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THE IMPACT OF AI INNOVATION ON RETAIL INVESTORS' DECISION-MAKING: THE MEDIATING ROLE OF SELF-ATTRIBUTION AND HINDSIGHT BIAS

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ABSTRACT

Background: *The integration of artificial intelligence (AI) in the financial market has essentially recognized that how retail investors make decisions. AI-powered tools, such as robo-advisors and predictive analytics, can help improve the quality of investment decisions. However, cognitive biases—particularly self-attribution bias and hindsight bias—may still distort judgment, even in AI-assisted environments.*

Objectives: *The current paper examines how AI innovation affects investment decision making of retail investors by exploring the potential role of self-attribution and hindsight bias in mediating this association. Six hypotheses were tested to evaluate direct and indirect effects among AI innovation, behavioral biases, and decision.*

Methodology: *A cross-sectional quantitative design was employed under a positivist paradigm. Primary data were collected through structured questionnaires from 349 retail investors on the Pakistan Stock Exchange (PSX). Standardized, validated scales were used to measure AI innovation (Parasuraman, 2000), self-attribution bias, hindsight bias (Baker et al., 2019), and investment decisions (Gill et al., 2018). SPSS and Hayes' PROCESS Macro (Model 4) were used to analyze reliability, correlations, regressions, and mediating effects between variables.*

Results: *The results indicated that AI innovation contributions raised investment decisions substantially and significantly affirming H1 ($B = 0.124$, $p = 0.002$). However, AI innovation did not significantly influence self-attribution bias ($p = 0.771$) or hindsight bias ($p = 0.619$), leading to the rejections of H2 and H3. Conversely, both hindsight bias ($B = -0.209$, $p < 0.001$) and self-attribution bias ($B = -0.328$, $p < 0.001$) proved to have significant negative impacts on investment decisions, supporting H4 and H5. In the case of H6a and H6b, mediation is conducted by way of Hayes PROCESS Macro (Model 4) showed that the indirect effects of AI innovation on investment decisions through self-attribution bias (effect = 0.0043) and hindsight bias (effect = 0.0060) were not significant, as their bootstrap 95% confidence intervals included zero ([H6a: -0.0210 to 0.0328]; [H6b: -0.0284 to 0.0379]). This indicates that neither bias significantly mediated the relationship, both H6a and H6b were rejected.*

Conclusion: *To sum-up AI innovation improves retail investors' decisions directly, it does not reduce self-attribution or hindsight bias. These biases independently and negatively affect decision quality, underscoring the need for bias-mitigation strategies within AI systems.*

Keywords: *AI Innovation, Investment Decisions, Self-Attribution Bias, Hindsight Bias, Behavioral Finance, Retail Investors, Mediation Analysis.*

1. INTRODUCTION

The integration of Artificial Intelligence (AI) in the financial markets has resulted in a significant shift in decision-making patterns of retail investors. AI tools currently become easily accessible, such as predictive algorithms and machine learning models to robo-advisors, which assist retail investors when making investment decisions (Alderucci, 2020). Historically retail investors used to put strong emphasis on personal opinion, advisors and external economic reports to strategize their investment portfolio (Iqbal, Hassan, & Kayani, 2022). As AI has become more mature, investors now do have access to more efficient, objective, and data-driven tools to make decisions that can scan massive volumes of market data, identify patterns and provide prognostic insights (Babina, et al., 2023). In the past, human cognitive biases, such as overconfidence, loss aversion, and series of related cognitive heuristics, have conditioned financial decision-making. The retail-level investors, in particular, are obscured with such cognitive biases, where the (self-attribution as well as the) hindsight bias has an impressive impact on their investment behaviour and thus determines the decision processes (Klinger, et al., 2020). Self-attribution bias is an inclination to blame the failures on external situations which are out of control, but take credit for the success themselves because of the reason that one learns facts or succeeds because of an internal reason (Pohl et al., 2003). On the contrary, there is the aspect of hindsight bias where the tendency is considered to be predictable than it was after determining the outcome (Kreis et al., 2023). These biases can cause a wrong judgment, which makes investment decisions more biased than rational. As the levels of AI activity in financial space raise, the question of whether AI tools can assist in avoiding such biases or, on the contrary, they might improve biases is raised as well. The power of predictive capability of AI may be objective so as to remove emotional or biased decision-making (Broekhuizen, Nguyen, & Fabian, 2024). However, there is a lack of studies on the prospects of AI innovation with the interaction of psychological and patent forms of items on self-attribution and hindsight difference (Seppala, 2025). This is the gap to which this study proposes to discover by analyzing what AI innovation is likely to contribute to the decisions making of retail investors with references to the self-attribution and hindsight biases as the mediators of this contribution.

