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Behavioral Biases and the Efficiency of AI-Driven Equity Investment Decisions: The Moderating Role of Digital Literacy in Sri Lanka

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ABSTRACT

Purpose: The contemplation of this study is to identify the impact of behavioral biases on the efficiency of AI-driven investment decisions.

Design/Methodology/Approach: The study was conducted as a quantitative study where primary data were collected through a questionnaire distributed among investors in Sri Lanka. The behavioral biases are measured through cognitive error and the emotional biases. The use of technology requires certain skills; therefore, the digital literacy was empirically identified to be moderating the impact of behavioral biases on the efficiency of AI-driven investments. The equity investors using AI recommendations for investment decisions were regarded as the population; and a sample of 384 respondents was selected, allowing a 5% margin of error.

Findings: The findings of the study revealed that there is a significant impact of cognitive error and the emotional biases on the efficiency of AI driven investments. Further, there is a significant moderating role of digital literacy between the behavioral biases and AI-driven investment decision making. The findings of the study provide insights into AI model training, enabling developers to incorporate these behavioral considerations into the model.

Originality: This study provides new insights into the impact of behavioral biases on the efficiency of AI-driven investments which are a practical significance for the investors; operating within a system where technology is increasingly integrated into the financial sector. The study provides novel knowledge by examining the cognitive errors and emotional biases of investors and how they deviate the efficiency of the investments they make.

KEYWORDS

AI driven Investments; Behavioral biases; Cognitive error; Digital literacy; Emotional biases

JEL CLASSIFICATION

G11, G41

I. Introduction

Artificial Intelligence (AI) has emerged across almost all aspects of the business world, including the financial sector (Devapitchai et al., 2024). Traditional investments are now becoming increasingly digital, where AI has a significant impact on investment decisions. Even though the traditional financial theorists believe that investors make rational decisions; behavioral finance has been a disruptive field that highly emphasizes the psychological aspects of decision making, thus, the investment decisions are irrational. Given the rapid development of technology, it has become widely used for several aspects, particularly for information discovery and subsequently evolved into decision making processes. (Benjamin Monday Ojonugwa et al., 2024). Hence, investments and investor decisions have now been largely impacted by technological factors.

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Emerging technologies have driven the first attempt of information discovery towards more complex activities and nowadays, the largest breakthrough to the investment is that the AI-driven investments. As noted by Sarin and Sharma (2024), AI driven investments depend upon the algorithms and using those algorithms, the investors are tending to analyze big data, analyzing trades, forecasting markets etc. to optimize their financial decisions and investment decisions (Sarin & Sharma, 2024). However, it is noticeable that a particular investor should have to have a broader range of knowledge to apply this or rather depend on the advisors. Therefore, in the context of AI driven investments, personal beliefs, attitudes, traits, knowledge, gender etc. which basically covers in the context of behavioral finance has a significant impact.

The impact of psychological factors on investment decisions has largely been studied and according to the findings of Jain et al., (2023), positive psychological factors are driving wealthy investment and on the other hand, negative psychological factors deviate the return on investment to the downside. It isn't a surprise at all for investors because they have already understood that their personal traits are significantly impacting on their investment decision. Hence, the studies are more focused towards measuring the impact, whether such impact is significant or not. Hence, the authors of the present study match these historical analyses to the present world context with AI, and therefore, the contemplation of this study is to analyze whether behavioral biases can significantly impact on the AI driven investments.

The present study is further differentiated from the existing body of knowledge as it employs behavioral biases rather than behavioral traits or factors. As behavioral biases, it identifies two forms namely, cognitive error and emotional biases. Cognitive error encompasses systematic thinking that is driven by the individuals' attempts to simplify the implications of information depending on personal experiences and preferences (Jain et al., 2023). Emotional biases are related to the feelings of individuals, and they are used to explain the impact of emotions and feelings on decision making. Given these two behavioral biases, and considering that AI driven investments are complex in nature and require a thorough understanding, scholars have emphasized that cognitive error is more likely to occur. Moreover, as long as the investors are seeking investment advice, emotional biases are also possible. Therefore, it is noteworthy to study the impact of these behavioral biases on AI driven investments.

