abstract

Artificial Intelligence comes more prominently as a driver for transformation in financial education, most notably for new investors who are sceptical about investing real money. While existing research has largely been focused on system effectiveness and forecasting ability, scant information exists about perceptions and adoption of AI-supported portfolio simulation tools by typical users. This study seeks to redress that by exploring behaviour and perceptual factors that might influence eventual user acceptance after such platforms come into existence. It studies how confidence, utility, and realism might influence exposure to a simulation that replicates real-world investment conditions in a safe, virtual world.

The study utilises a quantitative, cross-sectional research approach based on behavioural finance and technology acceptance theory. Data were obtained from retail investors and finance majors who are knowledgeable about digital investment tools. A structured questionnaire was used to assess constructs such as accuracy, speed, consistency, awareness, cost feasibility, confidence, as well as intention to use such tools. Structural Equation Modelling was applied to analyse relationships between such factors as well as influence on user perceptions, with measures for reliability and validity ascertained based on established indices.

The research results reveal that users' confidence has a major impact on users' willingness to engage with upcoming simulation platforms, which strongly relates to the level of system accuracy, speed, and consistency believed to pertain. On the contrary, general awareness and cost factors contribute little towards the adoption intentions of such technologies. What differentiates this work from others lies in its anticipatory bias, synthesising conceptual design with empirical research to predict users' responses towards AI-based investment tools before they are widely launched.

Keywords: Artificial Intelligence, Portfolio Simulation, Behavioural Finance, Technology Acceptance, User Confidence, Fintech Design, Investment Education, Speculative Research, Structural Equation Modelling

Introduction

In an era where financial literacy and technological innovation are increasingly intertwined, Artificial Intelligence (AI) offers new possibilities for individual investment strategies.

Traditional investing necessarily involves real capital and comes with built-in risk, which may deter inexperienced investors from participating meaningfully in financial markets. Simulation-based platforms supported by AI represent a viable alternative, allowing users to test strategies, develop confidence, and learn experientially about investment outcomes in a risk-free environment. This research uses a forward-looking perspective, exploring the likely adoption of such platforms by future users, both behaviourally related factors that may influence their acceptance, as well as perceptual factors. By integrating insights from both behaviour finance and from technology acceptance theory, this research aims to contribute to developing inclusive, educative financial technologies (fintech) tools that empower individuals to make informed investment choices in a risk-free environment.

Background

Investing is often seen as risky by beginners who fear losses and lack practical experience, and do not have real-world experience. Behavioural finance stresses how perceptions and emotions drive such choices. As Artificial Intelligence advances, features such as machine learning and reinforcement learning now allow precise predictions, portfolio optimisation, as well as risk management. With these features coupled with simulation, AI can produce realistic, customised, as well as safe platforms that enable users to practise investing with no risk of losing money, thus developing confidence as well as financial literacy.

Rationale

- Investing feels risky when you're just starting out. Most people don’t want to lose money while figuring things out, and there aren’t many tools that let you safely test strategies before diving in.
- AI can make learning to invest smarter and more personal- Instead of generic advice, simulations powered by AI can adapt to our style, show us what works, and help us build confidence without the pressure of real money.

Purpose

In today's rapidly evolving financial landscape, retail investors face increasing complexity in making informed investment decisions. While artificial intelligence (AI) has demonstrated significant potential in portfolio optimisation and predictive modelling, most AI-driven tools are designed for active trading or institutional use, requiring real financial commitment. This creates a critical gap for individuals who wish to explore investment strategies, test market scenarios, or build financial literacy without risking capital. Despite advances in machine learning, reinforcement learning, and generative AI, there is minimal integration of personalised feedback, explainable design, and behavioural finance principles into simulation environments. Users often struggle to trust or engage with AI systems, limiting their adoption and educational value. Addressing this gap requires the development of AI-powered portfolio simulation platforms that are intuitive, risk-free, and tailored to diverse investor profiles, empowering users to make better financial decisions through experimentation rather than exposure.

Aim

To investigate how AI-driven portfolio simulation tools can enhance investment decision-making by enabling individuals to evaluate strategies, manage risk perceptions, and build financial confidence without engaging in real-money transactions.

Objectives

1. To analyse how perceived cost feasibility, accuracy, consistency, and speed of AI-driven portfolio simulations contribute to building user confidence in their decision-making capabilities.
2. To explore the direct impact of cost, accuracy, consistency, and speed on users' intent to use AI-driven portfolio simulations.
3. To investigate the direct effects of cost, accuracy, consistency, and speed on users' intent to use AI-driven portfolio simulations, with confidence serving as a mediating variable.

Research Methodology

Research Design

This study uses a quantitative, cross-sectional speculative research design to look at the behavioural and perceptual factors that influence user acceptance of AI-driven portfolio simulation platforms. The approach combines ideas from behavioural finance and technology acceptance theory. It is operationalised through a structured questionnaire and analysed with Structural Equation Modelling (SEM) using SmartPLS.

The study aimed for at least 200 valid responses, as this meets the general SEM guideline of 10 responses per indicator and ensures reliable model testing. With 7 constructs and multiple indicators per construct, a sample size of 200+ is statistically adequate for SmartPLS analysis. The total collected responses were 210.