Problem Statement

Retail investors tend to have biases that come in the way of objective decision-making. Although the possibilities of the AI innovation to enhance investment decisions are good, it is not clear whether AI decreases or increases thinking traps (cognitive biases), like Self-attribution biases and hindsight bias. Such biases, in case of their absence, potentially persist to damage the capacity of AI-powered tools to improve the quality of investment choices. Thus, to construct the tools capable of delivering not only correct data but addressing other aspects of decision-making as well such as psychological ones, it is necessary to explore the connection between AI-based innovation and such biases like their impact on the investments decisions making-process.

Research Question (RQs)

The key research question (RQ) of the research is the following: **How does the AI innovation impact investment decision of retail investors and to what extent self-attribution and hindsight bias intervene in this relationship?**

The sub-questions as a result of the main research question are:

- RQ1: Does AI innovation significantly improve investment decision-making for retail investors?
- RQ2: How does AI innovation influence self-attribution and hindsight biases?
- RQ3: To what extent do self-attribution and hindsight biases mediate the relationship between AI innovation and investment decisions?

Research/Study Objectives (ROs)

The primary objectives of the study are:

- RO1: To assess the direct impacts of AI innovation on retail investors' investments decisions/choices.
- RO2: In order to examine the effect of the AI innovation on self-attribution bias in retail investors.
- RO3: To investigate how AI innovation influences the hindsight bias in the retail investors.

- RO4: To investigate the facilitating function of self-attribution and hind sight bias on linkage between AI innovation and investments choices.

Research Hypotheses

This paper research questions and objectives do intend to explain the following hypotheses:

→ H1: The impact of AI innovation on the retail investors is significant, positively affecting their investment decisions.

→ H2: AI innovation has a key impact on self-attribution bias among retail investors.

→ H3: AI innovation has a strong impact on hindsight bias in retail investors.

→ H4: The factor of self-attribution causes an influential bias in investments decision making.

→ H5: The hindsight bias has a significant impact on investment decisions.

→ H6a: The interplay between AI innovation and investment decision is mediated by Self-attribution bias.

→ H6b: The interaction between AI innovation and investment decision making is meditated by the hindsight bias.

Scope of the Study

This paper is devoted to the retails investors that choose AI-driven tools to make a decision about investments. The study has been carried out in the country of Pakistan where the use of AI tools in investment activities is also developing yet remains at the initial level. The research focused on the impacts of AI innovation on decision making of retail-investors, using the mediators of self-attribution and hindsight biases. Data was gathered in the research using the method of cross-sectional survey, where the participants were the retail investors using the AI-driven platforms living in four big cities of Pakistan including, Lahore, Karachi, Faisalabad, and Islamabad. The investors of above mentioned cities were selected due to the limited scope because of the availability of data and fast-paced fintech development of these cities.

Significance of the Study

The potential contribution of this research to the literature of behavioral finance is that it allows paying attention to the links between AI innovation and cognitive biases specifically self-attribution and hindsight, which emerged in relation to retail investors. Knowing how AI tools are likely to affect the psychology of different people is important to either investors or developers of technologies as they become more inculcated within the investment platforms (Alderucci, 2020). This study can provide enlightening information to fintech firms when it comes to developing AI-based applications that will enable investors to attain more logical and informed choices by understanding the impacts of AI innovation to various biases, including Self-attribution and hindsight biases. Moreover, the study will also have a practical implication to policymakers and financial educators who will be interested in enhancing the financial decision-making of retail investors by taking into account not only technological innovations but also psychological factors as well. Secondly, the results can be used to create more effective AI tools that take into consideration the existence of behavioral biases hence making these tools more effective in enhancing the success of investment decisions. The study is also applicable in the light of diminishing human intervention in financial services due to the prospect of AI, and the issue of probable cognitive biases among investors, as AI could offer meaningful information powered by data-driven knowledge.