As noted, there is a growing body of literature on the behavioral finance and the adoption of AI driven investments, yet a critical performance gap exists in understanding the impact of behavioral biases on the efficiency of AI driven equity investment decisions; especially in the context of emerging markets such as Sri Lanka. Prior studies have predominantly focused on AI adoption in relation to investment decisions, and behavioral settings in traditional banking contexts while leaving a space to study the combined impact of cognitive error and emotional biases in AI driven equity investment decisions. Therefore, this study addresses these gaps through empirically examining the impact of cognitive error and emotional biases on AI driven equity investment decisions among Sri Lankan equity investors while offering a more contextually grounded and holistic understanding by introducing digital literacy as a moderator as well.

While the existing literature is particularly rich in identifying factors affecting the adoption of AI driven-investments, the present study aims to investigate the behavioral aspect of investors; primarily evaluating whether behavioral biases impact the efficiency of AI-driven investments. Further, financial literacy has been a profound moderator in investment and financial related research, yet as the authors are focused on the AI driven investments, the digital literacy is regarded as the moderator for the study; thereby contributing new knowledge to the existing body of literature.

The findings of the study are beneficial especially for the investors, as they can tailor their behaviors and identify the impact of those different behaviors on their decision making. Further, the study emphasizes the AI driven investments hence the investors can clearly distinguish between their behavior during traditional investment process and AI driven investment process. The investment advisors are also getting the implications from the study whereas they can fully evaluate the client based on their behavioral traits.

The rest of the paper is structured as follows. The next section provides a review of the existing literature on behavioral biases, and decision making in investment. The methodology is presented in the third section, and the findings of the study are presented in the fourth section. The final section of the paper concludes with the implications of the study in of theoretical, practical and policy terms.

II. Literature Review and Hypotheses

Behavioral Biases

Systematic patterns of deviance from norms or rationality in judgment are referred to as behavioral biases. People may display decision-making biases when it comes to investments that diverge from strictly rational, objective decisions (Gabhane et al., 2023). Overconfidence, aversion to loss, and herding tendencies are typical instances. In the context of investments, behavioral biases are somewhat more possible because investors are highly dependent on the historical patterns and experiences.

Cognitive Error

Understanding cognitive errors; systematic departures from rationality resulting from defects in judgment and information processing, is essential to comprehending the dynamics of investment decision-making (Otuteye & Siddiquee, 2015). Investors who commit the common cognitive error of confirmation bias tend to favor information that supports their pre-existing beliefs or hypotheses. This bias can cause investors to selectively focus on data that confirms their beliefs while ignoring contradicting evidence in the field of investments (Khan, 2022). Confirmation bias can cause investors to make less-than-ideal decisions by preventing them from thoroughly and impartially weighing the benefits and risks of a given investment decision.

When discussing investments, anchoring is another notable cognitive error. While people make decisions, they tend to anchor themselves by placing an undue emphasis on the initial piece of information they come across (Gabhane et al., 2023). Anchoring occurs when investors stick to a price or valuation for too long, even when new information indicates that it should be adjusted. The investor's capacity to make intelligent and flexible decisions may be hampered by this cognitive bias, which can also make it more difficult to adjust in response to shifting market conditions or new trends. For both investors and financial professionals, identifying these cognitive errors is essential because it enables the creation of plans to lessen their effects and promote more logical decision-making.

Emotional Biases

Emotional biases are a term used to describe how emotions affect the way decisions are made. When it comes to investing, feelings like enthusiasm, greed, anxiety, and overconfidence may all have a big impact on how investors see, process, and respond to information from the market (Kumar & Chaurasia, 2024). Investors may make impulsive or irrational decisions based on emotional bias, diverging from a logical evaluation of risks and rewards.

Fear is one of the most prevalent emotional biases in investing, especially fear of losing money. During market downturns, fear-driven investors may panic sell, selling assets at a loss and incurring expenses (Sapkota, 2023). Although the need to prevent more losses frequently motivates this behavior, it may cause one to miss out on any market recoveries. On the other hand, greed can cause investors to overlook possible drawbacks and expose themselves to unnecessary risk in their quest for large returns.

Herd behavior, in which investors follow the crowd instead of doing their own independent research, is another result of emotional bias (Gupta, 2025). Due to investors' collective overreaction to market movements, this conduct has the potential to worsen market volatility and cause bubbles or crashes.

Self-awareness, self-control, and the application of techniques to blunt emotional impulses are necessary for mitigating emotional bias. Investors can avoid making snap judgments by employing strategies including clear investing goals, diversified portfolio management, and long-term investment plan adherence (Sapkota, 2023). In order to manage emotional biases, investors may also find it helpful to consult with financial experts who may offer unbiased counsel and assist in helping investors keep a level head during periods of market turbulence.