Constructs and Measurements

The research model includes seven latent constructs:

1. Awareness
2. Consistency
3. Cost Feasibility
4. Accuracy
5. Speed
6. Confidence
7. Intent to Use

Each construct was measured using multiple items taken from established scales in previous literature, adjusted for the context of financial simulations. Responses were recorded on a 5-point Likert scale that ranged from "Strongly Disagree" to "Strongly Agree."

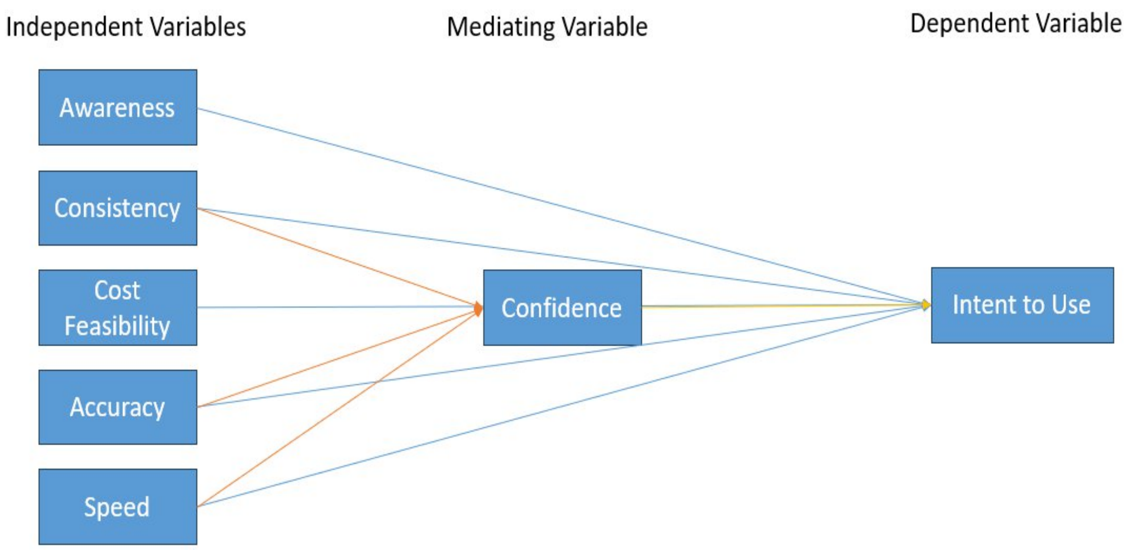

Figure 1- Shows the theoretical framework of the relationship between independent, mediating and dependent variables

Results and Findings

Results

Objective 1- To analyse how perceived cost feasibility, accuracy, consistency, and speed of AI-driven portfolio simulations contribute to building user confidence in their decision-making capabilities.

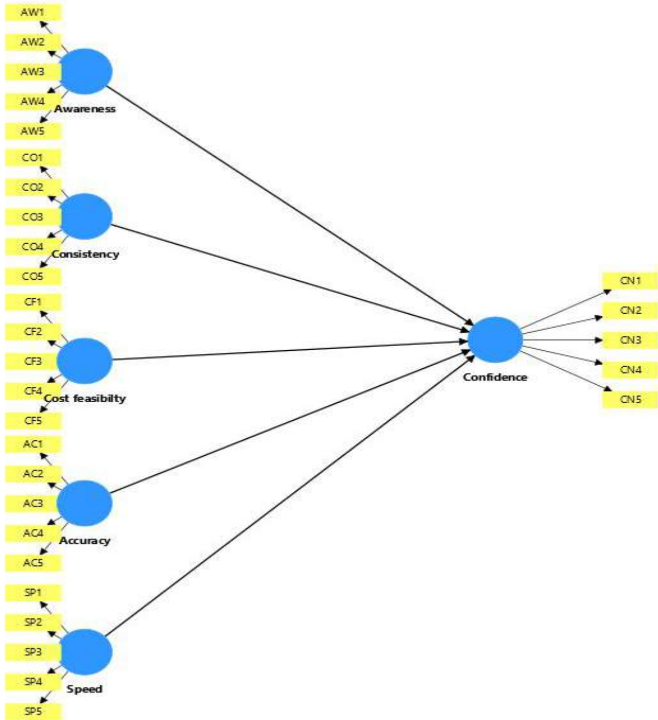

Figure 2- Objective 1 path coefficients derived through SEM analysis

Construct Validity and Reliability

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
Accuracy	0.885	0.886	0.916	0.685
Awareness	0.864	0.874	0.902	0.650
Confidence	0.888	0.889	0.918	0.691
Consistency	0.885	0.886	0.916	0.684
Cost Feasibility	0.897	0.899	0.924	0.708
Speed	0.883	0.884	0.914	0.681

Table 1- Cronbach's alpha, CR and AVE values for Objective 1

The constructs of Accuracy, Consistency, Speed, and Cost Feasibility demonstrate strong reliability and convergent validity. Cronbach's alpha values range from 0.864 to 0.897, and composite reliability values exceed 0.90 for all constructs, confirming internal consistency. Average Variance Extracted (AVE) values are all above 0.65, indicating that each construct captures sufficient variance from its indicators.