Organization of Paper

The paper is divided into five major parts. The Introduction presents the context of the research by giving the problem statement, research questions, objectives, and hypotheses, the importance and the significance/scope of the study. The literature review focuses past studies on AI innovation, self-attribution bias, hindsight biases, and their role in affecting the investment decisions. The theoretical framework section explains the theories employed in the study, in addition to the Behavioral Finance Theory, Technology Acceptance Model (TAM). In methodology section, the research designs of the study, sampling, data collection-procedures, and the statistically methods are described. The results and discussion section present and discuss the research findings on the relationship to the hypotheses leading to an insight into the research questions. Finally, the conclusion provides a description of the major findings, emphasizes the contribution of the study, and makes recommendations for future studies.

2. LITERATURE REVIEW

This paper explored the relationship between AI innovation and cognitive biases, specifically focusing on self-attribution bias and hindsight-bias, and their impacts on investment decision making among retail investors. It starts by explaining the role of AI in financial (choices) decisions making, including the way in which AI-based tools, like machine learning models and robo-advisors, are changing the classical approach towards investments by offering reliable information based on data and by decreasing human error. Many past studies found on AI tools and cognitive biases in financial decision making have significant correlations. Yet, previous studies indicated that besides maximizing accuracy of decisions made, AI-powered machine learning models (Robbins, 2020) and applications like robo-advisors (Onabowale, 2024) can potentially escalate the self-attribution bias, where investors credit positive outcomes in an AI-aided environment to their expertise and negative results to chance factors (Pareek et al., 2024; Koo & Yang, 2018). Additionally, hindsight bias (the bias of investors to underestimate their accuracy skills due to the results in the past (Miller & Ross, 1975; Fischhoff, 1975) was found to enhance overconfidence associated with AI-based explanations of hindsight. Based on the empirical evidence, retail investors are susceptible to automation bias, over-assistance (Candrian & Scherer, 2022) or under-assistance of the AI and trade sub-optimally, therefore, leading to a sub-optimality problem (Vereschak et al., 2024). The past studies demonstrated the independent power of AI to inhibit and intensify intellectual biases in investment scenarios (Sathya & Gayathiri, 2024). The review then takes into account theoretical basis concerning behavior biases such as self-attribution and hindsight biases which tend to divert rational decision making in financial decisions. There is a critical analysis of the relationship between AI and these biases by capturing the facts that AI has the potential to intensify and alleviate such cognitive distortions. The present study explores the existing empirical literature that includes the direct and indirect impact of AI innovation in decision making of investment by studying the mediatory roles of these biases that prepares the backdrop against which the hypotheses examined in this work are put forward.

AI Innovation and Investment Decision-Making

The recent developments in the field of Artificial Intelligence (AI) have considerably changed the process of financial decision-making, and most notably that of retail investors. The machine learning algorithms, as well as predictive models constitute the artificially intelligent tools that nowadays play a prominent role in the investment process as they provide a swift analysis of data, real-time information about the market and improved forecasts (Brock & Mekoche, 2019). In the traditional method, the retail investors depended mostly on individual reasoning, the financial advisors, and market studies which are subject to human flaws and prejudice to some extent. However, since the emergence of AI-based platforms, investors can currently make more sound and objective decision ns using data-based conclusions that can be calculated much faster than human computational capabilities (Rasouli et al., 2023). Artificial Intelligence tools have the specificity of being able to process high quantities of market data in real-time, find trends and patterns in it, as well as offer recommendations that could otherwise stay unidentified in the conventional decision-making framework (Igna & Venturini, 2023).