AI Driven Investments

In the world of investments, artificial intelligence (AI) has become a disruptive force that is redefining conventional methods of risk assessment, decision-making, and portfolio management (Devapitchai et al., 2024). Advancements in machine learning, natural language processing, and big data analytics have led to a notable development in the integration of AI technologies in the investment management sector. Numerous uses of artificial intelligence (AI) in the financial sector have been investigated by researchers, including sentiment analysis, risk management, portfolio optimization, and algorithmic trading (Gupta, 2025).

Numerous applications of AI in investment practices have been identified by studies. Machine learning algorithms, for example, are used to examine large volumes of financial data, spot trends, and create models that forecast how asset prices will change (Niyazli, 2023). Investors can assess market sentiment and make well-informed decisions by using natural language processing techniques to extract insights from unstructured data sources including news articles, social media, and earnings reports.

Studies have looked at how well AI-driven investing strategies perform in comparison to more conventional methods. While some studies show that AI has the potential to beat benchmarks and increase portfolio returns, others point out problems with data quality, algorithmic biases, and model overfitting that could compromise the robustness and dependability of recommendations made by AI (Hasan et al., 2023).

The use of AI in investing also raises significant issues with risk management and legal compliance. Researchers have looked into how AI-driven decision-making affects regulatory supervision, market stability, and systemic risk. Additionally, research has concentrated on creating frameworks and procedures to evaluate and reduce risks related to AI models, such as interpretability, accountability, and transparency.

The increasing use of AI in investing brings up moral and societal issues that require for further research. Researchers have looked into problems with algorithmic fairness, data privacy, and socioeconomic inequality brought on by unequal access to AI-driven investment technology. Furthermore, conversations have focused on the moral obligations of financial institutions, asset managers, and AI developers when implementing and overseeing AI systems in the investment sector.

Digital Literacy

Simply defining, digital literacy is the ability to find, evaluate, create and communicate the information using the digital technologies (Tinmaz et al., 2022). There are sets of skills required as well. The encompassing skills to use the internet, use the smart devices, platforms are all within those skills.

Role of Behavioral Biases on AI-Driven Investments

Given its complexity and diversity, behavioral biases in AI-driven investments are a problem that needs to be carefully considered. Although artificial intelligence (AI) technologies present the possibility of objective, data-driven decision-making (Bihari et al., 2022), human biases can nevertheless unintentionally impact the formulation, application, and results of AI-driven investment strategies.

The possibility of biases being included into AI systems through the training data needed to create predictive models is one important factor. AI systems may reinforce and magnify biases in human decision-making patterns found in historical data when making recommendations and forecasts (Schwartz et al., 2022). For instance, AI algorithms educated on such data may unintentionally include and reinforce emotional or cognitive biases that have influenced earlier investing decisions, resulting in skewed or inefficient investment outcomes.

Furthermore, additional behavioral bias is introduced through interactions between AI systems and human users. While evaluating and acting upon AI-generated recommendations, investors may display cognitive and emotional biases that cause them to selectively accept or reject advice based on subjective preferences or preconceived assumptions (Rao Podile et al., 2024). Furthermore, investors may differ in how much they trust and rely on AI systems, which may have an impact on their propensity to adopt AI-driven strategies and their vulnerability to errors in judgment.

The feedback loop that exists between AI systems and human users is also influenced by behavioral biases. Investors may acquire new biases or modify their behavior in response to perceived successes or failures as they observe the results of their investment decisions made using AI advice (Sathya & Gayathiri, 2024). Depending on the learning and adaptation mechanisms built into AI systems and the feedback methods made available to users, this feedback loop has the potential to reinforce preexisting biases, generate new biases, or gradually lessen prejudices.

AI-driven investments need to address the issue of behavioral biases, and doing so calls for a comprehensive strategy that takes into account algorithmic design (Schwartz et al., 2022), data governance, user interaction, and continuous monitoring and assessment. Diversifying training data to lessen reliance on biased sources, putting in place transparency and explainability mechanisms to improve user comprehension of AI-generated recommendations, and offering feedback mechanisms to promote thoughtful decision-making and lessen the impact of biases are some strategies used to mitigate biases (Kotecha & Kotecha, 2025). Through recognition and proactive measures to mitigate behavioral bias in AI-powered investments, interested parties can work to improve the equity, efficiency, and moral rectitude of AI-driven decision-making within the financial sphere.

