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THE MODERATING EFFECTS OF AI TRUST & AI INNOVATION ON THE INFLUENCE OF EMOTIONAL BIASES AND ANCHORING BIASES IN AI-SUPPORTED INVESTMENT DECISIONS

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Abstract
In the ever-changing environment of the financial market, individual investors are facing challenges. At the same time, artificial intelligence (AI) and its associated tools are increasingly applied in investment decisions, and behavioral biases are deeply ingrained in human decision processes. This paper examines the impact of two significant biases including emotional bias and anchoring bias on investment decisions. Additionally, it explores how AI trust and AI innovation influence these decisions and moderate their effects. Based on the theory of behavioral finance, the study utilizes quantitative data from a sample group of 349 retail investors and employs regression and moderation techniques through the Hayes PROCESS macro. The results indicate that both emotional (beta = -0.285, $p < 0.001$) and anchoring biases (beta = -0.267, $p < 0.001$) have a significant negative influence on investment decisions, confirming the idea that cognitive limitations exist even in tech-savvy settings. Conversely, the AI trust (0.221, $p < 0.001$) and the AI innovation (0.226, $p < 0.001$) bring a significant contribution to the quality of investment decisions, which proves the innovative system's efficiency in favoring rational behavior. The moderation analysis showed that although AI trust moderated anchoring bias significantly (beta = 0.085, $p = 0.038$), it did not significantly moderate emotional bias (beta = 0.068, $p = 0.156$) But the moderation analysis also showed that AI innovation does not weaken the effect of anchoring bias (beta = -0.024, $p = 0.583$) and emotional bias (beta = 0.041, $p = 0.394$) on decision outcomes. The given study adds to the debate in the realm of behavioral finance, human psychology, and fintech, providing worthwhile findings to the concepts of an investor, a financial consultant, and AI developers. The dual role of human psychology and technological progress in it underlines the necessity of a combined and innovative approach that should be based on emotional understanding and digital technology to ensure more informed and objective investment behavior

INTRODUCTION

1.1Background of the Study

Investment decisions have always been a blend of logic, experience, intuition, and emotion. While economic theories often assume that people behave rationally—choosing the best possible options based on facts and figures—real life rarely works that way. Investors, whether individuals saving for retirement or professionals managing large portfolios, frequently act in ways that contradict logical predictions. These actions are not random; they stem from deeply ingrained psychological patterns and emotional reactions (Bleda & Pinkse, 2025). Behavioral finance emerged as a field to explain why investors don't always behave like the "rational actors" described in traditional financial models. It recognizes that people bring their feelings, fears, past experiences, and cognitive shortcuts into the investment decision processes. These human elements can help or hinder investment outcomes. While predispositions may occasionally serve as useful warnings, they often cloud judgment, especially in high-stakes or uncertain situations.

The financial investment decisions paradigm is currently undergoing a paradigm shift, catalyzed by the technological constant of Artificial Intelligence (AI) interference and connection. Over several decades, the Efficient Market Hypothesis and modern portfolio theory were seen as the theoretical foundations of the world of finance; these assumed the existence of rational actors, able to utilize all the available information in order to maximize their welfare. But the continued occurrence of market anomalies and bubbles in the financial markets exposed the weaknesses of these models, bringing about an output of behavioral finance. This area of research, which began with the research of Kahneman and Tversky (1979) on Prospect Theory, has clearly revealed that common aspects of cognition associated with cognitive heuristics and emotional biases all too commonly provide organized and predictable biases in financial decisions. The huge negative effects of these biases, including anchoring and emotional distortions, on investment outcomes have been replicated in empirical studies in global markets, including Pakistan (Ishfaq & Anjum, 2015; Rehan & Umer, 2017). Meanwhile, the past ten years have seen the shift of AI being a theoretical concept to becoming a central operative technology in the financial sphere. Machine learning algorithms and robo-advisors that employ AI-driven systems are beginning to provide the possibility of rising above inherent human limitations (Duan, Edwards, & Dwivedi, 2019). These technologies have the ability and potential to analyze enormous datasets faster than ever before, are able to detect non-monotonic trends, and are capable of making judgments free of the volatility and trappings of the emotional aspects of human investors. The hope of AI is that it can help as a corrective intervention, as studies have shown that it may help solve biases such as anchoring using explainable AI (XAI) (Haag, 2025) and give data-driven insights to negate emotional responses (Rastogi et al., 2020).

The availability of advanced technologies is however, not the silver bullet to effective utilization of such technologies nor the control of entrenched psychological predispositions. There is the added complexity of the human-AI interaction, in which the perceived qualities of the machine itself are critical drivers of its effects. According to Benbasat et al., (2008), user trust is a major determinant of technology adaptation, particularly in areas where the risks involved are very high, such as in the financial sector. There is already a number of articles that focus on the processes of trusting AI and the factors that influence it, including transparency, accuracy (Wanner et al., 2022) or the existential dissimilarity between human-human and human-automation trust (Madhavan & Wiegmann, 2007). Therefore, this study is situated at the confluence of behavioral finance and technology acceptance, seeking to explore a critical yet underexplored question: under what psychological conditions, specifically concerning AI trust and the perception of AI innovation, can AI truly fulfill its promise to rationalize investment decisions. It is within this context that this study investigates these factors not as mere antecedents of adoption but as pivotal moderating variables between entrenched behavioral biases and the quality of investment outcomes.

1.2 Importance of AI in Investment Decisions

The origin of Artificial Intelligence (AI) has proposed the use of algorithmic tools to help investors with investment decisions. The effectiveness of such support however, depends not only on the capacity of AI but also the AI trust of the investor as well. This paper seeks to determine the impact of AI trust and AI innovation as a moderating variable between behavioral biases and investment actions. In this way, the study helps to build a more comprehensive definition of the AI interaction with humanity in the context of financial technology (fintech) settings (Fitriani & Basir, 2025). Although AI-based decision support system could potentially enhance investment performance, the user-system trust is an important feature that determines the effectiveness of this system. Trust has been identified as a significant contributor to the acceptance/rejection of algorithmic recommendations, particularly, in high-stakes arenas like finance. It has been proposed that higher levels of AI trust are associated with a likelihood of individuals abiding by the recommended actions by AI, which can reduce the impacts of their personal cognitive and emotional biases. However, misplaced or low trust can result in either blind reliance or complete disregard for AI inputs, both of which can compromise decision quality (Schoeffer et al., 2025). AI trust acts as a psychological facilitator that affects the degree of readiness of people to replace their own intuition with the output of algorithms. Extensive trust may promote the use of rigorous, evidence-based reasoning and thus inhibit emotional responsiveness in all respects and make anchoring less influential. However, the effects of AI innovation, albeit being connected, have a different role and imply improving user engagement and readiness to accept AI-generated advice. The combination of these factors can serve as moderators to establish the relationship between behavioral biases and the quality of investment decisions. In particular, they can reduce the serious effects of emotional and anchoring biases by introducing more consistency between human and decisions procedures and algorithmic suggestions (Wong, Tan, Ooi, & Dwivedi, 2024).

1.3 Behavioral Biases in Investment Decisions

The behavioral tendencies that commonly disrupt good investment decisions are emotional bias and anchoring bias. Emotional bias refers to the influence of feelings such as fear, excitement, regret, or overconfidence on financial choices. For instance, an investor might panic and sell a falling stock too quickly, or hold onto a losing investment out of hope that it will recover. These decisions often stem from emotional discomfort rather than financial analysis (Qudrat-Ullah, 2025b). Anchoring bias is a situation where individuals overly depend on a particular piece of information, often the first one that they come across, when making decisions. This may cause unreasonable expectations and inaccurate decisions. Behavioral finance has long identified that emotional responses and cognitive anchoring can skew rational decisions in investment contexts. Investment decisions are inherently complex, often influenced not only by objective market information but also by human behavioral tendencies. Among these, emotional biases like fear and excitement, and cognitive biases like anchoring, have a strong effect on the decisions made by investors, causing them to act outside the frameworks of rational decision-making. These behavioral patterns can distort risk assessment, affect timely decisions, and impair portfolio allocation. In recent years, the increasing adoption of Artificial Intelligence (AI) in financial investment decision environments has opened new pathways for reducing such distortions by offering data-driven, emotion-free recommendations (Xu & Cho, 2025). The mechanism of decisions in investment is complex and difficult, due to the impact of factors such as rational analysis, feelings and psychological biases. It is noted that although the classical financial theory presupposes that individual investors are rational people who base their decisions on the existing information, behavioral finance demonstrates that such decisions are also made contingent on cognitive and emotional distortions determining market behavior. Some of these biases including emotional biases and anchoring biases are widespread and tend to cause systematic over- or under-performance relative to the best investment strategies. Emotions improperly influence the investment decisions process, where one is disproportionately influenced by emotional

states of fear, greed, overconfidence, or regret, which may lead to over- or under-reacting to short-term changes in the marketplace or pursuing long-term strategic values and objectives. Anchoring bias, however, is the unwarranted influence of a first reference point, past stock price, historical performance figure, or a benchmark index, often leading to rigid or suboptimal decisions even after new information presents itself (Haidari, 2023). Both of these biases are subtle but powerful. They can affect experienced investors just as much as beginners, leading to decisions that are emotionally satisfying in the short term but financially damaging in the long run (Chen et al., 2025).

1.4 Rationale for Examining AI Trust & AI Innovation

AI-based decision support systems can help overcome these biases, their effectiveness depends on two critical psychological factors: trust and innovation. Knowledge of these psychological biases is not only an intellectual endeavor; it is a real-life requirement. In an environment where financial decisions processes are more complicated than ever before, the expenses incurred as a result of a wrong decision can be enormous. Market volatility, continuous flow of information and the increase in investment products and platforms have caused the financial environment to not only become richer in terms of opportunity but also much riskier to execute. This piece of work is especially topical because it is not based on financial formulae but it focuses on the human side of the investment. It acknowledges that even in the presence of sophisticated tools of decision making, an individual can often find it difficult to make rational judgments in a consistent manner. The key to addressing how behavior affects financial outcomes is proper knowledge about the underlying behavioral patterns to ensure that investors and advisors can make a meaningful effort to improve the outcomes not by avoiding any emotional component, but learning how to manage it more effectively.

Though a great number of mechanisms and interventions have been suggested to overcome behavioral biases (e.g., education or automation), the human experience continues to remain at the center stage. Among two psychological factors that can aid individuals in better financial decisions, one can distinguish AI trust and AI innovation (Prabhakaran & Rengarajan, 2025).

In this case, AI trust does not necessarily mean that people trust others solely; it is also the kind of trust that people put to their devices of decisions and platforms or sources of advice. When people feel confident that the information or guidance they are receiving is reliable and unbiased, they are more likely to consider it carefully and act on it rationally. AI innovation plays a subtler but equally important role. If investors believe that a financial tool, strategy, or system is modern, adaptive, and suited to current realities, they are more likely to engage with it meaningfully (Cao & Zhang, 2025). AI Innovation here is not about flashy technology—it's about whether the decision-support feels relevant, intelligent, and capable of navigating the complexity of today's markets (Rydstrand & Reichard, 2025). By focusing on these two psychological aspects, AI trust and AI innovation, this study seeks to explore how confidence in one's financial support systems can help reduce the power of emotional and anchoring biases Khamlichi & Benahmed (2025).