Discriminant Validity

	Accuracy	Awareness	Confidence	Consistency	Cost Feasibility	Speed
Accuracy						
Awareness	0.723					
Confidence	0.925	0.751				
Consistency	0.808	0.875	0.812			
Cost Feasibility	0.819	0.721	0.835	0.785		
Speed	0.954	0.651	0.903	0.822	0.811	

Table 2- Discriminant Validity for Objective 1

Discriminant validity is confirmed using the Fornell-Larcker criterion, where the square root of AVE for each construct is greater than its correlations with other constructs. This ensures that each construct is statistically distinct and free from multicollinearity, validating the uniqueness of Accuracy, Consistency, Speed, and Cost Feasibility in shaping user perceptions.

Model Fit

	R-square	R-square adjusted
Confidence	0.758	0.752

Table 3- R square values derived for Objective 1

The structural model shows that these four constructs collectively explain 75.8% of the variance in user confidence ($R^2 = 0.758$), indicating strong predictive power. This supports the statement that performance-related perceptions significantly contribute to building user confidence in AI-driven portfolio simulations, aligning with trust-based extensions of technology acceptance models.

Objective 2- To explore the direct impact of cost, accuracy, consistency, and speed on users' intent to use AI-driven portfolio simulations.

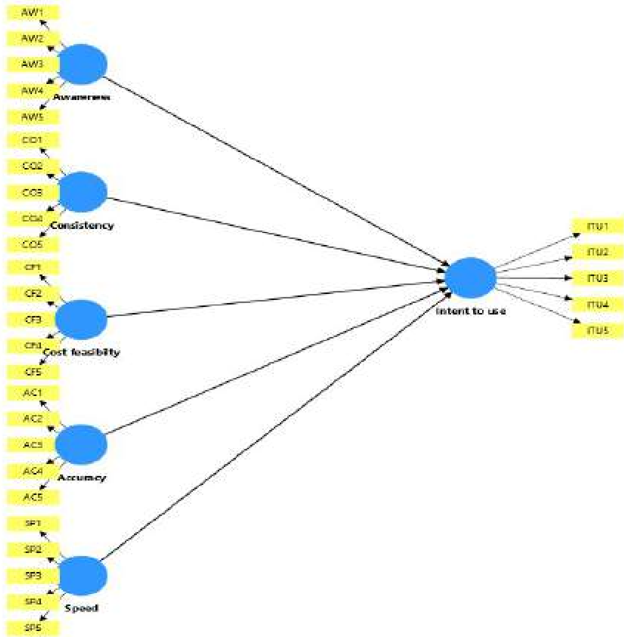

Figure 3- Objective 2 path coefficients derived through SEM analysis

Construct Validity and Reliability

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
Accuracy	0.885	0.886	0.916	0.685
Awareness	0.864	0.869	0.903	0.651
Consistency	0.885	0.889	0.915	0.684
Cost Feasibility	0.897	0.897	0.924	0.708
Intent to Use	0.906	0.909	0.930	0.727
Speed	0.883	0.884	0.914	0.681

Table 4- Cronbach's alpha, CR and AVE values for Objective 2

The constructs used to assess user intent- Accuracy, Consistency, Speed, Cost Feasibility, Awareness, and Intent to Use demonstrate high internal consistency. Cronbach's alpha values range from 0.864 to 0.906, while composite reliability scores exceed 0.90 across all variables, confirming dependable measurement. Additionally, AVE values surpass the 0.65 threshold, indicating that each construct captures a sufficient proportion of variance from its indicators and meets the criteria for convergent validity.

Discriminant Validity

	Accuracy	Awareness	Consistency	Cost Feasibility	Intent to Use	Speed

Accuracy						
Awareness	0.723					
Consistency	0.808	0.875				
Cost Feasibility	0.819	0.721	0.785			
Intent to Use	0.854	0.657	0.750	0.748		
Speed	0.954	0.651	0.822	0.811	0.881	

Table 5- Discriminant Validity for Objective 2

The square root of AVE for each construct was greater than its correlations with other constructs, confirming that no overlap exists between latent variables. For instance, Intent to Use ($\sqrt{AVE} \approx 0.853$) shows lower correlations with Accuracy (0.854), Consistency (0.750), Speed (0.881), and Cost Feasibility (0.748), validating the independence of each construct within the model.

Model Fit

	R-square	**R-square adjusted**
Intent to use	0.675	0.667

Table 6- R square values derived for Objective 2

The structural model reveals that Accuracy, Consistency, Speed, and Cost Feasibility collectively account for 67.5% of the variance in users' intent to adopt AI-driven portfolio simulations ($R^2 = 0.675$). This substantial explanatory power highlights the direct influence of performance-related perceptions on behavioural intention. The findings reinforce the relevance of system quality and perceived utility in shaping user adoption, consistent with established technology acceptance theories.

Objective 3- To investigate the direct effects of cost, accuracy, consistency, and speed on users' intent to use AI-driven portfolio simulations, with confidence serving as a mediating variable.