Hypotheses

Cognitive Error and Efficiency of AI Driven Investment Decision Making

As noted in Khan (2022) cognitive error has significantly deviated investment decision-making, as well as the efficiency of the decisions. While previous studies have examined cognitive error and investment decision, the present study integrates the Artificial Intelligence (AI), where it studies about whether the cognitive error would deviate the efficiency of investment decision made upon the AI recommendations. Therefore, the study contemplates identifying whether,

H_1: Cognitive error significantly impacts the efficiency of AI-driven investment decisions

Emotional Biases and the Efficiency of AI Driven Investment Decision Making

Depending on the risk averseness and the emotional readiness to bear the consequences, Kumar and Chaurasia (2024) have studied the relationship between emotional biases and investment decision making. Adding the practicality of the context, the present study investigates whether,

H_2: Emotional biases significantly impact the efficiency of AI driven equity investment decisions.

Digital Literacy

As understanding AI platforms and algorithmic recommendations requires adequate digital competence, digital literacy plays a pivotal role. Rao Podile et al., (2024) emphasize that digital literacy plays a significant role in enabling users to understand suggestions and recommendations made by AI algorithms. Therefore, the impact of behavioral biases on the efficiency of AI driven investment decision making has important implications for digital literacy.

H_3: Digital literacy moderates the impact of behavioral biases on the efficiency of AI driven investment decisions.

III. Methodology

Research Design

The study was conducted using a quantitative approach following the positivism research philosophy. The method of the study is deductive. The positivism philosophy allows the author to acquire the knowledge through observations while the deductive method enables the author to implement a top-down approach where starts with a theory and then narrows down to the context of the study. Following the quantitative study, the authors intend to collect data through a questionnaire as part of primary data collection. The numeric data will be analyzed using SPSS, and descriptive statistics, correlation and multiple regression analysis was employed as the data analysis techniques. The variables of the study consist of indicators which are presented in the operationalization table below. The quantitative data was collected using a structured questionnaire based on 5-point Likert scale varying from strongly disagree to strongly agree.

Population and Sample

The aim of the study is to identify the impact of behavioral biases on the AI driven investment decision making. Therefore, the population of the study encompasses all the capital market investors using AI recommendations for their investment decisions in Sri Lanka. However, the population is accounted to be infinite where a census cannot be performed; hence, a sample needs to be drawn from the population. Allowing a 5% margin of error, the Morgan table suggested a sample of 384 investors.

Given the absence of a comprehensive sampling frame for equity investors using AI platforms or algorithms in their investment decision making, purposive sampling was employed in the study to ensure respondents met the inclusion criteria; specially equity investors using AI driven platforms for their investment decision making. To expand the reach within the niche population, snowball sampling was further applied wherein initial participants referred further eligible respondents.

Conceptual Framework

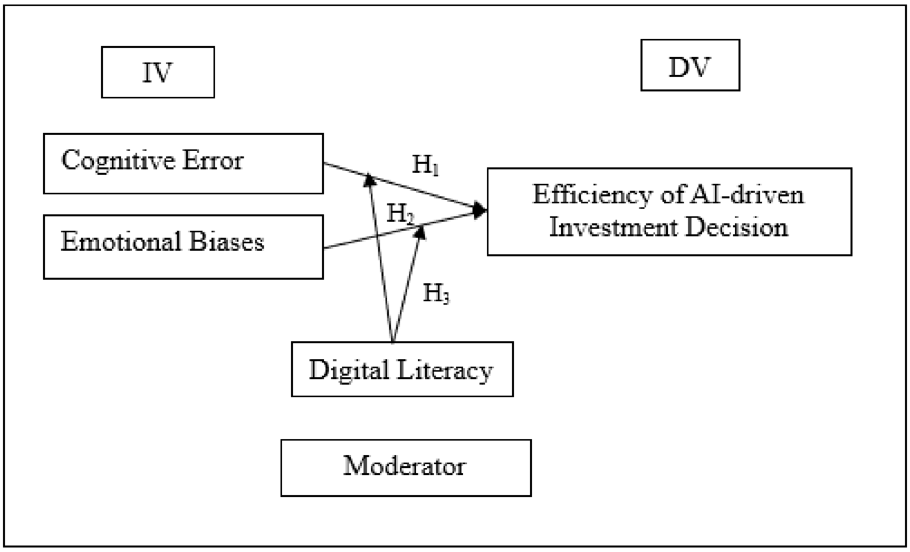

Figure 1. Conceptual Framework, Authors (2025)