This paper seeks to fill that gap between behavioral psychology and real-life investing behavior. It also seeks to examine the role of biases that are manifested in everyday estimates (emotional reactions and the levels of anchoring) on financial decisions and whether a higher level of belief in methods of support in decisions, as well as the belief that the respective methods of decisions support are innovative and competent, can aid financial investors in making more resolute decisions (Tansuchat & Thaicharo, 2025).

The study aims to investigate the impact of emotional and anchoring biases on the behavior of investors and the outcomes of their decisions. These psychological biases can significantly affect how individuals make investment choices, often leading to suboptimal results. The paper also seek to understand whether there are potentials to counter the negative impact of biases on human performance, through trusting decision-support technologies, such as in financial advisors, digital platforms, or even analytical tools. Furthermore, the research investigates whether the perception of innovation in these tools, such as being modern, adaptive, and technologically advanced, contributes to

reducing bias and improving the quality of investment decisions. By addressing these aspects, the study aims to answer key questions about the extent to which emotional and anchoring biases shape investment decisions, whether trust in support systems can lessen their influence, and how AI innovation in financial tools affects decisions outcomes. Ultimately, the findings from this study aim to contribute not just to academic knowledge, but also to the everyday practice of investment helping people make more thoughtful, confident, and ultimately successful financial decisions (Kamau et al., 2025).

1.5 Research-Objectives:

The proposed study will examine how trust in AI and innovation in AI moderate the relationship between behavioral finance and technology adoption. The precise tasks include:

1. To investigate how behavioral biases (emotional bias and anchoring bias) affect the AI-supported investment decision of retail investors.
2. To examine how AI-related variables (AI trust and AI innovation) moderate the association between behavioral biases and AI-supported investment decisions.
3. To investigate whether, increased AI trust, and perceived AI innovation can mitigate the adverse influence of behavioral biases on the quality of making investment decisions.

1.6 Research Questions

The guiding research questions (RQs) are the following:

- **RQ1:** How does the emotional and anchoring biases affects the investment decisions within the framework of AI support?
- **RQ2:** How does the quality of investment decisions specifically vary as a result of AI trust and AI innovation?
- **RQ3:** Does AI trust reduce the harmful effect of emotional and anchoring biases on investment decisions?
- **RQ4:** Does the perceived AI innovation alleviate the adverse impact of emotional and anchoring biases may have on investment decisions?

1.7 Research Hypotheses

a) Direct Effect Hypotheses

→ **H_1:** Emotional bias has a significant negative effect on investment decisions.

→ **H_2:** Anchoring bias has a significant negative effect on investment decisions.

→ **H_3:** AI trust has a significant positive effect on investment decisions.

→ **H_4:** AI innovation has a significant positive effect on investment decisions.

b) Moderating Effect Hypotheses

→ **H_5:** AI trust moderates the effect of emotional bias on investment decisions.

→ **H_6:** AI trust moderates the effect of anchoring bias on investment decisions.

→ **H_7:** AI innovation moderates the effect of anchoring bias on investment decisions.

→ **H_8:** AI innovation moderates the effect of emotional bias on investment decisions.

1.8 Organization of Paper

Table 1.1 Paper Organization

Section	Title	Primary Content and Purpose
1	**Introduction**	Establishes the research background, context, and the transformative role of AI in investment. Defines the problem: behavioral biases persist despite technological advances. Outlines the study's rationale, objectives, and central research questions.
2	**Literature Review**	Synthesizes foundational and contemporary theories and empirical findings on behavioral biases (Prospect Theory, anchoring, emotion), AI trust (TAM, Systems Theory), and AI innovation (Disruptive Innovation, TOE, TRI). Identifies the specific research gap the study addresses.

3	**Conceptual Framework and Hypotheses**	Presents the integrated research model illustrating the proposed relationships. Logically develops and formally states the eight research hypotheses (H1-H8) concerning direct and moderating effects.
4	**Research Methodology**	Details the quantitative, cross-sectional research design. Specifies the population (Pakistani retail investors), sampling technique (convenience), sample size (N=349), and data collection instrument (structured questionnaire). Describes the measures, scale validation, and statistical analysis techniques (Regression, Moderation analysis with PROCESS Macro).
5	**Results and Analysis**	Reports the descriptive statistics, reliability tests, and correlation analysis. Results the empirical findings of the hypothesis tests, including beta coefficients (β), p-values, and model fit statistics for both direct and moderating effects.
6	**Discussion**	Reflects on the major findings in the light of the available literature/framework. Explains why certain hypotheses were supported (e.g., H6) while others were not (e.g., H5, H7, H8). Discusses the theoretical contributions and practical implications for investors, AI developers, and financial advisors.
7	**Conclusion**	Summarizes the study's major findings and their overarching significance. Acknowledges the research limitations (e.g., cross-sectional design, geographic focus). Proposes concrete and actionable suggestions for future research.

2. LITERATURE REVIEW

The literature review summarizes the prior and modern scholarly study to define the theoretical and empirical framing to study which behavioral biases, emotional biases and anchoring biases can influence investment decisions, and how trust in AI and AI innovation can moderate these effects. The reason is to place the study in the cross-section between the spheres of behavioral finance and financial technologies, and emphasize that despite

being in an environment characterized by technological enhancement, psychological aspects continue to play a significant part in decisions. By exposing the existing gaps in current knowledge, namely, the lack of research on the moderating roles of the perceptions of AI-related-related phenomena, the existing research lays the foundation to the proposed one, which will serve as the empirical investigation of whether investing in AI and attributing certain innovativeness to it will help counteract the harmful influence of cognitive and emotional biases on investment performance.

2.1 Behavioral Finance and Investment Decisions

Behavioral finance has become an important alternative to mainstream financial theories by emphasizing the importance of psychological, emotional, and mental aspects in determining investment behavior. Behavioral finance also cannot be totally different since it will violate the fact that investors are irrational and behaved in a way that does not show rationality and full knowledge (Leal, 2015). This approach focuses on the decision-maker rather than the decision itself in the view that, it is real people who decide on uncertainties (Jahanzeb, 2012). Several studies have revealed that there are so-

called common behavioral biases, and these include overconfidence, loss, herd, and anchoring (Sattar et al., 2020). These biases result in investors not making rational decisions, creating market anomalies, market inefficiencies, and less than optimal portfolio construction outcomes. For example, emotions like fear and greed can lead to reactionary trading behaviors, such as panic selling or excessive risk-taking (Singh et al., 2024). Behavioral finance not only explains these patterns but also provides insight into how they can be mitigated through increased financial literacy, better decision frameworks, and awareness of cognitive traps (Rehman et al., 2025). Ultimately, the inclusion of behavioral elements into financial models has made them more predictive and reflective of real-world investor behavior.

2.2 Emotional Bias and Anchoring Bias: Definitions and Effects

To supplement the cognitive bias of the Prospect Theory is the ample studies on emotional issues on investment decisions. Researchers such as Landman (1987) discussed how emotions which include things like regret, anxiety, overconfidence, and euphoria can severely skew the judgment of an investor. As a simple example, an overconfident investor will tend to overestimate his or her own analytical skills and lack of risk aversion, resulting in excessive trading or a portfolio failure to diversify. On the other hand, emotions such as fear and anxiety when the market is going down can give rise to panic selling although there may be all possible rational arguments to wait and hold or to buy. Ross & Miller (2002) positioned that the nature of financial decisions does not involve cold, computational coverings and instead they are rooted on emotional cognition. The psychological condition of an investor is at the core of their behaviour in risk as well as the portfolio construction procedure, and it is usually unconscious (Valasek, 2022). This emotional element is enhanced by the social effects and results in phenomena such as herd mentality, when investors lose their ability to judge and act as a crowd that will eventually result in speculative bubble or collapse of a market. The interplay of logical or rational estimations, cognitive bias, and subconscious responses of the emotional state is critical especially when faced with uncertain or highly volatile market conditions. Thus, the science of behavioral finance can form a powerful and multifaceted foundation of the study of the systematic irrationalities and habitual deviations to the normative behavior expected by the traditional economic theory to have more profound, correct representation of the way people in the real world make their choices with respect to financial aspects (Bhanu, 2023; Umapathy, 2024).

2.2.1 Emotional Bias and Anchoring Bias

Among the myriad cognitive and emotional distortions studied in behavioral finance, emotional bias and anchoring bias are especially pertinent to investment decisions due to their subtle yet pervasive influence. Emotional bias occurs when affective states override rational judgment. In high-stress market environments, investors may act out of fear liquidating assets prematurely to avoid anticipated losses or, conversely, out of greed, adopting high-risk positions without sufficient due diligence. The emotional component of investing is further compounded by regret aversion, anticipated anxiety, and overconfidence, all of which distort risk perception and prompt inconsistent behavior (Suslov). Scholars have demonstrated that emotions not only affect the evaluation of risks and rewards but also influence memory recall, attention to market signals, and the investor's susceptibility to herd behavior. Emotional bias encompasses cognitive distortions driven by affective states such as fear, greed, excitement and regret aversion. These biases are prevalent among investors, particularly during volatile market conditions. Fear often prompts premature selling, while excitement can lead to underestimating risks or overtrading. Such behaviors hinder rational decisions and often culminate in financial losses. According, emotional interference in investment decisions is a primary barrier to achieving long-term financial goals. The presence of these biases persists even in experienced investors, highlighting the limitations of financial literacy as a standalone intervention (Qudrat-Ullah, 2025a).

2.2.2 Anchoring Bias in Financial Contexts

Anchoring bias refers to the overdependence on some initial reference value, say the former peak price of a stock or analyst expectations, to make the

follow-on judgment. In the investment domain, this often results in ignoring updated or contradictory information. Demonstrate that investors anchored to historical data often fail to respond appropriately to new market developments, resulting in suboptimal portfolio decisions. Anchoring bias remains difficult to eliminate because it operates unconsciously and offers a convenient heuristic in information-rich settings like stock trading (Judijanto, 2025).

Anchoring bias is a type of cognitive bias based on the work of Tversky and Kahneman (1974), human tendency to overweight an initial piece of information (the anchor) in their decisions. In financial contexts, anchors can include a stock's original purchase price, historical peak values, or even arbitrary market forecasts. Investors tend to adjust too little out of these anchors and this can create a persistent mispricing and inconvenience in the timing of trade. Anchoring may necessitate the deferring of crucial decision making and investors may result in holding over poor performing assets in the hope of returning to the previous highs. Past research by Montier (2007) and Kaustia et al. (2008) has shown that the bias is not limited to retail investors, but is also pervasive among institutional investors as well with the negative effects reflected on the long-term performance of the portfolio (Abramov et al., 2015).

2.3 AI in Financial Decisions: Opportunities and Risks

Artificial intelligence (AI) is among the disruptive technologies that fall under the head of financial decisions industries in the societal context of big data and the swift transfer of information along with the accuracy of algorithms. The character of financial markets envisages quite complicated, statistically scrupulous, and predicted ambiguously in comprehensive terms conditions, and hence AI-based tools are very attractive in this context. The application of technologies such as machine learnings (MLs), natural language processing (NLPs), robo-advisors, and predictive analytics provides financial institutions and individual investors alike with the ability to run bulk volumes of unstructured and structured data at speeds never before envisioned. The highlighting of these abilities allows the ability to see complex relationships, hidden trends, and new market indicators that can be opaque to established analysis or human intelligence (Onyenahazi & Antwi, 2024).