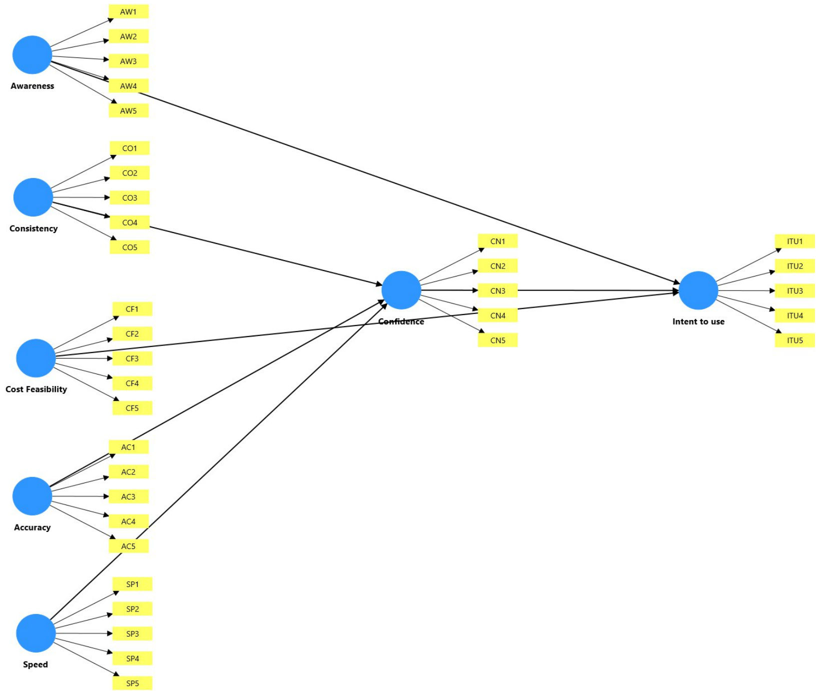

Figure 4- Objective 3 path coefficients derived through SEM analysis

Construct Validity and Reliability

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
Accuracy	0.885	0.886	0.916	0.685
Awareness	0.864	0.869	0.903	0.651
Confidence	0.888	0.889	0.918	0.691
Consistency	0.885	0.886	0.916	0.684
Cost Feasibility	0.897	0.897	0.924	0.708
Intent to Use	0.906	0.908	0.930	0.727
Speed	0.883	0.884	0.914	0.681

Table 7- Cronbach's alpha, CR and AVE values for Objective 3

The constructs involved in the mediation model-Accuracy, Consistency, Speed, Cost Feasibility, Confidence, and Intent to Use demonstrate excellent measurement reliability. Cronbach's alpha values range from 0.883 to 0.906, while composite reliability values exceed 0.91 across all constructs, confirming strong internal consistency. Average Variance Extracted (AVE) values are all above 0.68, indicating that each construct captures sufficient variance from its indicators and meets the criteria for convergent validity.

Discriminant Validity

	Accuracy	Awareness	Confidence	Consistency	Cost Feasibility	Intent to Use	Speed
Accuracy							
Awareness	0.723						
Confidence	0.925	0.751					
Consistency	0.808	0.875	0.812				
Cost Feasibility	0.819	0.721	0.835	0.785			
Intent to Use	0.854	0.657	0.951	0.750	0.748		
Speed	0.954	0.651	0.903	0.822	0.811	0.881	

Table 8- Discriminant Validity for Objective 3

Discriminant validity was assessed using the Fornell-Larcker criterion. For each construct, the square root of AVE is greater than its correlations with other constructs, confirming that the latent variables are statistically distinct. For example, Confidence ($\sqrt{AVE} \approx 0.831$) shows lower correlations with Accuracy (0.925), Speed (0.903), and Cost Feasibility (0.835), validating its role as a separate mediating construct. This ensures that the predictors and outcome variables are conceptually independent and suitable for mediation analysis.

Model Fit

	R-square	R-square adjusted
Confidence	0.732	0.728
Intent to use	0.732	0.728

Table 9- Cronbach's alpha, CR and AVE values for Objective 3

The structural model demonstrates strong explanatory power, with R^2 values of 0.732 for both Confidence and Intent to Use. This indicates that Accuracy, Consistency, Speed, and Cost Feasibility collectively account for 73.2% of the variance in both the mediator and the outcome variable. Such results support the hypothesis that Confidence mediates the relationship between performance perceptions and behavioural intention, reinforcing trust-based extensions of technology acceptance models in the context of AI-driven portfolio simulations.

Findings

Objective 1-

The analysis showed that the constructs of perceived accuracy, consistency, speed, and cost-effectiveness positively influence building user trust in AI-augmented portfolio simulations, as the structural model explained 75.8% of the variance in confidence levels. All of the constructs had high reliability as well as validity, with discriminant analyses affirming their conceptual distinctness.

Objective 2-

Findings showed that accuracy, consistency, speed, and cost feasibility were significant predictors of users' behavioural intention to use AI-powered portfolio simulations, since the model contributed to 67.5% of behavioural intention variance. Reliability and validity thresholds were surpassed by measurement indicators, with discriminant validity ensuring distinctness between individual constructs.

Objective 3-

The study corroborated that confidence was a significant mediator between accuracy, consistency, speed, cost feasibility, performance perceptions, as well as users' intent to adopt AI-based portfolio simulations. Indirect effects through confidence were statistically significant, while cost feasibility and awareness had insignificant direct effects, with the model explaining 73.2% of the variance in confidence as well as intent to use.