According to Babina et al., (2023) the ability to minimize uncertainty is one of the primary benefits of AI in the field of investment decision-making. AI can also assist investors to more accurately predict the direction of the market by analyzing big volumes of data and finding correlations that can guide investment decisions (Haag et al., 2024). Investor portfolios are managed using AI-driven features, including robo-advisors, which ensures accord to the risk level of the investor and the targeted financial plans without the guesswork included in a man-driven scheme of investment planning. Furthermore, the capabilities of AI to conduct high-frequency trading provides a possibility to execute trades more rapidly and more precisely, which is of significant importance in cases where the time factor is critical, such as volatile markets (Gang, 2024).

Vijayakumar (2021) indicated that AI invention is beneficial to investment choices because it enhances the quality of information and efficiency in its processing. An example would include AI tools that allow more complicated processing and analyzing data than human beings can possibly provide and the information provided by such benefits would be feasible and accurate (Haenlein & Kaplan 2019). Although it has been accepted that AI could assist in the removal of human errors, its intervention does not feature in the decision making process without complications. Biases in AI models themselves may be another risk because AI models may inherit the bias in data they are trained on, which can result in biased suggestions (Mittermaier et al., 2023). This formulates a paradox in that AI can decrease as well as increase biases in decision making in investment. However, literature has been consistent in its argument that on the whole, AI innovation has an overwhelming positive impact on investments decisions, both in terms of the accuracy of decisions and in improving market forecasts (Chakraborty & Parida., 2024). This results into the following hypothesis:

H1: The impact of AI innovation on the retail investors is significant, positively affecting their investment decisions.

AI Innovation and Self-Attribution Bias

Self-attribution biases, flipped attribution biases, or self-servings biases describes the tendency of people to explain successes attributable to internal factors and failures attributable to external factors, overestimating personal control and underestimating chance or external events (Miller & Ross, 1975). This bias may appear when an investor credits a favorable result in investing to his skill or predictive capabilities, without considering the component of luck, marketplace conditions, or alternative outward factors. Self-attribution biases often lead to overconfidence. This overconfidence usually translates into more risky behavior on future investment choices as the investor thinks that the successes, they have had up to this point has just been on account of their own ability (Priyadarsini & Prithi, 2023). AI innovation typically based on Technology acceptance model (TAM) proposed by Davis (1989), postulates the two core components including perceived usefulness, the extent to which a person believes either the using technology will increase the task performance and perceived ease of use, the extent to which the investor perceives that how easy the use of technology is.________________

According to Trehan & Sinha, (2017) self-attribution bias has found its own peculiar place in the literature on decision-making in consumer and finance. As it is identified by Mahina et al., (2018) self-attribution bias can be a strong motivator when it comes to influencing the development of investment choices, since the investor can be more confident in their capabilities when positive results are achieved. This sense of self-efficacy can easily translate into overconfidence that ultimately influences the next investment decisions (Czaja & Roder, 2020).

Ullah (2015) studied the impacts of self-attribution bias on investment behaviours of the Pakistani-investors also showed that participants who were more informed about financial knowledge had a greater sensitivity to the effects of self-attribution bias. The paper has discussed how self-serving biases contribute to making rational choices in an emerging financial market where external factors like economic instability or transparency may sometimes influence rational decision-making (Koo & Yang, 2018).

Baker et al., (2019) explored the use of AI tools can also mitigate the self-attribution bias by keeping the data objective and transparent, which can question the assumptions held by an investor concerning their capabilities. An AI tool could present a series of possible outcomes and strategies, and it would be evident that the success of an investment depends not only on the judgment of an investor but a series of factors that involve the capabilities of the AI (Schoeffer, et al., 2023). The possibility to reduce the self-attribution bias through AI represents a valuable avenue of inquiry since the study of such an intersection is currently an emerging field (Yuksel & Metin, 2025). Considering the inconclusive results of the previous research, the present hypothesis is postulated:

H2: AI innovation significantly influences self-attribution bias among retail investors.

AI Innovation and Hindsight Bias

According to Iqbal et al., (2022) hindsight bias (the inclination to believe that something may have been anticipated occurring as it had once happened (Fischhoff, 1975) is a well-established cognitive distortion. In the case of investors, hindsight bias might appear as a predisposed predictability of past results on future investments that are done after the event and results in overconfidence in making future analysis. This may skew the learning which takes place through past error as in the mind of the investors they will feel that they knew all along and hence the future investments may seem risk free to them (Fu & Lu., 2023).