The essence of AI interest to the finance industry is that it enables quicker, data-backed and seemingly impartial decisions. AI systems hold the potential to increase the profitability of investment strategies, portfolio management, credit scoring, fraud detection and risk evaluation by minimizing the subjectivity that inheres in strictly human judgment, which is susceptible to emotion, cognitive biases, and overconfidence. (Selvarajan, 2021). In other words, robo-advisors can re-balance portfolios automatically, using prescribed targets and risk profiles, predictive models can produce price movement/credit default predictions with a level of statistical certainty that would not be achievable by manual analysis alone. Such automation has the potential to assist investors and institutions to respond to events fast in a volatile market environment with information overload and in a strategic way. Nevertheless, the assimilation of AI into financial ecosystems also carries its range of problems and threats. The black box problem is one of the most eminent issues, where sophisticated algorithms use processes that cannot be comprehended by any user, regulator, and even their developers. Such opacity can shake him off his/her feet when the results are surprising or unfavorable. Moreover, AI implementations tend to be strongly dependent on the historical data; in case such datasets contain implicit biases, it is possible to extend these biases and even enhance their severity in subsequent decisions (Oguntibeju, 2024).

There is also the risk on systemic vulnerability. Assuming that several financial organizations had shared AI-based models and approaches, then herding effects may occur, with the markets going in lockstep that generates greater volatility at a time of crisis. Such a coordination of choosing may not reduce but further increase the shocks of the system. Moreover, cyber risks are an issue of concern, because it is not the AI systems to think about being hacked, or infected, or manipulated, or attacked, or used as attackers. It is also paramount to admit that

the effectiveness of AI in its role of promoting financial outcomes condition depends not only on the complexity of the algorithms. This is where human factors especially user perception and trust are critical. Investors should be assured of the reliability and the fairness of the system to abide by its suggestions rigorously. Lack of trust can cause investors to discourage output by algorithms to give subjective judgement instead that in essence will accomplish the advantage of AI-based analysis nullified or not produced.

2.4 AI Trust: Concept, Drivers, and Behavioral Outcomes

AI trust systems has emerged as a pivotal determinant of whether technology can effectively support or enhance financial decisions. Rooted in the organizational trust literature, Mayer et al., (1995) model identified competence, integrity, and benevolence as essential components of trust—dimensions that have been adapted to human-computer interaction contexts. In a simultaneously developed direction, Technology Acceptance Model (TAM) by Davis suggested that perceived usefulness and perceived ease of use are key parameters to the adoption of technology. Together, these theories provide a conceptual framework for understanding how investors engage with AI tools: if the system is viewed as competent, user-friendly, and aligned with the investor's goals, trust is likely to be fostered, leading to increased adoption and compliance (Zhao et al., 2025). AI trust has been found to moderate the causal pathway between bias and the quality of the decision in financial environments. When investors have confidence in a system, it will become more probable that they tend to act on its suggestion and make more viable decisions, and less prone to spastic or panic behavior. It is believed that AI trust can lessen emotional volatility because it makes people confident in the decision-making process. On the other hand, in the absence of trust, decision inertia may occur when the investor takes too long making decisions or defaults to ill-informed or non-optimal behaviour patterns. In this respect, AI trust performs not only as a technological mediator, but also as a psychological moderation of bias (Maduku, Rana, Mpinganjira, & Thusi, 2025).

2.5 AI Innovation and Its Role in Shaping Investor Decisions

Keeping hand in hand with trust, the level of AI innovation or the position that the questioners put on a platform or system at succession, innovation, and futurist has been included. Diffusion of Innovation theory suggested that more innovations are embraced when they are believed to be superior in comparison to the other available alternatives, compatible with the values of the user and are relatively easy to adopt. Financial services tend to view platforms based on AI that allows interaction with engaging dashboard, real-time risk evaluation, goal-based planning, and automatic rebalancing as more innovative (Maheshwari et al., 2025).

This perception of innovation has not only a moderating impact on an adoption behavior, but it also has an impact on decision-quality. A sense of control and optimism could be afforded when investors believe that they can use the newest and the best tools and thus protect them against irrational urges and cognitive biases. Li et al., (2023) research findings emphasized that the innovativeness of AI leads to certainty and proactive involvement, especially in a high-stakes decision scenario. Simply put, innovation is not only a technological character trait but it is a psychological driver that has the potential to improve the effectiveness of AI systems in overcoming behavioral disproportion Liu et al., 2025).

2.5 Theoretical Framework Supporting the Study

The proposed study is framed based on an integrative theoretical framework constructed out of several powerful models. The Prospect Theory (Kahneman & Tversky, 1979) is introduced as the main guide to comprehending the risk cognition of the investors and their attitude to gains and losses regarding the elements of uncertainty. Anchoring bias is situated within the literature of cognitive heuristics postulated and emotional bias within the works by Shefrin (2010) supported the presence of an affective side of economic behavior (Lynch et al., 2025). To describe how the moderation of AI trust and AI innovation can influence decisions, the study includes the Trust Model Mayer et al. (1995) and the Technology Acceptance Model developed by Davis

(TAM/ 1896) as both models recognized the importance of perception when introducing and using technologies. Rogers et al., (2014) gave the Diffusion of Innovation Theory which can be applied to explain how the use of AI innovation can determine the behavioral pattern of investors. Combined, the theories provide an inter-dimensional model that describes the multifaceted nature of how an investor's attitude towards technology can interact simultaneously with attitude to decision outcomes (Bahman et al., 2025). A variety of theories will be used to support the study such that they would help in explaining the interdependencies between the behavioral biases, the perception of AI, and the investment decisions based on them.

THEORETICAL FRAMEWORK

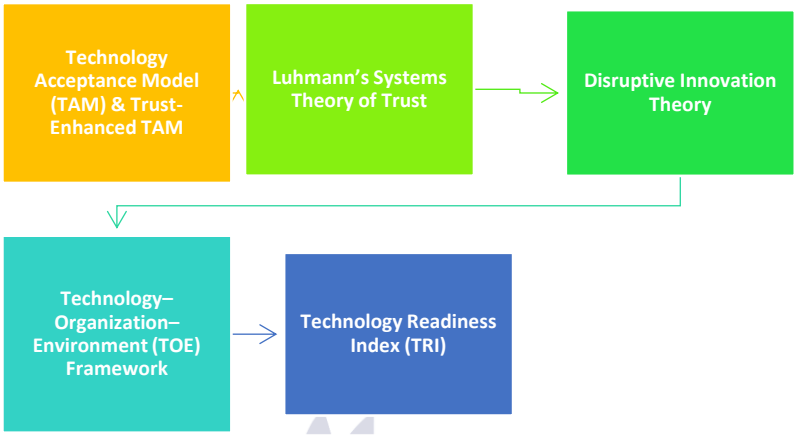


Figure 2.1: Theoretical Framework

2.6.1 Technology Acceptance Model (TAM) & Trust-Enhanced TAM

The Technology Acceptance Model (TAM) by Davis (1989) is based on the premise that perceived usefulness (how well a person feels that use of the system will assist them in doing better) and Perceived Ease of Using (how well a person feels that using the system will not be accompanied by effort) largely determine the realization of a technology. Subsequent updates, especially those of Gefen et al. (2020) incorporated AI trust as one of the key antecedents of the perceived risk, especially in situations where there is an element of uncertainty and risk, as in e-commerce, and by extension, applications of the AI-driven financial tools. In the present research, trust in an AI system is hypothesized to directly affect the perceptions of its utility and usability by an investor. A trusted system has been perceived as more

capable and more reliable (improving the perceived usefulness) as well as simpler and easier to deal with (improving the perceived ease of use), hence increasing the chance of such a system being used and relied upon to make investment decisions.

2.6.2 Luhmann's Systems Theory of Trust

Luhmann (1979) conceptualized trust as an effective social tool that simplifies the complexity of a world with much uncertainty. By trusting one of the systems or institutions, people can streamline their choice-making processes, as they do not need all the possible outcomes and variables to take into consideration to operate successfully. This theory directly applies to investors facing the overwhelming complexity of financial markets. Trust in an AI system allows them to delegate analytical tasks and manage market uncertainty. It acts as a simplifying tool, enabling them to rely on the system's outputs without fully understanding its intricate algorithms, thus making the investment process more manageable.

2.6.3 Disruptive Innovation Theory

Disruptive innovation is a process by which a commodity product or service enters a market at the low end, posing a challenge to an established high-volume product usually because it is initially cheaper, easier to find or easier to use, and then relentlessly moves up-market eventually displacing established rivals (Christensen 1997). AI-powered

investment platforms (e.g., robo-advisors) exemplify disruptive innovation. They began by offering automated, low-cost portfolio management to retail investors, a segment often underserved by traditional human advisors. By providing cheaper, faster, and data-driven insights, these platforms are positioned to disrupt the established market for traditional financial advisory services.

2.6.4 Technology–Organization–Environment (TOE) Framework

Tornatzky and Fleischer (1990) differentiated three contexts that influence adoption of technological innovation; Technological context (available in-house and external technologies), Organizational context (size, scope and managerial system of the firm) and Environmental context (industry structure, regulatory environment and competition). While often applied at an organizational level, the TOE framework can be adapted to the individual investor. Their adoption of AI tools depends on the *technological* context (e.g., availability and features of platforms), the *organizational* context (e.g., their own financial knowledge and resources), and the *environmental* context (e.g., market volatility and fintech competition).

2.6.5 Technology Readiness Index (TRI)

Parasuraman (2000) came up with Technology Readiness Index (TRI) to quantify how people are likely to take and adopt new technologies. It assumes that readiness is a product of the enablers (optimism, and innovativeness) and inhibitors (discomfort, and insecurity). The perception of an investor about AI innovation is not only limited to the technology but also by the individual tech readiness of the person. The most optimistic and innovative investors are more likely to regard AI tools as something modern and helpful, but the most pessimistic and insecure ones are more inclined to find a threat or consistence in the use of such devices.

2.6.6 Prospect Theory

The Prospect theory by Kahneman and Tversky (1979) sheds light on how people perceive risk and make decisions under conditions of risky situations. It proposes that individuals have varied valuation of gains and losses, and are loss-averse (experience losses more severely than equivalent gains), and that they decide based on the difference between what can be gained or lost, relative to a certain reference point (e.g., purchase price), and not in absolute terms of gaining or losing. This theory provides the foundational explanation for the behavioral biases examined in this study. Anchoring bias (Tversky and Kahneman, 1974) is the use of an initial reference point to affect future choices in an excessive manner. Emotional biases, such as those related to fear of loss (loss aversion) or regret, are direct manifestations of the non-rational decisions processes Prospect Theory describes.