Operationalization

Table 1. Operationalization, Authors (2025)

Variable	Indicators	Source
Cognitive error	Confirmation bias	Costa et al., (2017)
	Anchoring bias	Costa et al., (2017)
	Overconfidence bias	Hirshleifer (2015)
Emotional bias	Loss aversion	Khilar & Singh (2020)
	Gambler's fallacy	Sattar, Toseef & Sattar (2020)
	Herding effect	Sattar, Toseef & Sattar (2020)
Digital literacy	Real-time digital skill	Komlayut & Srivatanakul (2017)
	Information digital skill	Komlayut & Srivatanakul (2017)
Efficiency in AI driven investments	Market trend prediction	Liu, Zhang & Zhang (2024)
	Portfolio optimization	Liu, Zhang & Zhang (2024)
	Reduced time consumption and operational costs	Liu, Zhang & Zhang (2024)

IV. Findings and Discussion

Reliability and Validity

Table 2. Cronbach's Alpha, Author (2025)

Variable	Cronbach's Alpha
Cognitive Error	0.821
Emotional Bias	0.784
Digital Literacy	0.801
Efficiency in AI Driven Investment Decisions	0.856

The Cronbach's alpha values determine the internal consistency of the measurements and the thumbnail states that the value is better if greater than 0.7 threshold. Considering the Cronbach's alpha values for each variable of the study which are lying are all above 0.7, this implies that the measurements demonstrate an acceptable internal consistency and are therefore, reliable and valid for the study.

Descriptive Statistics

The univariate analysis presents the data about the single data points, whereas the authors present the frequency distributions for the demographics of the respondents.

The gender of the respondents was divided as 22.2% for females and 77.8% for males. The age groups start from 18 years, and the majority of the respondents were between 26 to 35 years. The graduate respondents accounted for 57.6% and post-graduate respondents accounted for 42.4%.

The monthly income of the respondents was categorized to ensure that they possessed investment ability. A total of 33.3% of respondents had a monthly income between 300 000 and 400 000 rupees and 26.3% had an income of more than 400 000 rupees. The majority of the respondents therefore have an income higher than 300 000 rupees. The investment experience of the respondents was 5 to 10 years in majority while 5.1% had the experience of more than 10 years. Meanwhile, 41.4% of respondents had less than 5 years of experience.

Correlation

Table 3. Correlations, Authors (2025)

	(1)	(2)	(3)	(4)
Cognitive Error (1)	1.000			
Emotional Bias (2)	0.224	1.000		
Digital Literacy (3)	-0.011	0.037	1.000	
Efficiency in Decisions (4)	0.598	0.599	0.232	1.000

The bivariate analysis examines the correlations between two variables, and the Pearson correlation coefficient between the cognitive error and efficiency in AI driven investments was 0.598 which indicates a moderate positive relationship. It indicates that when cognitive error triggers the behavior it has a positive impact on the efficiency in AI driven investment decisions, yet the impact is moderate. The correlation between the emotional biases and the efficiency in AI driven investment is 0.599 which is again showing a positive moderate relationship. Similarly, when emotional biases act in behavioral biases, the efficiency of AI driven investments positively stimulates but that is again moderate. The significance of these positive relationships is high as both variables had 0.000 P value for each correlation coefficient.

The correlation coefficient between cognitive error and digital literacy is -0.011 which is a very weak negative relationship and indicating that having no digital literacy would reduce the cognitive error in decision making. The digital literacy has a coefficient of 0.037 to the emotional biases; implying that digital literacy stimulates the emotional biases.

Regression Analysis

The multiple regression analysis was performed as the multivariate analysis. The first model tests the hypothesis regarding the impact of behavioral biases on the efficiency of AI driven investments. The second regression model tests the moderating role of digital literacy in impact of behavioral biases on the efficiency of AI driven investments.

Table 4. Regression Model 01, Authors (2025)

	Coefficient	t	P value
CE	0.116	2.853	0.005**
EB	0.101	2.893	0.005**
Constant	1.481	4.599	
Adjusted R Squared			0.397
F Value			33.195
P Value			0.000**

*p<0.5, **p<0.01

The estimated model summary has the adjusted R squared value of 0.397 which indicates that 39.7% of the variation in the efficiency in AI driven investment is caused by behavioral biases.