The hindsight bias has gained a lot of prominence in investment literature especially in as far as market behavior and risk perception are concerned. When investors are subjected to hindsight bias, Biais et al. (2009) revealed that it causes under-estimation perceived risks and this may lead them to make non-optimal investments. This bias lowers the capability to evaluate future risks as the investors expect that past investment results were less random than they really (Knoll & Arkes., 2017).

Ahmad & Shah (2022) explored the hindsight bias, when investment since it relates to investment decisions made by investors when they update their forecast once an event actually happens. Tchai (2012) clarified that the investors will be optimistic that they can predict/foresee the market trend once they get to know the result. This overconfidence may misrepresent the way investment will be done in future and may result in poor risk management because the investor will be more confident in what he predicts as opposed to before the incidence takes place (Toft, 2019).

Sa and Madhavi (2025) additionally verified that hindsight bias mostly affects the decisions of investors and makes them too confident in their power to forecast the market trends. Their argument is based on the fact that investors affected by the hindsight bias adopt a dismissive approach to viewing alternative eventualities and are overconfident about their decisions. The trend discourages learning in the past investment errors, and the cycle tabulates to a bad judgmental process.

The AI tools and their predictive abilities can increase this bias further since they would make it appear that the investment predictions were bound to be successful. In cases where the AI-suggested recommendations lead to positive results, an investor can later rationalize the results as due to its expertise or knowledge to strengthen the confidence in its decision-making performance (Fessel, Epstude, & Roese, 2009). This may overestimate their predictive skills and they will not be able to correct their previous errors. Conversely, researchers believe that the predictability of the AI models can assist in alleviating the hindsight bias. As an example, assuming that the AI tool is easily interpretable in the context of its own rationales and internal processes, investors might become less inclined to perceive the successful result as the effect of their own intuition (Rydstrand et al., 2024). Consistent with these opposing view-points this research is going to analyze how an AI innovation affects the hindsight bias. The proposed hypothesis is the following:

H3: AI innovation significantly influences hindsight bias among retail investors.

Self-attribution Bias and Investment Decisions

It is a well-known fact that self-attribution bias is largely responsible in contributing towards poor choices of rational decisions taken in the finance field. The judgment errors of overconfidence, that tends to be created by self-attribution effects, may also cause investors to make poor decisions, such as unwarranted risk or neglect of expert opinions (Li, 2010). Libby & Rennekamp (2012) have determined that overestimation of investors' own skills resulted in the greater incidence of trading between investors, commonly to the detriment of the investors themselves (Gervais & Odean, 2001). The self-attribution bias is based on overestimation or underestimation of the investors' own skills and abilities, resulting in concentrating failure on causal channels outside the control of individuals and success on the skill of individual also may make investors repeat their previous mistakes which may result in bad performance when it comes to their finances (Mishra & Metilda, 2015).

Mahina, Muturi, & Florence, (2018) explored the empirical research on self-attribution bias entailing overconfidence which then adversely affects the performance of investors during investment decisions. Baker et al., (2019) explored investors who see the success of investments as the result of their own strengths would be more inclined to make more serious decisions in a follow-up issue, since they fully believe in their potential to determine the market situation (Priyadarsini & Prithi, 2023). Such a practice may give rise to increased costs of transactions, poor performance and susceptibility to the market volatility. Thus, there is a need to comprehend how self-attribution biases may influence investing choices and enhance the quality of money-making choices (Kim, et al, 2020). Following these facts, the hypothesis stating the following is proposed:

H4: The factor of self-attribution causes an influential bias in investments decision making.

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Hindsight Bias and Investment Decisions

Koo & Yang, (2018) identified just like self-attribution bias, hindsight bias can also be a significant factor in the inability of the investor to find out the history of his past decisions and reflect them in the style of work. This bias leads to false hindsight by investors, who come to believe that an event was more predictable than they should have. This significantly miscalculates risk and return (Hawkins & Hastie, 1990). Consequently, there is also a potential of lessening the likelihood of investors with hindsight bias critically re-reviewing of their past investment decision, thus making investment at a later date fall into the same mistake (Shefrin, 2007). Moreover, the oversensing overconfidence that follows the hindsight bias may lead to the overestimation of predictive power of an investor regarding the future market trends (Chung, Choi, & Fard, 2024).