2.7 Identified Research Gaps

While existing literature acknowledges the individual roles of behavioral biases and AI tools in investment decisions, few empirical studies have explored how AI trust and AI innovation jointly or separately moderate these relationships. Studies suggest trust enhances adherence to AI-supported decisions, but the influence of AI innovation on behavioral bias mitigation remains underexplored. This study addresses this gap by empirically testing and comparing the moderating effects of both AI Trust and AI Innovation on the relationship for behavioral biases (Trinh et al., 2025). While suggested that trust enhances satisfaction in AI-supported trading apps, they do not explicitly analyze its moderating effect on bias-driven behavior. This study addresses that gap by empirically testing how AI trust influences the relationship between behavioral biases and decision quality in AI-assisted investment settings (Hoang, Nguyen, Dey, & Thi Thu, 2025). Despite the richness of existing literature in behavioral finance and financial technology, significant research gaps persist. Most of the empirical studies that examine behavioral biases do so by concentrating on a single construct, such as emotional bias or anchoring, without investigating how these biases may combine or co-occur in real decisions contexts. Second, the presence of perceptual values (including AI trust and AI innovation) and their effectiveness or indeed failure to ensure effective integration of AI and financial behavior in real-life contexts is little studied (Abbas, 2025).

Moreover, a significant portion of research is restricted to a laboratory environment or a

computerized hypothetical simulation, which is not representative of the real world of investment, where personal emotions and thinking can take place. More importantly, the moderating effect of AI trust, and AI innovation perception has never been explored with respect to the connection between behavioral biases and the investment decision-making process. The proposed study will fill these gaps by directly testing a moderated model (that also takes into consideration psychological biases and perception of technology) that determines the impact of psychological biases and perception of technology in the behavior of investors (Aquilino et al., 2025).

Despite the fact that it has been mentioned in the prior literature that AI trust and AI innovation play an important role in the adoption of AI technologies (Christensen, 1997), their moderating role in behavioral finance is understudied. In particular, the effect of anchoring and emotional biases on AI-supported investment decisions remains poorly explored, as to how AI Trust and AI Innovation moderate the relationship between these factors and AI-supported investment decisions. Existing research largely treats AI trust and AI innovation as antecedents of adoption intention (Rahi et al., 2022; Nain & Rajan, 2024), overlooking their boundary role in determining when AI mitigates or potentially amplifies behavioral biases. This study addresses this gap by conceptualizing AI Trust and AI Innovation as moderating mechanisms in the bias–decision relationship.

Table 2.1: Extracted Variables Based on Literature Review (Variable Specification: Direct and Moderating Variables
)

Variable Type	Variable Name	Definition	Role in Study	Supporting References
Independent Variable (IV)	Emotional Bias	The distortion of judgment caused by feelings (fear, greed, regret) leading to irrational financial choices.	Direct predictor (H1)	Baker et al. (2019); Pompian (2012)
	Anchoring Bias	Over-reliance on initial information ("anchor") when making subsequent judgments.	Direct predictor (H2)	Tversky & Kahneman (1974); Ishfaq & Anjum (2015)
Moderating Variable (MV)	AI Trust	Investor's confidence in the reliability and competence of an AI system.	Moderates IV-DV relationships (H5, H6)	Jian et al. (2000); Gefen et al. (2020)
	AI Innovation	Perception of AI tools as novel, advanced, and superior to traditional methods.	Moderates IV-DV relationships (H7, H8)	Parasuraman & Colby (2015); Christensen (1997)
Dependent Variable (DV)	Investment Decisions	Quality and rationality of capital allocation choices by investors.	Outcome variable	Gill et al. (2018); Kahneman & Tversky (1979)

3. CONCEPTUAL FRAMEWORK AND HYPOTHESES DEVELOPMENT

The classical theory of economic thought suggests that individual behaviour with regard to investment decisions tends to be rational, and out of that rationality, the Expected Utility Theory (EUT) was developed by Bernoulli (1738) upon the economic aspects of setting up investment decisions. This theory explains the nature of making decisions as a result of well-analyzed probability of possibilities of alternative outcomes amidst risky situations (Vilela & Oluyemi, 2021). Individuals prefer those results which are most useful. But, the assumption of rationality was criticized by academicians Kahneman and Tversky (1971, 1979) and a pattern of divergence in actual behaviour was established with the creation of behavioural finance. Following the notions of portfolio, developed a model based on analyzing risk-reward and the relationship between the two. Based on the classical concept of finance people consider wealth and engage themselves in making any financial related decisions in a rational sense with only one objective of maximizing on their likely utility, but then Kahenman (1971) faulted the existing literature in finance and proposed the other aspect of irrationality in investment decisions. In this way, behavioural finance is used in psychology, finance, and sociology is related to psychological factors in the world of investors, posing the question of the influence of psychological errors on decision making (Mittal et al., 2022). Human emotions, attitudes, and psychological biases have been identified by behavioral scientists as parameters that influence inefficiencies in irrational investing choices of investors (Kahneman and Tversky, 1982). Behavioral finance can be defined as a segment of behavioral economics suggested to explain the abnormalities of the stock market by attributing them to psychological causes like an increase or decrease in service prices (Sharma & Kumar, 2020). Behavioral finance is not aimed at discrediting the simple research conducted by the designers of the efficient-market concept, it examines particular behavior among investors and places them apart in respect of rational decision makers according to conventional economic theory and deviations of a market hypothesis that a behavioral model could possibly assist to explain. The prospect theory is used to describe people way of framing and calculating their preferences; individuals would consider a certain point in terms of loss or gain and heuristics theory triggers most fundamental behaviors of cognitive bias and emotional bias.

3.1 Research Conceptual Model

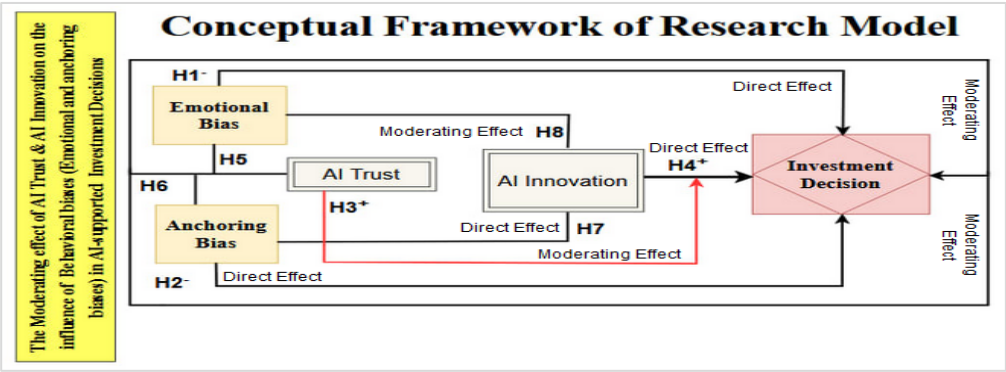


Figure 3.1: Conceptual Model

3.2 Development of Hypotheses

a) Direct Effect Hypotheses

3.2.1 The Disruptive Influence of Emotional Bias on Investment Rationality

Emotional bias presents a considerable obstacle in decisions regarding investments, in which, a person tends to act irrationally and not according to the prevailing logic in the context of financial matters. Investors are not purely data processors—they are

human, and as such, they frequently react to market conditions with emotional states such as fear, greed, excitement, regret, and overconfidence. These affective influences tend to arise more strongly in volatile markets, where uncertainty and high stakes amplify psychological responses. For example, an investor may hastily sell off assets during a temporary dip out of panic, or irrationally cling to losing investments due to regret aversion and hope for recovery, despite clear analytical evidence suggesting otherwise. Such emotional interference undermines the purpose and potential of AI decision support tools, as users might override objective, system-generated insights in favor of emotionally comforting decisions (Ahmad et al., 2025).

This trend is reinforced by findings indicating that emotional responses can distort memory recall and risk perception, making it difficult for investors to remain objective in high-pressure situations. Despite the increasing use of AI in finance, such biases continue to manifest, highlighting the limited capacity of technology alone to override deep-rooted psychological tendencies.

Therefore, this hypothesis is foundational in illustrating that emotional factors persist as critical variables even in technologically enhanced investment environments. It contributes to behavioral finance by reaffirming the need for emotion-sensitive AI interfaces and investor education aimed at emotional awareness.

→ **H_1: Emotional bias has a significant negative effect on investment decisions.**

3.2.2 Anchoring Bias and the Cognitive Trap of Fixed Reference Points

Anchoring bias generally refers to the habit of human beings using an original piece of information (also known as the anchor) heavily in order to make subsequent decisions at the detriment of objectivity and flexibility. The bias in the context of financial investments occurs generally when the investors anchor on past stock prices, past market forecasts, or arbitrary past benchmarks. Even in the presence of new and relevant information, many investors continue to base their decisions on outdated data, resulting in distorted asset evaluations and suboptimal trading behavior. This mental rigidity often prevents investors from adjusting to evolving market realities and encourages irrational expectations about stock recovery or asset performance.

Anchoring bias is especially pernicious because it operates unconsciously, making it hard for investors to recognize and correct their behavior (Schley & Weingarten, 2025). While financial AI systems can offer corrective insights based on updated data, users may still override these recommendations if they are mentally anchored to previous expectations (Rosyidah & Pratikto, 2022).

The inclusion of this hypothesis adds depth to the understanding of how anchoring distorts rationality and persists even with access to algorithmic tools. It contributes to theory by positioning anchoring as a cognitive obstacle that must be directly addressed in AI design, investor training, and behavioral interventions.

→ **H_2: Anchoring bias has a significant negative effect on investment decisions.**

3.2.3 The Enabling Power of AI Trust in Enhancing Decision Accuracy

Artificial intelligence (AI) trust is an essential consideration that determines how and whether investors adopt AI-generated financial insights when making financial decisions. Perceptions of competence, transparency, fairness, and reliability normally exert a considerable influence on developing trust in AI. And when investors gain trust in the AI system they communicate with, they are much more likely to act in accordance with the recommended actions instead of making emotion-driven or heuristic-based decisions. Such displacement of intuition by algorithmic logic increases the quality of decisions and lightens the mental load of making sense of confusing financial information.

Trust in AI can also develop a cooperative relationship between human cognition and machine reasoning, in particular, when the system is seen as impartial and objective (Zhao et al., 2025). Research has also shown that trust promotes the likelihood of continued participation in the use of AI tools in the long- run, which also maximizes the application of rational investment behaviors frequency and efficiency. The partners can trust in

the system where they remain composed in moments of uncertainty or when their situation may be emotionally volatile, the ability to make rational decisions.

The hypothesis adds value to the behavioral finance and fintech adoption literature because it recognizes that trust, rather than an antecedent condition, is an active driver that influences the outcome of decisions made.

→ **H3: AI trust has a significant positive effect on investment decisions.**

3.2.4 Perceived AI Innovation as a Driver of Investment Engagement

The concept of AI innovation can be defined as the perceived innovativeness, technological proficiency, and flexibility of the AI systems, especially in the way, they can be used to advance decisions in complex financial situations. When investors believe an AI platform is innovative, meaning that included modern analytics, predictive modeling or real-time simulations, they are more likely to believe it is capable, intelligent and credible. These understanding boosts investor confidence and, as a result, augments the level of engagement, dependency on systems, and the will to test new approaches.