Discussions

Objective 1: What Builds User Confidence

The study found that users' confidence in AI-based portfolio simulations was primarily established by users' perceptions of accuracy, consistency, speed, as well as cost-effectiveness of the system. They, in general, explained over 75% of confidence level variance, which indicates a notable percentage. The constructs were statistically strong with high reliability as well as clear conceptual boundaries. These findings are similar to prior work on trust in automation as well as technology acceptance, which validated that users are likely to trust systems that are both reliable as well as efficient. From a practical perspective, this advises that technical accuracy as well as communicating value should receive equal attention by developers in order to boost users' trust.

Objective 2: Direct Impact on Intent to Use

The second segment of the study investigated how much these same performance perceptions influence users' intentions to adopt AI tools directly. Nearly 68% of the variance in behavioural intention was explained by the model, therefore validating accuracy, consistency, speed, and cost-effectiveness as significant predictors. The findings are in agreement with validated models of technology acceptance, in which perceived usefulness and ease of use hold central places. Interestingly, while all four constructs had contributions, some factors, like speed and accuracy, may hold more salience in affecting users' decisions. This further implies a need for developing systems that perform excellently but that also look novice-friendly and useful to users, a need more imperative in high-stakes financial contexts.

Objective 3: Confidence as a Bridge to Adoption

The final model identified confidence as a mediator between system perceptions and use intention. The findings supported the belief that confidence plays a central role, with indirect effects frequently being greater than some of its direct effects. Both confidence and intention to use presented high explanatory power ($R^2 = 0.732$), such that users do not merely act based on perceptions the users respond to feelings they get from perceptions as well. Thus, confidence is a bridge between evaluation and behaviour. For professionals, this implies that confidence-building extends beyond product performance to making users trust themselves and feel competent in decision-making processes.

Conclusions

The study aimed at understanding how portfolio simulations based on artificial intelligence can benefit individuals in refining investment decisions with minimal stress of losing real capital. Applying the principles of behavioural finance as well as technology acceptance, the research studied individual responses to key simulation characteristics, including accuracy, trustworthiness, speed, and affordability. The results suggest that if users perceive such platforms to be trustworthy and efficient, they feel more confident in their decision-making. This confidence plays a pivotal role, as it not only strengthens their faith in the system but also increases their willingness to use it. It's interesting to note that confidence does not just result from efficient design but instead acts as a bridge between technical features and true consumer participation. This research employed SmartPLS for its data analysis, corroborating this model's strength with high validity and reliability scores. This framework demonstrates its strength and offers beneficial insights for fintech developers, teachers, as well as designers.

Arguably, this work demonstrates that AI models will facilitate access to investment, more so for newbies or conservative users. With a controlled environment for learning as well as experimenting, such tools might revolutionise financial participation, more so in countries such as India, where financial literacy as well as risk issues are significant.

Suggestions for future work

While this study offers valuable insights into how users perceive and engage with AI-driven portfolio simulations, there are several areas worth exploring further:

- Real-time behavioural tracking: Future research could include observational or longitudinal methods to track how users interact with simulations over time. This would help uncover patterns in learning, confidence-building, and decision-making beyond self-reported data.
- Cross-cultural comparisons: Since financial behaviour and technology adoption vary across regions, comparing user responses from different countries could reveal cultural influences on simulation acceptance and trust.
- Integration of emotional feedback: Adding features that respond to user emotions such as frustration, hesitation, or excitement, could make simulations more adaptive and supportive. Exploring how emotional cues affect confidence and learning would be a valuable next step.

- Gamification and engagement strategies: Future platforms could test how elements like challenges, rewards, or progress tracking influence user motivation and sustained use.
- Ethical and regulatory considerations: As AI tools become more personalised, future studies should examine how transparency, data privacy, and ethical design affect user trust and platform credibility.
- Simulation realism and market dynamics: Incorporating more realistic market conditions, including volatility, news events, and sentiment analysis, could make simulations more immersive. Research could explore how realism affects user preparedness and decision quality.
- Personalised strategy recommendations: Further investigation is needed into how tailored AI suggestions based on user goals, risk tolerance, and behaviour impact learning outcomes and long-term adoption.

Practical Implications

The findings of this study offer meaningful and actionable insights for fintech developers, simulation platform designers, and financial educators who are striving to improve user engagement with AI-driven portfolio management tools. These insights go beyond technical optimisation; they speak to the human experience of interacting with financial technology, especially in environments where trust, control, and perceived value shape user behaviour.

Firstly, the importance of trust and simulation realism emerged as a foundational theme. Users are more likely to engage with platforms that feel transparent, credible, and easy to navigate. This suggests that developers should prioritise clarity in design and communication. Incorporating explainable AI features such as visual breakdowns of how algorithms function, or scenario-based feedback that shows how different inputs lead to different outcomes, can help demystify the technology. When users understand what's happening behind the scenes, they're less likely to feel uncertain or overwhelmed, and more likely to build confidence in the system.

Secondly, the role of perceived control highlights the psychological need for agency in financial decision-making. Users want to feel that they're not just passive observers but active participants in shaping their investment strategies. Platforms that offer interactive elements such as sliders to adjust risk levels, toggles to explore different market conditions, or personalised dashboards can create a sense of responsiveness and adaptability. When users feel that the simulation environment reacts to their choices and preferences, they're more inclined to stay engaged and return for future sessions.