According to Henriksen & Kaplan (2003), the hindsight bias may negatively affect the learning process by decreasing the complexity of financial markets. Investors might feel that they would have predicted the market movements in the past and might underrate the risks involved in making future investments. This false sense of security may lead to poor decision-making, with investors being less attentive in evaluating the situation in the market and more inclined to overconfidence. Thus, the hypothesis is:

H5: The hindsight bias has a significant impact on investing decisions.

Mediating Role of Self-attribution and Hindsight Biases

Naveed & Taib, (2021) highlighted the possibility of cognitive biases (Self-attribution and hindsight mediating the connection between AI innovation and investment choice is a poorly studied area in the literature. According to studies conducted earlier, biases are proposed to be a psychological tool that has an external influence in form of external factors like changes in technology leading to change in conduct (Bhattacharya et al., 2020). The question connected to the take-up of the study is: Are AI-driven tools able to impact cognitive biases of retail investors, and in this case, do their biases mediate investment decision-making?

In case AI innovation compounds the self-attribution bias by strengthening the investor in their own forecasting skill, it may promote riskier investment choices. Similarly, the predictive potential of the AI could strengthen hindsight bias such that investors would be overconfident in future predictions. The mediation of such biases would run deep since the investors would be more inclined to trust the abilities perceived than the hard facts (Kazemi et al., 2022). In this respect, the following hypotheses are suggested:

H6a: The interplay between AI innovation and investment decision is mediated by Self-attribution bias.

Self-attribution bias has the potential to mediate the relationship between AI innovation and investment choice, since it modifies how an investor interprets the events of the past, making him/her perceive as easier to tell the future performance of an investment that occurred than actually (Li, 2010). In the case where the AI tools result in successful investment predictions or recommendations, this may lead the investor to feel that they knew all along, which would increase the feeling of control and confidence when making future decisions. This new confidence, brought on as result of the self-attribution biases, can make them over-confident in their forecasting abilities and eradicate perception of risk in future investments (Almansour et al., 2023). Additionally, the greater an AI-based system seems to be able to predict market behaviour, the more the self-attribution bias will be, with the investors recognizing the good results as their own decision but not the one by the AI-based analysis (Daniel et al., 1998). Consequently, the integration of AI can strengthen the issue of self-attribution bias without prompting intended results, as investors will feel more confident in their skills and make riskier investment decisions without considering the level of market uncertainty (Sa & Madhavi, 2025). Such a mediating effect indicates that although AI can have a positive effect on decision-making, it also causes cognitive distortions, which might spillover on future investment activities.

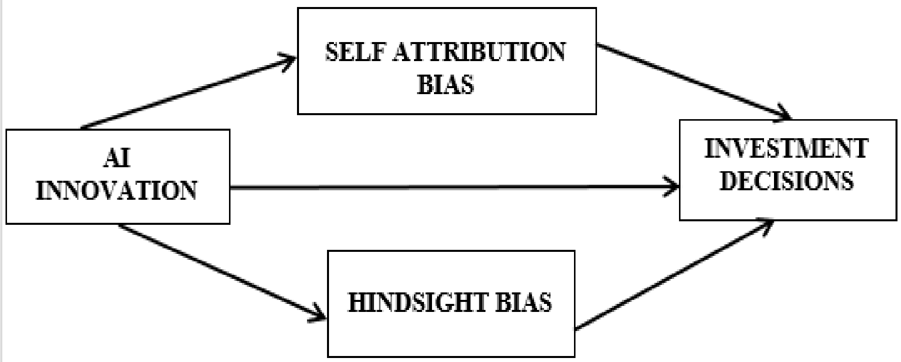
H6b: The interaction between AI innovation and investment decision making is meditated by the hindsight bias.