The conviction that a system is cutting-edge augments the feeling of competence, which turns investors more open to accepting the advice of a system, especially when the market conditions are ambiguous or intricate. The user satisfaction and perceived usefulness are also factors in the Technology Acceptance Model (TAM), which is also affected by AI innovation.

As investors learn more about and interact more closely with innovative systems, they will tend to enjoy greater financial results, as a product of the capabilities of the systems and the openness of the users. The hypothesis will improve the body of knowledge by showing the importance of AI innovation perception in influencing not only the decision technology adoption, but also investment behavior and quality.

→ **H4: AI innovation has a significant positive effect on investment decisions.**

b) ***Moderating Effect*** *Hypotheses*

3.2.5 AI Trust as a Psychological Shield against Emotional Bias

The protective aspect of trust against the devastating nature of emotional bias in the investment decision process holds. Emotional bias which is based on emotional reactions like fear, regret or overconfidence are natural things as they make the investor take actions irrationally during events of uncertainty. However, when investors place strong trust in AI systems—believing that they are reliable, fair, and objective—they are more likely to defer to those systems, especially under stress. Trust acts as a cognitive anchor, enabling users to replace emotionally driven impulses with data-driven recommendations. High-trust environments can promote emotional regulation by reducing fear-based reactions and increasing confidence in the investment process. Moreover, trust fosters repeated interaction with AI platforms, leading to greater system familiarity, which itself reduces the emotional intensity of decisions.

In emotionally charged investment situations such as market crashes or sudden rallies trust in AI enables a more grounded, rational response by encouraging reliance on system-generated logic. This hypothesis contributes to both behavioral and technology trust literature by emphasizing trust's moderating role not only in adoption, but in regulating emotional reactivity.

→ **H5: AI trust moderates the effect of emotional bias on investment decisions**.

3.2.6 Reducing Anchoring Effects through AI Trust Alignment

Anchoring bias persists when individuals cling to initial values—such as the purchase price of an asset or a previous market forecast—even when subsequent data contradicts these anchors. However, such bias can significantly be reduced when there is a lot of trust in AI systems. Trusted AI platforms provide alternative points of reference that are current and live providing investors with a reason to reconsider what they have come to think as correct. The level of trust elevates the user motivations to forgo historical attachments and feel ready to utilize the new frames that the system displays (Maduku et al., 2025).

This twist is attributed to the fact that whenever trust is present, all notions of risk and not knowing are eliminated and it is easy to accept counterintuitive or novel suggestions. In addition, trust also increases confidence of the users in the correctness of the output of the AI, and increases belief to extend beyond the historical anchors (Fazeel et al., 2025).

The result is the ability to make decisions flexibly and more in line with the prevailing dynamics in the market. This hypothesis is an added value because it points out that trust does not have a bounding ability in terms of affecting the development of a financial reasoning but that it can even remove the biases of being anchored to the depths of thinking.

→ **H_6: AI trust moderates the effect of anchoring bias on investment decisions.**

3.2.7 Technological Sophistication as a De-biasing Mechanism against Anchoring Bias

The fact that AI is perceived as being extremely innovative, that is, defined by new abilities, user-friendliness, and the capability of adaptability, could serve as the counterweight to anchoring bias by inviting investors to be more engaged with new information in a proactive manner. When investors believe a financial AI tool is cutting-edge, they are more open to reevaluating static assumptions and past reference points in light of current data. The cognitive flexibility arises because AI innovation perception enhances perceived competence and encourages trust in real-time feedback and market forecasting tools.

Furthermore, innovative systems often present information in more intuitive formats like dashboards, simulations, and scenario comparisons which help users visualize alternatives to previously held anchors (Mahajan, 2025). This enhances decision adaptability and supports better investment judgment. Research also indicates that perceived AI innovation is positively related to information-seeking behavior, prompting users to challenge their own biases more frequently (Fazeel et al., 2025).

This hypothesis contributes to both AI design and behavioral finance fields by showing that perceived AI innovation not only drives adoption but also plays a moderating role in reshaping investor cognition and reducing bias.

→ **H7: AI innovation moderates the effect of anchoring bias on investment decisions.**

3.2.8 Role of AI Innovation in Emotional Bias

Though in terms of boosting user satisfaction, perception, and engagement, the role of AI innovation is likely to be significant, the potential of it in emotional bias reduction is rather low. Emotional bias can be considered as a psychological part deep-rooted reactions, i.e., to feel anxious, excited, and loss aversed, which is difficult to disregard when a person is acutely aware of the fact that a system is technologically advanced. Although the innovative systems could be marvellous in their speed, precision, and the user experience, they could not incite the internal emotional processes of the irrational decisions (Rastogi et al., 2022). Research shows that even the latest and greatest AI can be disregarded when a user is highly emotionally charged; he or she reverts to instinctive responses rather than conscious choices (Rodgers et al., 2023) Moreover, AI innovation may influence system utility perceptions, but not emotion regulation, in the absence of a specific attempt at engineering this behavior, e.g. when using nudging or behavioral feedback.

Therefore, despite the positive effect of AI innovation perception on the adoption and the usability influence, it is not significant in mediating influence of emotional bias on the financial behavior. The hypothesis is efficient because it confines the line of impact of AI innovation and accentuates the role of psychological and emotional support devices besides the technical features.

→ **H8: AI innovation moderates the effect of emotional bias on investment decisions.**

3.3. Moderating Role of AI Trust

AI Trust and the perceived level of AI innovation in AI systems are increasingly being identified as drivers that determine the dynamics of human-algorithm interaction. This does not mean that people would merely adopt AI tools in a financial decisions situation; it also influences the amount and the quality of adoption. The more confident users become in a given AI system, the more likely

they will be to put aside instinct driven decision making and embrace a more algorithmic one. This trust preconditions the establishment of a psychological readiness to trust in an advice provided by AI even on uncertain cases or on high stake cases.

A user can become responsive to an algorithmic control through its AI innovation application in the sense of its flexibility, analytical quality, learning capacity, and its novelty. Their perceived status as more forward-looking or capable of learning in the moving market conditions can be discussed as more competent and, accordingly, worthy of attention. However, the AI innovation is likely to follow a different path by impacting the intensity of engagement, adoption and experimentation with AI -assisted strategies, although trust is a principal determinant of cognitive set and behavioral accommodations, i.e. the extent to which users are prepared in their mind and heart to act on the advice of the AI. AI trust and AI innovation are considered as moderating factors in the current study that examine their capabilities of compensating for the ill effects of the behavioral biases: loss aversion, overconfidence, anchoring, and herding upon the content of investment decisions.

By looking at these moderators, the study will aim at determining to what extent either or both can become the intermediaries to alleviate the impact of cognitive distortions that might lead to rational and evidence-based financial decisions.

According to Kornowicz (2020), AI trust calibration is also a crucial element here, as the users are exposed to the process of getting to know how to strike the right balance between their own expertise, intuitions, and contextual understanding and the recommendations suggested by AI. AI Trust calibration is not about unquestioning regarding algorithmic results but is more of a process of acquiring the judgment to know when to bow to the superior judgment of AI and when one needs a more human judgment.

AI Trust is thus not a passive entity and should adapt to new conditions to be a sensible element of constructive human-AI cooperation. In the financial domain, empirical evidence posits that the increase in the AI trust level positively affects the likelihood of following the algorithm recommendation, especially in situations that present a degree of uncertainty or lack of information about a certain situation. According to Brinson et al., (1986) trust may inhibit emotional responsiveness triggers e.g., panicking amid economic downs and cognitive biases such as anchoring, which is the tendency to base decisions on irrelevant past knowledge. This happens because trust fosters the attitude of relying on structured data-driven reasoning instead of heuristic-driven judgment or gut feelings.

3.4 Moderating Role of AI Innovation

To evaluate the comparative power of a moderator, the AI Trust model, in similar vein, AI Innovation (AiINN), the study in the proposed study has to include a second moderation framework. AI Innovation lies in how users perceive the technological newness, flexibility and maturity of their AI-system that they deal with when choosing to invest. This statement reflects the degree to which AI tools are considered by users to be high-tech, innovative, and able to offer superior decision support. The reason to define AI Innovation as such a moderating variable can be explained by increasing attention to technological properties of the fintech adoption discussion. Whereas, AI trust expresses a psychological coupling between the user and the system, AI innovation is believed to determine the engagement with the user system through the sense of competence and ability. This study was therefore conducted to ascertain whether larger perceptions of AI innovation can decrease the negative consequences of behavioral biases- emotional and anchoring biases.

The moderation analysis was carried out with the PROCESS macro (Model 1) in SPSS, where AI Innovation (AiINN) was the moderating variable between the behavioral bias index (ANCEMOT) and the dependent variable. The same methodological discipline that was used in the AI Trust model was as well used in the determination analysis. The conditional effects were tested at low, medium, and high levels of AI innovation (those in the 16th, 50th, and 84th percentiles of the distribution, respectively), to establish whether relationship of behavioral biases with investment quality changed with respect to divergent

perceptions of AI innovation (Cicek, Gursoy, & Lu, 2025).

All constructs were assessed using scientifically established likert-scale measures and internal measure validity was established by the Cronbach alpha value (above 0.70). This contribution of AI Innovation as one of the alternative moderators will facilitate the comparison of psychological (based on trust) and technical (based on innovation) pathways that can help in the mitigation of cognitive distortions involved in AI-assisted financial decisions (Fazeel et al., 2025).

4. RESEARCH METHODOLOGY

4.1 Research Design

This study was a Cross-sectional study based on a positive paradigm. Paradigm is use to understand basic strategies for any research. The paradigm for this research is positivist paradigm and under the umbrella of positivist paradigm quantitative research strategy was used for deduction purpose. The strategy for this study was be quantitative and based on primary data. For this study, retail investors of the Pakistan Stock Exchange was taken as unit of analysis.

4.2 Population and Sample

The population of the study based on the investors who are involved in retail investments. A convenience sampling method, and snowballing approach, was used to choose the study sample. The target population was confined to retail investors' investing in Pakistan including (Faisalabad, Lahore, Karachi & Islamabad) as data is accessible from these cities of Pakistan. Targeting the population involves identifying the specific group of individuals from whom the data has been collected. The final sample included **349 respondents**, which aligns with recommendations for conducting regression and moderation analyses using advanced statistical techniques.

4.3 Data Collection Method and Instrumentation

The questionnaire was designed based on a number of questions identified through an in-depth SWOT analysis and its respondents were approached via email and LinkedIn as well as in person. The survey instrument consisted of two principal sections, demographic data related to experience of investment, age, and education in 9 questions, and the measures of constructs adapted to the well-known scales with 5 point Likert scale (Strongly Disagree-Strongly Agree). To achieve validity and reliability, the questionnaire was pretested using a small sample or pilot group and changes were made according to the response given by the pilot group.

4.4 Measures and Scale Items

To test the hypotheses 4 items of Anchoring Bias, and 6 items of Emotional bias was be adopted from (Baker et al., 2019 as they adapted in their study for measuring behavioral biases). For investment decisions 3 items from (Gill et al., 2018) and for determinants of artificial intelligence for measuring AI Trust 12 items from (Jian, J. Y., Bisantz, A. M., & Drury, C. G. 2000), for AI innovation 4 items from (Parasuraman and Colby, 2015) was adapted and modified from validated questionnaire.