Third, the impact of perceived usefulness on the intention to use these tools underscores the importance of clearly communicating value. Users need to see how simulations translate into better real-world decisions. This could be achieved through integrated learning modules, reflective summaries after each simulation, or contextual prompts that link simulation outcomes to core investment principles. When users can connect the dots between virtual experimentation and tangible financial literacy, the platform becomes not just a tool but a trusted guide.

Finally, for financial educators and institutions, these findings offer a roadmap for curriculum design and onboarding strategies. Embedding AI-driven simulations into training programmes, especially when paired with behavioural nudges, guided walkthroughs, and peer discussion, can significantly enhance learning outcomes. Such approaches not only improve technical understanding but also build emotional confidence in navigating financial decisions, particularly for novice investors who may feel intimidated by traditional tools.

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Originality Value

This manuscript was prepared by the authors with limited support from generative AI and AI-assisted technologies, used solely to enhance clarity, structure, and presentation. Microsoft Copilot and ChatGPT were employed at selected stages to refine academic phrasing, interpret statistical terminology such as HTMT discriminant validity and assist in organising literature insights. These tools also supported the drafting of narrative sections, including limitations and future research directions, with all suggestions critically reviewed and adapted by the authors. Grammarly was used throughout to ensure grammatical accuracy, consistency in style, and improved readability. However, none of these tools were used to generate original research content, conduct data analysis, or draw conclusions. All decisions regarding research design, methodology, theoretical framing, and interpretation of results were made independently, based on my academic judgement and domain expertise.

None of these technologies was used to generate original research content, formulate hypotheses, conduct data analysis, or draw conclusions. The use of all AI-generated suggestions was carefully evaluated, and the final manuscript reflects the authors' own thinking, analysis, and scholarly effort.

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Biography

Shreelakshmi G B is currently pursuing her MBA in Business Analytics at MS Ramaiah University of Applied Sciences, Bengaluru. Her thesis, titled "AI-Driven Portfolio Simulations: Enhancing Investment Decision-Making Without Financial Commitment," explores the role of artificial intelligence in empowering investors through simulated environments. She holds a Bachelor of Commerce degree from Seshadripuram Institute of Commerce and Management. Her research interests include behavioural finance, portfolio management, and simulation modelling. Outside academia, Shreelakshmi is a professional badminton player and a self-taught artist.

Dr Udaykumar Jagannathan is an Associate Professor in the Department of Management Studies, Faculty of Management and Commerce, MS Ramaiah University of Applied Sciences, Bengaluru. He holds a PhD in Finance from RUAS, an MBA in Finance from UCLA, and a B.Tech in Aeronautical Engineering from IIT Madras. With over 33 years of combined experience, 17 years in global consulting and 16 years in academia, Dr Jagannathan specialises in corporate finance, valuation, portfolio management, and applied Python in financial analytics. He has received multiple Best Paper Awards at national and international conferences and was honoured with the Best Teacher Award at RUAS. His industry tenure includes roles at Infosys Ltd, Fortna Inc., and CGS Inc., across India, France, and the USA. He continues to mentor students in simulation-based financial research and decision modelling.

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Appendix

Questionnaire

Section A- Demographic Information

1. Age Group

   Under 20 21-30 31-40 41-50 Above 50
2. Occupation

   Student Working Professional Others
3. Investment Experience

   None Less than 1 year 1-3 years More than three years
4. Have you ever used a stock investment platform?

   Yes No
5. Have you interacted with any simulation-based investment tool (paper trading)?

   Yes No

Section B- Awareness of Finance Bots

	1	2	3	4	5	
Strongly Disagree	○	○	○	○	○	Strongly Agree

1. I am aware that finance bots can assist in personal finance decisions.
2. I frequently come across information about finance bots online or via social media.
3. I understand how finance bots generally function.
4. I can differentiate between human advisors and bot advisors in personal finance.
5. I have previously explored finance bots for managing my personal finances.

Section C- Consistency of Finance Bot Behaviour

	1	2	3	4	5	
Strongly Disagree	○	○	○	○	○	Strongly Agree

1. Finance bots should give consistent recommendations when asked similar questions.
2. I perceive finance bots to behave consistently across sessions.
3. Using a finance bot would reduce the variability in my financial decisions.
4. Consistency is an important factor for me when choosing financial advisory tools.
5. I trust that a finance bot will always follow the same decision logic.

Section D- Financial Viability of Finance Bots

	1	2	3	4	5	
Strongly Disagree	○	○	○	○	○	Strongly Agree

1. Using a finance bot would be more affordable than hiring a human advisor.
2. Finance bots would be more economically feasible for my financial management.
3. I believe finance bots could help reduce my overall personal finance management costs.
4. Finance bots should ideally offer a good balance between cost and features.
5. I am willing to pay for a high-quality finance bot service if it is cost-effective.

Section E- Accuracy of Finance Bots

	1	2	3	4	5	
Strongly Disagree	○	○	○	○	○	Strongly Agree

1. I believe finance bots would reduce human error in personal finance advice.
2. Accuracy is critical when I evaluate any financial tool.
3. I would trust the accuracy of financial recommendations given by bots.
4. I believe finance bots are calibrated to minimise biases in recommendations.
5. Accurate recommendations from finance bots would improve my trust in automated decision tools.