This extensive literature review has emphasized the pertinent connections existing between the AI innovation, cognitive biases, and investment decision-making. It implies that AI can complement decision-making process by presenting data-driven evidence; however, it might potentially improve, without any intention, the efficacy of some cognitive shortcomings, like self-attribution and hindsight bias that can negatively affect the rationality of investment decision-making. The hypotheses described in the current review are the foundations on which further empirical testing took place to examine the relationships between AI innovations on the one hand and the behaviors and decision-making processes of retail investors on the other hand.

THEORETICAL BACKGROUND

The study is based on two major theoretical constructions, which include Behavioral-Finance-Theory's and the Technology-Acceptance-Model (TAM). These theories help us understand the back-end mechanisms that determined the decisions of retail investors, especially when they utilize or took any investment decision by forecasting of the AI tools.

Figure 2.1: Theoretical Framework



This shows AI Innovation influencing Investment Decisions both directly and indirectly through the mediating effects of Self-Attribution Bias and Hindsight Bias.

Behavioral Finance Theory

The behavioral finance theory criticizes the conventional theory of finance which assumes that investors are rational and would always act to what is in their financial interest. The behavioral finance theory instead argues that psychological issues such as cognitive bias and emotional developments make major impacts on financial decision-making (Pandey, Moid, & Vishnani, 2024). According to this theory, investors are not consistently rational, but also deviate rationally under the influence of such factors as overconfidence, loss aversion, among other biases, which results in their poor investment decisions (Kahneman & Tversky, 1979).

According to Brooks and Byrne (2008) behavioral finance is based on two major biases investigated in the current study, including hindsight bias and self-attribution biases. The self-attribution biases acknowledged the tendency by individuals to attribute successful follow-up to internal, self-bestowed dispositions credit , and failure outcomes to external contingencies, which in turn bring into existence the feelings of perceived enhanced control and enhanced competences (Mishta and Metilda, 2015). This bias is also significant in the investment situations where retail investor might think that their decisions are more competent than it actually is (Mezulis et al., 2004). The other important cognitive distortion is the hindsight bias whereby one will feel that certain issues in the past could have been foreseen better than they were done. Hindsight bias may cause distortion of the knowledge of risk held by investors and also decreases investor learning caused by hindsight bias, and ultimately affects the future investment decisions (Fischhoff, 1975). The consequences of such biases on investment (decision) selection are paramount in understanding how AI innovation may or may not mitigate the negative effects of cognitive biases. The behavioral finance theory offers the framework in which these biases interfere with rational decision-making and influence the behavior of investors (Sattar et al., 2020).

Technology-Acceptance-Model (TAM)

TAM by Davis (1989) focus exclusively on the mechanisms of how people reach a point of accepting and using technological systems. In this model, two important constructs, which include, perceived ease of use, as well as perceived utility have been addressed as the main determinants of adoption. In the scenario of the AI innovations in the financial sector, TAM can contribute to the analysis of how the mass investors can accept the AI tools to inform their decision-making. AI tools are considered helpful when they increase decisions related to investments and give crucial insight into future decisions or help solve complex procedures. In the event that these tools are convenient and not cumbersome to the investor, they would be embraced and incorporated in the daily decisions making process of the investor (Mahalakshmi & Anuradha, 2018). TAM within AI-based financial instruments is particularly important in circumstances that involve investor biases. It has been determined that the correlation between simplicity and instrumental usefulness is a critical influence on intellectual prejudice among those investors who perceive that the AI system is providing objectively correct (Chen et al., 2021). The fact that such systems are seen as so intuitively easy to use and useful in some practical situation will help it to reduce cognitive distortions produced by overconfidence or confirmation bias. On the other hand, these distortions may be amplified by lack of either ease of use or usefulness. Cognitive bias results when investors apply a particular subjective perspective to the AI-generated insights, but they can be reduced with usability at a high level (Gridach, et al., 2025). Hussain, Shah, Latif, Bashir, & Yasir, (2013) conversely, in case of the limited trust of investors in the efficacy of the AI or in case the technology is found too complicated, the investors might reject such an approach and resort to their biases when making decisions regarding investment. The model provides a basis of how AI tools can be used to manipulate the behavioral patterns of retail investors and form a basis of investigation on how AI innovation can be used to reduce or increase the extent of biases like self-attribution and hindsight bias (Baker, et al., 2019).