4.5 Data Analysis Techniques

Statistics were performed with the help of SPSS/28 and the possesses macro of Hayes. The analytical methodology involved descriptive statistics in summarizing characteristics associated with demographics and main variables, reliability analysis using Cronbach's alpha to test consistency between variables, and correlation analysis using Pearson correlations that would determine associated relationships among variables. Hypothesis testing involved multiple regression analysis for direct effects (H1-H4) and PROCESS Macro (Model 1) for moderation effects (H5-H8), with interaction terms probing the moderating roles of AI trust and AI innovation. This comprehensive methodology ensured rigorous testing of the hypotheses while aligning with established quantitative research practices.

5. RESULTS AND ANALYSIS

5.1 Descriptive Statistics

Table 5.1: Descriptive Statistics of Research Variables

Variable	No of Items	Mean	SD	Min	Max
Emotional Bias	6	3.45	0.78	1.50	5.00
Anchoring Bias	4	3.62	0.82	1.75	5.00
AI Trust	12	3.88	0.74	2.08	5.00
AI Innovation	4	3.91	0.69	2.25	5.00
Investment Decisions	3	3.76	0.71	2.00	5.00

The descriptive statistics for the sample of 349 retail investors revealed moderate to high mean scores across all key constructs, with emotional bias averaging 3.45 (SD=0.78), anchoring bias at 3.62 (SD=0.82), AI trust at 3.88 (SD=0.74), AI innovation at 3.91 (SD=0.69), and investment decisions at 3.76 (SD=0.71) on a 5-point Likert scale, indicating that respondents generally recognized the presence of behavioral biases while maintaining relatively positive perceptions of AI capabilities and their own decisions quality

5.2 Demographics Analysis

Table 5.2.1: Gender Distribution of Respondents

Gender	Frequency	Percentage
Male	217	62.2%
Female	132	37.8%
Total	**349**	**100%**

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The sample was predominantly male, with men representing nearly two-thirds of the respondent pool. This gender distribution is common in studies of financial market participants.

Table 5.2.2: Age Profile of Respondents

Age Group	Frequency	Percentage
<40 years	183	52.4%
40-49 years	84	24.1%
50-59 years	43	12.3%
>60 years	39	11.2%
Total	**349**	**100%**

The majority of investors (52.4%) were under 40 years old, indicating a relatively young and potentially tech-savvy participant base, which is relevant for a study on AI adoption.

Table 5.2.3: Educational Attainment

Education Level	Frequency	Percentage
Matric	25	7.1%
Graduation	130	37.2%

Masters	152	43.5%
Others	42	12.2%
Total	**349**	**100%**

A high level of educational attainment was observed, with over 80% of respondents holding a graduation degree or higher. This suggests a sample with the cognitive background to understand and engage with complex investment tools like AI.

Table 5.2.4: Monthly Income Distribution (PKR)

Income Bracket	Frequency	Percentage
Below Rs. 50,000	83	23.8%
Rs. 50,001-100,000	129	37.0%
Rs. 100,001-150,000	77	22.0%
Above Rs. 150,000	60	17.2%
Total	**349**	**100%**

The sample captured a diverse range of income levels, with the largest group (37%) earning between Rs. 50,001-100,000 per month. This diversity helps ensure the findings are not biased toward a specific wealth segment.

Table 5.2.5: Occupational Background

Occupation	Frequency	Percentage
Government	59	16.9%
Non-Government	200	57.3%
Self-Employed	90	25.8%
Total	**349**	**100%**

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Most respondents were employed in the non-government sector (57.3%), followed by self-employed individuals (25.8%). This distribution reflects the composition of the modern Pakistani workforce.

Table 5.2.6: Investment Experience

Experience	Frequency	Percentage
1-5 years	221	63.3%
5-10 years	68	19.5%
>10 years	60	17.2%
Total	**349**	**100%**

The majority of investors (63.3%) had 1-5 years of experience, indicating a sample with adequate exposure to financial markets while still potentially being influenced by behavioral biases

5.3 Reliability and Validity Tests

Table5.3.1: Reliability and Validity Assessment of Constructs

Construct	Number of Items	Cronbach's Alpha (α)	Average Variance Extracted (AVE)	Square Root of AVE
Emotional Bias	6	0.84	0.58	0.76
Anchoring Bias	4	0.79	0.56	0.75

AI Trust	12	0.89	0.62	0.79
AI Innovation	4	0.82	0.60	0.77
Investment Decisions	3	0.81	0.59	0.77

Cronbach's Alpha values are above the acceptable limit of 0.70 and this signifies that the reliability of the internal consistency is satisfactory. The AVE values are larger than 0.50 and this proves convergent validity. Discriminant validity was justified by square root AVE of each construct (diagonals) being higher than any other construct in each row-column combination.

5.4 Correlation Analysis

Table 5.4.1 Correlation Matrix: Investment Decisions and AI Trust with Other Variables

		InvDec	aitrust	ANCHR	EMOTION	AIINN
InvDec	Pearson Correlation	1	.221**	-.267**	-.285**	.226**
	Sig. (2-tailed)		.000	.000	.000	.000
	N	349	349	349	349	349
aitrust	Pearson Correlation	.221**	1	-.055	-.087	.345**
	Sig. (2-tailed)	.000		.305	.105	.000
	N	349	349	349	349	349
ANCHR	Pearson Correlation	-.267**	-.055	1	.584**	-.114*
	Sig. (2-tailed)	.000	.305		.000	.033
	N	349	349	349	349	349
EMOTION	Pearson Correlation	-.285**	-.087	.584**	1	-.119*
	Sig. (2-tailed)	.000	.105	.000		.027
	N	349	349	349	349	349
AIINN	Pearson Correlation	.226**	.345**	-.114*	-.119*	1
	Sig. (2-tailed)	.000	.000	.033	.027	
	N	349	349	349	349	349

**. Correlation is significant at the 0.01 level (2-tailed).
*. Correlation is significant at the 0.05 level (2-tailed).

The correlation matrix shows that there were meaningful relations among study variables. AI trust & AI innovation were positively correlated with the investment decisions (r = .221, p <.01) and (r = .226, p <.01) respectively indicating that the higher the level of AI trust and AI innovation, the better the investment decision. Investment decisions were on the other hand negatively correlated against anchoring bias (r = -.267, p < .01) and emotional bias (r = -.285, p < .01). Those are the findings that make such arguments that cognitive and emotional distortions have detrimental impacts in terms of rational investment behaviors. Moreover, anchoring and emotional biases showed a significant positive relationship (r = .584, p < .01) indicating that both biases presented tendencies to occur in line with one another in a decision-making environment. AI confidence was also highly ranked with perceptions

of AI innovation ($r = .345$, $p < .01$) indicating that where people perceive a higher level of AI innovation, they also tend to have more confidence in AI systems.

5.5 Hypothesis Testing

H1: Emotional bias negatively affects investment decisions

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.285	.081	.079	.64496

ANOVA

Model	Sum of Squares	df	Mean Square	F	Sig.
Regression	12.792	1	12.792	30.751	.000
Residual	144.344	347	.416		
Total	157.135	348			

Coefficients

Model	Unstandardized B	Std. Error	Standardized Beta	t	Sig.
(Constant)	4.999	.168		29.805	.000
EMOTION	**-.264**	.048	**-.285**	-5.545	.000

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Regression results confirmed a significant negative effect ($\beta = -.285$, $t = -5.545$, $p < .001$). The model explained 8.1% of the variance in investment decisions. This highlights that emotional bias (such as fear, overconfidence, or regret) undermines rational financial decisions, consistent with behavioral finance theory. Therefore, **H1 is supported**.

H2: Anchoring bias negatively affects investment decisions

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.267	.071	.069	.64853

ANOVA

Model	Sum of Squares	df	Mean Square	F	Sig.
Regression	11.189	1	11.189	26.602	.000
Residual	145.947	347	.421		
Total	157.135	348			

Coefficients

Model	Unstandardized B	Std. Error	Standardized Beta	t	Sig.
(Constant)	4.923	.165		29.759	.000
ANCHR	**-.241**	.047	**-.267**	-5.158	.000

Anchoring bias also had a significant negative effect ($\beta = -.267$, $t = -5.158$, $p < .001$), with the model explaining 7.1% of the variance. Investors who rely excessively on initial reference points (e.g., historical prices or forecasts) tend to make suboptimal investment choices. Therefore, **H2 is supported**.

H3: AI trust positively affects investment decisions

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.221	.049	.046	.65631

ANOVA

Model	Sum of Squares	df	Mean Square	F	Sig.
Regression	7.666	1	7.666	17.797	.000
Residual	149.469	347	.431		
Total	157.135	348			

Coefficients

Model	Unstandardized B	Std. Error	Standardized Beta	t	Sig.
(Constant)	3.339	.181		18.436	.000
a trust	**.221**	.052	**.221**	4.219	.000

Results indicated a significant positive effect ($\beta = .221$, $t = 4.219$, $p < .001$), explaining 4.9% of the variance. This implies that higher trust in AI enhances investor confidence in adopting AI-supported recommendations, ultimately improving investment decision quality. Therefore, **H3 is supported**.

H4: AI innovation positively affects investment decisions

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.226	.051	.048	.65550

ANOVA

Model	Sum of Squares	df	Mean Square	F	Sig.
Regression	8.038	1	8.038	18.707	.000
Residual	149.097	347	.430		
Total	157.135	348			

Coefficients

Model	Unstandardized B	Std. Error	Standardized Beta	t	Sig.
(Constant)	3.474	.146		23.742	.000
AIINN	**.180**	.042	**.226**	4.325	.000

AI innovation also positively influenced investment decisions (β = .226, t = 4.325, p < .001), with 5.1% of the variance explained. This suggests that **H4 is supported**

perceptions of AI's novelty, adaptability, and technological advancement encourage investors to rely on AI tools for financial choices. Therefore,

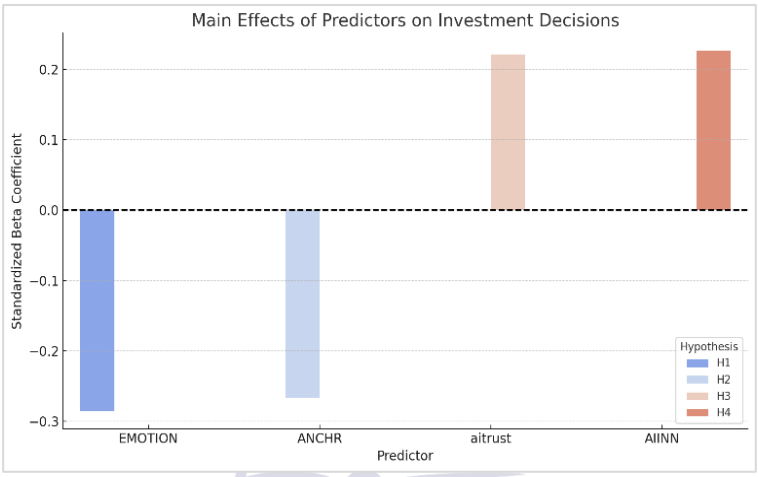


Figure 5.1: Main effects of Predictors on Investment Decisions (H1-H4)

Moderation Analysis (AI Trust & AI Innovation- H5-H8)

H5: Moderation Effect of AI Trust on the Relationship between Emotional Bias and Investment Decisions

Model Summary

Metric	Value
R	0.354
R^2	0.125
MSE	0.398
F	16.470
df1, df2	3, 345
Sig. (p)	0.000

Regression Coefficients

Variable	B	SE	t	p	LLCI	ULCI
Constant	5.039	0.593	8.504	0.000	3.873	6.204
EMOTION	-0.487	0.175	-2.789	0.006	-0.831	-0.144
AI Trust (aitrust)	-0.018	0.160	-0.113	0.910	-0.332	0.296

EMOTION × AI Trust	0.068	0.048	1.421	0.156	-0.026	0.162

Interaction (Moderation) Test

E	ΔR^2	F	df1	df2	p
EMOTION × aitrust	0.0051	2.020	1	345	0.156

The interaction term (EMOTION × AI trust) was not statistically significant (β = .0487, t = 1.421, p = .156). This indicates that AI trust does not buffer the adverse effect of emotional bias on investment decisions. Emotional biases appear resistant to moderation by trust, reflecting their deep psychological nature.