Section F- Response Speed of Finance Bots

	1	2	3	4	5	
Strongly Disagree	○	○	○	○	○	Strongly Agree

1. Finance bots would respond faster than human advisors.
2. I would value the quick response time of finance bots when making financial decisions.
3. Quick service from finance bots would make them preferable to other tools.
4. Speed of response would enhance the overall value of finance bots.
5. I believe fast responses would not compromise the quality of advice from bots.

Section G- Confidence in Finance Bot Usage

	1	2	3	4	5	
Strongly Disagree	○	○	○	○	○	Strongly Agree

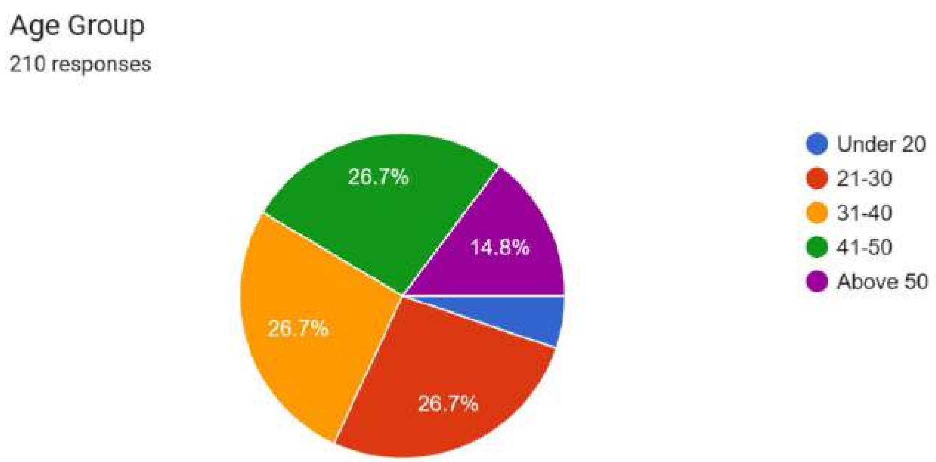
1. I would feel confident in the financial advice provided by bots.
2. I would rely on a finance bot for key personal finance decisions.
3. Using finance bots would improve my confidence in managing money.
4. I would be comfortable trusting financial data generated by bots.
5. I believe bots could handle complex financial queries confidently.

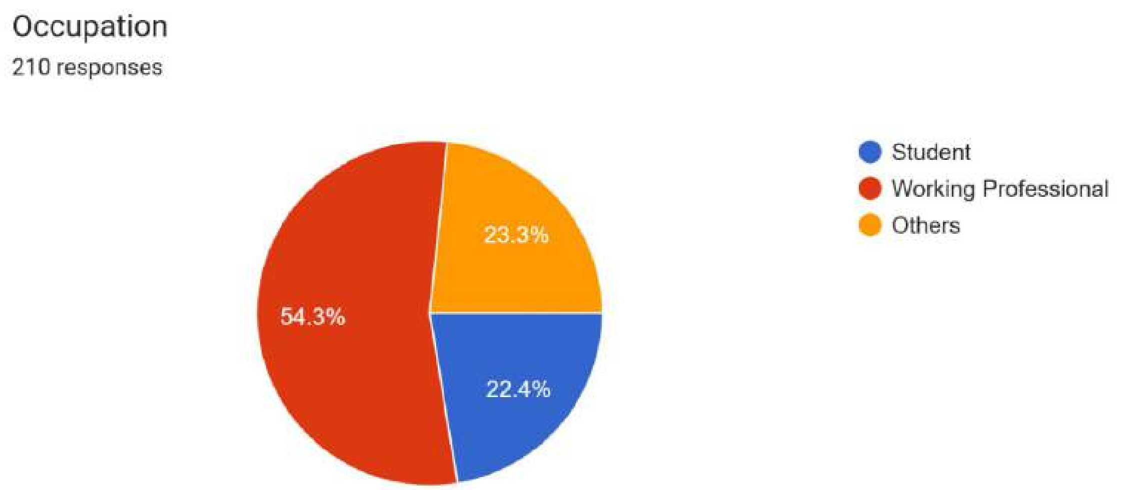
Section H- Intent to Use Finance Bots

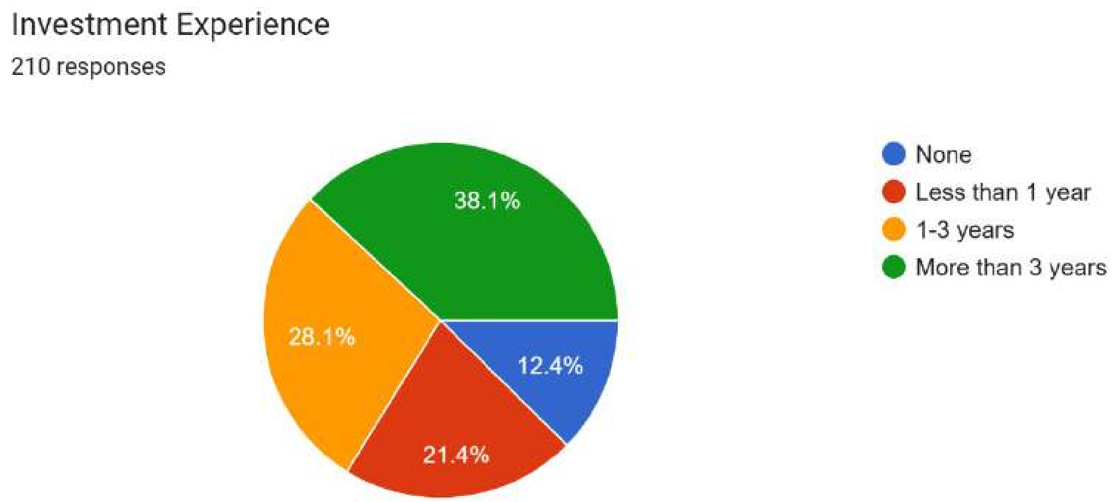
	1	2	3	4	5	
Strongly Disagree	○	○	○	○	○	Strongly Agree