Even though the explanatory power of the model lies below 50%, the ANOVA table indicates the statistical significance of which the P value is 0.0000, less than 5% of significance level. That enables the authors to conclude that there is a significant impact from behavioral biases on the efficiency of AI driven investments.

The contribution of each independent variable is estimated with the coefficient table, where the cognitive error has the coefficient of 0.116 and emotional biases has the coefficient of 0.101. The P values for both the variables are 0.005, which is less than 5% of significance level. It enables the authors to conclude that cognitive error and emotional biases significantly impact on the efficiency in AI driven investments.

Table 5. Regression Model 02, Authors (2025)

	Coefficient	t	P value
CE	0.103	3.022	0.003**
EB	0.114	3.876	0.000**
DL	-0.337	-6.435	0.000**
Constant	2.817	8.268	
Adjusted R Squared			0.575
F Value			45.247

P Value	0.000**

*p<0.5, **p<0.01

The second model tests for the role of digital literacy as a moderator in between behavioral biases and the efficiency of AI driven investments. The adjusted R square value of 0.575 indicates that 57.5% of changes in efficiency in AI driven investments are determined by the behavioral biases whereas the investors need to have digital literacy in order to achieve the investment efficiency. The statistical significance of the model is high as the P value is 0.000 which is less than 5% of significance level. Therefore, authors are concluding that digital literacy plays a critical moderating role between behavioral biases and the efficiency of AI driven investments. The coefficient table also shows that the individual variables are highly significant as the determinants as their P values are all below the 5% of significance level.

Hypothesis Testing

H_1: Cognitive error significantly impacts the efficiency of AI driven investment decisions.

The P value of the test statistic is 0.003 which is less than 5% of significance level, hence the hypothesis is not rejected at 5% significance level. Therefore, the authors conclude that there is a significant impact from cognitive error on the efficiency of AI driven investment decisions.

H_2: Emotional biases significantly impact the efficiency of AI driven investment decisions.

The P value of the test statistic is 0.000 which is less than 5% of significance level, hence the hypothesis is not rejected at 5% of significance level. Therefore, the authors conclude that there is a significant impact from emotional biases on the efficiency of AI driven investment decisions.

H_3: Digital literacy moderates the impact of behavioral biases on the efficiency of AI driven investment decisions.

The P value of the test statistic is 0.000 which is less than 5% of significance level, hence the hypothesis is not rejected at 5% significance level. Therefore, the authors conclude that the digital literacy significance moderates the impact of behavioral biases on the efficiency of AI driven investment decisions.

V. Conclusion

AI has become vital in the financial sector buzzing with investments and investment decisions. Even though many investment websites are AI-enabled now, human decision-making drives the understanding of AI recommendations and guiding actions based on them. Hence, it is important to comprehend the psychological biases impacting investors while availing AI-based investment services. The purpose of this study was to examine the effect of behavioral bias on the efficiency of investment decision-making using AI. The research employed a quantitative method, and data were gathered via a structured survey questionnaire.

The results of this study help emphasize the presence of emotional and cognitive biases in highly advanced technological investing environments. This study also has primary uses of interest to investors, policymakers, and AI developers in the Sri Lankan financial market.

Investors are provided insights through the focus on the findings to understand the value of digital literacy and financial awareness to AI-based investment systems. Investors with digital skills and analytical ability to assess AI-driven recommendations and avoid emotionally or cognitively biased decisions are more likely to be successful. In Sri

Lanka, financial regulators and policymakers must focus on the importance of the digital literacy and financial education of investors to grasp the AI-based financial technologies. Invisible regulators can encourage the construction of explainable, transparent AI systems that improve the quality of recommendations and the decisions of investors. The findings are also valuable for AI developers and fintech companies. AI investment platform developers should use behavioral finance insights when creating user interfaces that help investors identify their biases and provide decision-support tools. Risk alerts, behavioral nudges, and simple AI investment advice explanations can mitigate bias and improve decision making.

The authors suggest further investigation of this topic to include qualitative or mixed-method approaches as these may provide better understandings of the intricacies of investor perceptions and experiences with AI-driven investment systems. Moreover, subsequent studies may consider incorporating variables such as personality, financial risk aversion, and confidence in technology, as these may yield greater insights into the intricacies of investor behavior in technologically sophisticated financial ecosystems.

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