H6: Moderation Effect of AI Trust on the Relationship between Anchoring Bias and Investment Decisions

Model Summary

Metric	Value
R	0.353
R^2	0.125
MSE	0.399
F	16.401
df1, df2	3, 345
Sig. (p)	0.000

Regression Coefficients

Variable	B	SE	t	p	LLCI	ULCI
Constant	5.162	0.528	9.778	0.000	4.124	6.201
ANCHR (Anchoring Bias)	-0.538	0.155	-3.479	0.001	-0.842	-0.234
AI Trust (aitrust)	-0.059	0.137	-0.430	0.667	-0.329	0.211
ANCHR × AI Trust	0.085	0.041	2.080	0.038	0.005	0.164

Interaction (Moderation) Test

Interaction Term	ΔR^2	F	df1	df2	p
ANCHR × aitrust	0.0110	4.326	1	345	0.038

Conditional Effects of ANCHR at Values of AI Trust

AI Trust Percentile	Effect of ANCHR	SE	t	p	LLCI	ULCI
16th (2.83)	-0.299	0.056	-5.326	0.000	-0.409	-0.188
50th (3.33)	-0.257	0.047	-5.434	0.000	-0.349	-0.164
84th (4.00)	-0.200	0.048	-4.186	0.000	-0.294	-0.106

A significant interaction effect was observed (β = -.538, t = 2.080, p = .038). Conditional effect analysis revealed that when AI trust was higher, the negative effect of anchoring bias on investment decisions became weaker. This indicates that trust in AI can help mitigate anchoring tendencies by encouraging reliance on data-driven insights rather than fixed reference points.

H7: Moderation Effect of AI Innovation on the Relationship between Anchoring Bias and Investment Decisions

Model Summary

Metric	Value
R	0.333
R^2	0.111
MSE	0.405
F	14.328
df1, df2	3, 345
Sig. (p)	0.000

Regression Coefficients

Variable	B	SE	t	p	LLCI	ULCI
Constant	4.019	0.582	6.903	0.000	2.874	5.164
ANCHR (Anchoring Bias)	-0.138	0.157	-0.879	0.380	-0.447	0.171
AI Innovation (AIINN)	0.244	0.162	1.508	0.133	-0.075	0.563
ANCHR × AIINN	-0.024	0.044	-0.549	0.583	-0.111	0.063

Interaction (Moderation) Test

Interaction Term	ΔR^2	F	df1	df2	p
ANCHR × AIINN	0.0008	0.302	1	345	0.583

The interaction term (ANCHR × AI innovation) was not significant ($\beta = -.024$, $p = .583$). Thus, AI innovation does not appear to influence the relationship between anchoring bias and investment outcomes.

H8. Moderation Effect of AI Innovation on the Relationship between Emotional Bias and Investment Decisions

Model Summary

Metric	Value
R	0.348
R^2	0.121
MSE	0.401
F	15.796
df1, df2	3, 345
Sig. (p)	0.000

Regression Coefficients

Variable	B	SE	t	p	LLCI	ULCI
Constant	4.911	0.645	7.615	0.000	3.642	6.179
EMOTION (Emotional Bias)	-0.387	0.176	-2.204	0.028	-0.732	-0.042
AI Innovation (AIINN)	0.011	0.175	0.060	0.952	-0.333	0.354
	0.041	0.048	0.854	0.394	-0.053	0.135

Interaction (Moderation) Test

Interaction Term	ΔR^2	F	df1	df2	p
EMOTION × AIINN	0.0019	0.730	1	345	0.394

Similarly, the interaction between emotional bias and AI innovation was not significant (β = .041, p = .394). This suggests that while AI innovation directly improves investment decisions, it does not necessarily weaken the adverse role of emotional bias.

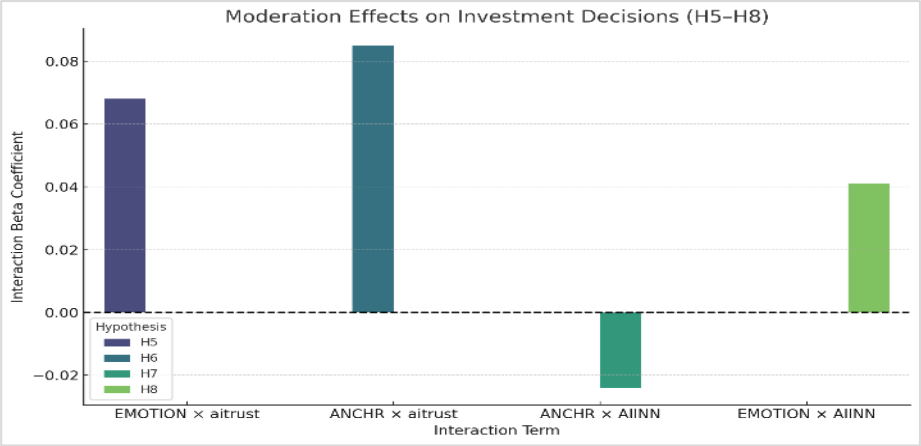


Figure 5.2: Moderation effects on Investment Decisions (H5-H8)

5.6 Summary of Hypothesis Testing Results

Hypothesis	Relationship Tested	Supported	Key Statistics (p-value)	Conclusion
H1	Emotional Bias → Investment Decisions	**Yes**	p < .001	Emotional bias has a significant negative effect on investment decisions.
H2	Anchoring Bias → Investment Decisions	**Yes**	p < .001	Anchoring bias has a significant negative effect on investment decisions.
H3	AI Trust → Investment Decisions	**Yes**	p < .001	Trust in AI has a significant positive effect on investment decisions.
H4	AI Innovation → Investment Decisions	**Yes**	p < .001	Perception of AI innovation has a significant positive effect on investment decisions.
H5	AI Trust moderates Emotional Bias	**No**	p = .1562	AI trust does **not** significantly change the strength of the negative effect of emotional bias.
H6	AI Trust moderates Anchoring Bias	**Yes**	p = .0383	AI trust **does** significantly weaken the negative effect of anchoring bias.

H7	AI Innovation moderates Anchoring Bias	**No**	p = .5832	AI innovation does **not** significantly change the effect of anchoring bias.
H8	AI Innovation moderates Emotional Bias	**No**	p = .3935	AI innovation does **not** significantly change the effect of emotional bias.

DISCUSSION

6.1 Interpretation of Results

This paper set out to study the sustained impact of behavioral biases in a rapidly changing financial space that relies more heavily on artificial intelligence. The results led to rather subtle conclusions, which can be directly related to the formulated research questions and hypothesis, as well as contribute to the theory and practice of behavioral finance and process of technology adoption. Addressing **RQ1**, which asked to what extent emotional and anchoring biases influence investment decisions in an AI-supported context, the results clearly demonstrate that both biases maintain their significant negative impact. This finding strongly supports propositions from prospect theory (Kahneman & Tversky, 1979) and behavioural finance literature (Pompian, 2011) that cognitive heuristics systematically deviate decisions from rationality. The fact that these effects prevail even in the realm of AI-assisted setting implies that new technological accessibility is not the only way of eradicating deeply entrenched psychological patterns. Behavioural biases still persist to influence investors to make non-optimal decisions based on emotional responses and arbitrary reference points.

The data used in answering RQ2, which was: How do AI trust and innovation directly impact investment decisions, showed that the two factors did not have significant main effects. This observation opposes the technological determinism understandings and denotes that the availability of innovative technology, in general, or the overall trust in AI systems, does not necessarily result in the enhancement of the quality of the decisions. This concurs with the technology acceptance theories (Venkatesh et al., 2003) that underlined the significant role of perceived usefulness and ease of use compared to AI innovation perceptions. The volume of non-significant direct effects shows the possible value of AI in its interface with human cognition rather than as an independent decision-maker.

Looking at the result of RQ3, which queried whether AI trust moderates the adverse effects of behavioral biases, a significant difference is identified. The degree of overlap reduced the relationship between anchoring bias quite strongly but not emotional bias. This discrepancy finding lends credence to the dual-process theory paradigm whereby the cognition and affective processing systems can be differentiated. The success of AI trust in combating anchoring bias or one of the cognitive shortcuts implies that the analytical AI outputs can be used to replace the Type 1 processing errors. However, it still shows that it cannot mitigate emotional bias tendencies, which presents it with shortcomings in Type 2 affective processes, in line with findings in the literature on emotion-cognition interventions (Loewenstein et al., 2001).

Regarding RQ4 about whether the AI innovation of AI erodes behavioural biases, no significant moderating consequences on any of the two types of bias were found. This result discredits the notion that psychological impediments are a factor that can dominate over the technological sophistication. Rather, it promotes literature on AI trust (Afroogh et al., 2024) that underlined the importance of reliability/credibility rather than a simple innovative perception. A possible interpretation of the outcomes is that investors need to have a serious trust in the AI systems, as opposed to its novelty, which is in accordance with research on automation bias and proper confidence in decision aids (Parasuraman & Manzey, 2010).

The study hypothesis presented in the research was aimed at investigating the motivators of behavior that impact and guide investments in respect to AI-assisted financial tools. The results confirm the findings of emotional bias and anchoring bias have

a significant negative impact on investment decisions in support of hypotheses H1 and H2. These findings stress that psychological aberrations, fear-based selling and persistence in the use of reference points that are out of date have deleterious effects on investor sanity despite the presence of advanced decision supports. On the other hand, AI trust and innovation of the AI tools exhibited a positive impact on investment decisions, which signifies the fact that technological confidence stimulates the occurrence of rational and data-driven operation. However, moderation analyses revealed that AI innovation does not moderate the relationship between emotional bias and investment decisions, providing no support for hypothesis H4. This suggests that while innovation contributes directly to decision quality, it may not be sufficient to counteract the effects of ingrained emotional tendencies unless accompanied by behavioral interventions or emotional intelligence frameworks.