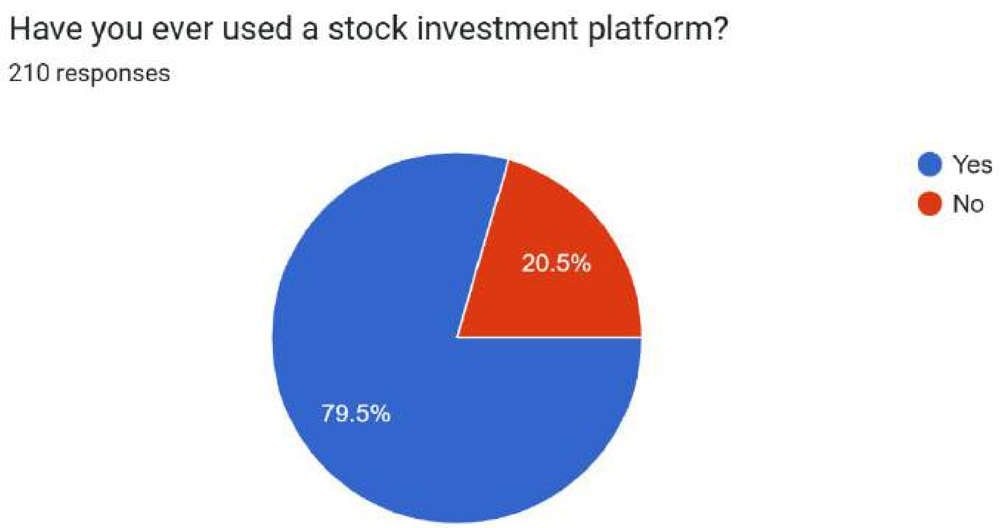
1. I intend to use finance bots for managing my personal finances in the near future.
2. I would recommend finance bots to friends and family.
3. I plan to explore different finance bots to improve my financial management.
4. I am likely to shift from traditional methods to finance bots for personal finance.
5. I expect finance bots to play a key role in my financial decisions soon.

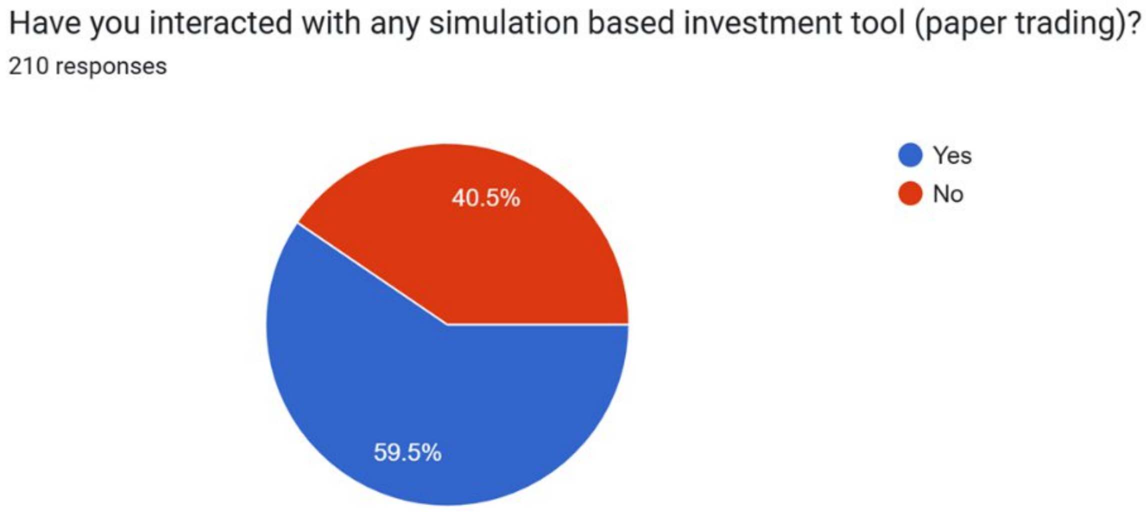
Descriptive Statistics for demographic variables




Occupation
210 responses
23.3%
54.3%
22.4%
Student
Working Professional
Others


Investment Experience
210 responses
38.1%
28.1%
12.4%
21.4%
None
Less than 1 year
1-3 years
More than 3 years


Have you ever used a stock investment platform?
210 responses
20.5%
79.5%
Yes
No


Have you interacted with any simulation based investment tool (paper trading)?
210 responses
40.5%
59.5%
Yes
No