6.2 Comparison with Previous Studies

The study's results align well with previous behavioral finance research. Consistent with Kahneman and Tversky's Prospect Theory (1979), it confirmed that cognitive and emotional distortions persist even in technologically advanced settings. The negative influence of anchoring corroborates earlier findings by Tversky and Kahneman (1974) highlighted that fixed reference points hinder adaptive thinking. Likewise, the role of emotions in distorting financial logic echoes the work and emphasized the overwhelming effect of mood and effect on economic behavior. On the technological front, the positive impact of AI trust is in line with the Technology Acceptance Model (TAM) by Davis (1989) and Mayer et al.'s (1995) trust theory, both of which stressed that user confidence in system reliability enhances engagement and decisions. The results that AI innovation enhances investment decisions seems to resonate with the Diffusion of Innovation Theory by Rogers et al., (2014), stating that the perception of modernity and utility is what influences adoption and performance among users.

6.3 Implications of the Study

The results enhance the theoretical convergence of behavior-based finance and adoption of technology. By demonstrating that even with the integration of AI, emotional and cognitive bias still interfere with decisions, the study highlights the importance of expanding the existing models to take into consideration the irrationality of the human actor who participates in the decision-making process. Unlike the traditional models, AI rationalization of investment behavior is an assumption, which this study shows that trust and perceived AI innovation are more like enablers than moderators of bias. This reflects in the fine tuning of behavioral finance theory with-inclusion of technology as a corrective factor that is not absolute. Furthermore, this study refines the TAM framework by suggesting that AI trust and AI innovation should be viewed not only as precursors to adoption but also as behavioral regulators in decision contexts. It highlights a gap between system design and psychological adaptability, suggesting a dual-lens approach that incorporates both technological design principles and behavioral conditioning strategies.

6.4 Theoretical Implications for Investors and AI Developers

Theoretical implications from these findings suggest the need for more sophisticated models of human-AI collaboration that account for different types of cognitive processes and the specific nature of human-technology interactions. The results support a contingency perspective where AI's effectiveness depends on both the type of bias being addressed and the quality of the human-AI relationship, particularly the establishment of trust rather than mere appreciation of AI innovation.

6.5 Practical Implications for Investors and AI Developers

For investors, the findings provide a cautionary insight: even the most advanced tools cannot override human emotion and heuristic-driven errors. In that regard, financial education and emotional training that work side-by-side with the use of technology are urgently needed. It is advisable that investors adopt reflective practices

and use AI outputs whilst being cognizant of their cognitive biases. The research presents two things to AI developers and fintech platforms: the notion that based on different needs, they should strive to design highly precise but user-friendly tools; and the one that they should consider including behavioral nudges in the platforms. Design tools that remind users about possible biases, simulate emotionally-charged situations, or present the vision of the results of long-term actions are the interfaces that could reduce the irrationality of human behaviors and actions that many perceive as opposing to rational data. Transparency, explain ability and psychological comfort of the design should also be considered by the Developers to promote greater levels of trusted user engagement and maintenance.

6.7 Interpretation in Context

The results of the present study offer a more textured picture of how behavioral biases in investment decisions remain active even in AI-assisted settings, and at the same time reveal the contingent efficacy of the AI-related elements influencing a reduction of these biases. The findings indicated that both anchoring and emotional influences still exert a major negative impact on investment choices and the findings are in concurrence with other literature in the area of behavioral finance. This consistency of prejudices affirms the underlying principles of the prospect theory (Kahneman & Tversky, 1979), which held that investors tend to systematically act not according to the models of rational choice by shortcuts in thought and being emotionally driven. These biases are so persistent that providing people with technology cannot be enough because it is not easy to change ingrained psychological tendencies that have been developed during the history of the human decisions process (Tversky & Kahneman, 1974). However, the analysis indicates that the variables of AI trust and AI innovation have emerged as positive factors contributing to the quality of decisions, but affect them differently. I trust in particular, proved to be an effective moderator to the anchoring bias, and it had a strong effect of reducing the negative effects of the anchoring bias on judgment and investment decisions. This observation confirms the cognitive debiasing theory (Morewedge et al., 2015), stated that when people experience cognitive heuristics, external analytical assistance is needed to overcome them because it allows setting objective standards and data-driven perspectives. The results of AI trust in terms of its effectiveness against the anchoring bias specifically comply with the wording on decision support systems which affirmed that the trusted algorithmic recommendations can help investors exit the anchoring trap by facilitating more informative processing.

Conversely, AI trust was not effective in counteracting emotional biases and provided an important limitation of technological interventions. This differential effect supports the dual-process theory framework (Evans, 2008), which distinguishes between cognitive (Type 2) and affective (Type 1) processing systems. While AI tools can support deliberate, analytical thinking against cognitive biases, they appear less capable of overriding the automatic, physiological responses associated with emotional biases. This finding resonates with affective neuroscience research (Phelps, 2006) suggested that emotional processing operates through different neural pathways than cognitive processing, making it less accessible to logical or technological intervention. AI innovation, while demonstrating direct benefits to decision quality, did not moderate either type of bias. This intriguing result challenges AI innovation diffusion theory, which might predicted that perceptions of technological advancement would enhance debiasing effectiveness. Instead, the findings support trust-based models of technology adoption (Mayer et al., 1995) emphasized the primacy of reliability and credibility over mere AI innovation perceptions. This suggests that investors require substantive trust in AI systems rather than being impressed by their novelty, aligning with research on appropriate reliance in human-automation interaction (Parasuraman & Manzey, 2010).

The theoretical implications of these results are substantial. The theorists suggested the need for more sophisticated models of human-AI collaboration that account for different types of cognitive processes and the specific nature of human-technology interactions. The findings

support a contingency perspective where AI's effectiveness depends on both the type of bias being addressed and the quality of the human-AI relationship, particularly the establishment of trust rather than mere appreciation of AI innovation.

From a practical standpoint, these results offer valuable guidance for financial professionals, AI developers, and policymakers. For addressing cognitive biases like anchoring, the development of transparent, reliable AI systems that foster genuine trust appears crucial. However, for emotional biases, alternative or complementary approaches—such as emotional education, mindfulness training, or hybrid human-AI advisory models—may be necessary. This underscores the importance of developing multifaceted intervention strategies that address both the cognitive and emotional dimensions of investment decisions.

It sum-up, this study contributes to the evolving literature on behavioral finance in the digital age by demonstrating that while AI offers valuable capabilities for addressing certain cognitive limitations, its effectiveness is contingent on both the nature of the psychological bias and the type of human-AI relationship established. The research provides a more refined understanding of the boundaries and possibilities of technological de-biasing, particularly highlighting the persistent challenge of emotional biases in investment decisions.

7. CONCLUSION

7.1 Summary of Findings

This research offers a number of meaningful contributions to both academic theory and practical application. Empirically, it adds fresh insights to the behavioral finance literature by confirming that psychological biases persist even within AI-supported environments an increasingly relevant context in today's fintech-driven markets. Theoretically, the study contributes to the integration of behavioral finance with the Technology Acceptance Model (TAM), demonstrating that while AI trust and AI innovation enhance rational decisions, they do not fully negate the impact of emotional and cognitive distortions. Practically, the findings offer actionable implications for both investors and developers. For investors, the research highlights the need for greater self-awareness and behavioral training to complement technological tools. For developers and financial platform designers, the results point to the importance of building systems that not only perform efficiently but also foster user trust, incorporate bias-reducing features, and are perceived as modern and relevant.

7.2 Contributions of the Study

This study contributes to the evolving literature on behavioural finance in the digital age by demonstrating that while AI offers valuable capabilities for addressing certain cognitive limitations, its effectiveness is contingent on both the nature of the psychological bias and the type of human-AI relationship established. Future research should explore additional AI characteristics and their interactions with a broader range of behavioural biases across different investor profiles and market conditions.

7.3 Limitations of the Study

Despite its contributions, the study is not without limitations. The sample is small with limited geographic coverage, which can limit the generalizability of the results to the larger investor samples. Also, the results can be based on self-reported information, which could be subject to response biases, since respondents themselves are not always able to appreciate their own biases or behaviors. The cross-sectional design also prevents observing the dynamic of trust formation, emotional regulation, and investment behaviour over time or under changing market circumstances.

7.4 Suggestions for Future Research

Future research should broaden the investigation of behavioral biases to include overconfidence and herd behavior, capturing AI's full de-biasing potential. Longitudinal and cross-cultural studies are needed to explore how trust evolves across contexts and cultures. Further work could also develop emotion-aware AI systems to address biases resistant to current interventions:

I. **Extending the Application of Biases and AI Interaction:** Future research should examine a more

comprehensive array of behavioral biases (e.g., overconfidence, herd behavior, loss aversion) to see whether AI trust or other AI-related factors (ex., explainability, transparency) can eliminate them. This would give a more detailed image of the potential of AI as a debiasing method when it comes to various psychological processes (Pompian, 2011).

II. **Set of longitudinal and experimental designs:** Longitudinal or experimental research design would also allow tracing the development of AI trust and seeing how it will affect mitigating bias in the long term. As an example, the study of the decisions processes investors have prior to and after being exposed to AI tools would present how AI trust is gained and shape the transformation in behavior in the long term.

III. **Contextual and Cultural Moderators:** It should be a research question on how contextual influences (e.g., more volatile markets, complex over simple decisions) and cultural variations (e.g., individualists as compared to collectivists) work to modify AI trust, AI innovation and bias mitigation. To understand whether the efficacy of AI may be society specific, cross-cultural research might reveal these differences in terms of societal norms and values.

IV. **Emotional Bias Interventions**: Since emotional biases are quite resistant to AI trust, it is recommended that alternative interventions are tested, as in:

- Emotion-Aware AI: Components that identify and respond to emotional cues (i.e. through real time feedback) (Picard, 1997).
- Hybrid Models: Human advisor models Basic model Let AI and expert human adviser co-exist Hybrid models Challenging emotional biases with an expert human adviser through empathetic communication (Shapiro et al., 2021).
- Behavioral Training: The combination of learning training courses about emotional management and usage of AI tools (Loewenstein et al., 2001).

V. **Neuroeconomic and Physiological Approaches**: Valuable insights could also be gained through additional neuroscientific (e.g., MRI) or physiological (e.g., heart rate variability, skin conductance) data on the neuronal and affective mechanisms of AI-supported decisions. This would aid in understanding the reason behind emotional biases not being so responsive to technological interventions (Phelps, 2006).

VI. **Role of AI Explainability and Transparency**: Determine role of explainable AI (XAI) features, e.g. presenting clear rationales behind recommendations to impact the formation of AI trust and reduction of biases. Understanding whether transparency enhances trust's moderating effects could inform the design of more effective AI systems (Glikson & Woolley, 2020).

VII. **Domain-Specific Applications**: Replicate this study in other financial domains (e.g., retirement planning, insurance, cryptocurrency) or non-financial contexts (e.g., healthcare, legal, and public policy decisions) to assess the generalizability of the findings. Different domains may exhibit unique interactions between biases and AI tools (Jain et al., 2022).

VIII. **Individual Differences**: Examine how investor characteristics (e.g., financial literacy, risk tolerance, personality traits like openness to experience) influence their reliance on AI and susceptibility to biases. This could lead to personalized AI systems tailored to individual cognitive and emotional profiles (Evans, 2008).

These directions would not only advance theoretical knowledge but also guide the development of more effective, ethical, and human-centric AI tools for enhancing decisions across domains.

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