Interaction of Behavioral Biases and AI

The Technology Acceptance Model offers theoretical perspectives through which AI adoption and decision-making behavior can be understood, and the behavioral finance theory specialized in addressing the biases and their impacts on investor decisions making. This study is focused on how AI tools interact with these biases (Kim, et al., 2020). By committing to designing AI systems effectively, biases including overconfidence and loss aversion could be addressed with objective insights courtesy of increased datasets and real-time analysis (Villegas et al., 2024). However, again as mentioned previously, AI in itself can also turn into an agent of bias when it upholds particular beliefs or thinking errors. As an example, AI-powered machines may concentrate on effective investment performance, which unintentionally contributes to self-attribution bias among investors (Naveed & Taib, 2021). This may lead to a false sense of confidence and willingness to take risks, even where the AI tools would be aimed at reducing the biases. In a similar case, the prediction capabilities of the AI tools might increase retrospective bias, with the investors saying they knew it all along after their prediction was real (Allam, et al., 2025). Therefore, although AI may provide a helpful means of minimizing biases, it is also critical to be mindful of how AI-based tools can interplay with pre-existing cognitive behavior. The close relationships between these factors are critical to comprehend, and theoretical frameworks such as Behavioral Finance Theory and TAM, can be discussed (Raut & Kumar, 2024). On the basis of literature the list of extracted variables is as follows:

Table 2.1: List of Extracted Variables

Variable Type	Variable	Definition
Independent Variable	**AI Innovation (AiINN)**	The AI technologies have facilitated the implementation of new tools, systems, and processes that became the defining characteristics of how to improve investment decision-making practices. A meticulous evaluation of this change can be attained through the analysis of the perception of usefulness and novelty towards AI by the investors (Dernis, et al., 2021).
Mediating Variables	**Self-Attribution Bias (selfattr)**	The disposition of investors to consider their achievements as self-performance and failures in life as external circumstances. Measured by how investors attribute the outcomes of their investment decisions (Iqbal, Hassan, & Kayani, 2022).

	Hindsight Bias (hindsgh)	The perception that one "knew it all along" after an events took place." Measured by how investors perceive the predictability of past market events after they have happened (Priyadarsini & Prithi, 2023).
Dependent Variable	**Investment Decision (INVDECISIO)**	The quality, rationality, or risk-level of investment choices made by retail investors. Measured by the investor's decision-making quality, reflecting their risk tolerance and judgment (Pandey, Moid, & Vishnani, 2024).

3. RESEARCH METHODOLOGY

Research Paradigm

This paper works in the context of the positivist paradigm, which is prevalent in quantitative research because of its emphasis on objective data collection and analysis. The positivist approach assumes that reality exists independently of the researcher's perceptions and that it can be objectively studied through observable facts. The current study investigates the interplay between AI innovation and investment decisions making with references to the mediators role of cognitive biases, namely, Self-attribution-bias and hindsight-bias. A positivist approach is considered appropriate since it can be used to determine causal relationships due to its ability to analyze statistics that may produce transparent and empirically supported findings.

Sampling and Population

In the current study, the target population being studied is retail investors who actively trade in the securities market of Pakistan, specifically the Pakistan Stock Exchange (PSX). The selection of this cohort is based on the fact that retail participants, characterized by less capital and exposure to experience, tend to be highly susceptible to cognitive biases, like self-attribution and hindsight bias, compared to better-funded institutional investors. The study aimed to gather insights from investors in Faisalabad, Lahore, Karachi, and Islamabad, as these cities represent major financial hubs where retail investment activity is prominent. Since behavioral bias and its effect on decisions-making have attracted the scholarly community regarding the necessity to learn more about this phenomenon and explain how it influences decision-making processes, the current study will focus on people working in the field of trading stock or managing portfolios, thus ensuring that the conclusions that will be drawn will have an impact on practice but in a way relevant to investors using AI tools or being part of the decision-making process of any investment-related matters. A convenience sampling technique, combined with snowball sampling, was used to recruit respondents. Thereby, convenience sampling allowed for easy access to retail investors in the selected cities, while snowball sampling facilitated participant referral, expanding the sample base. This non-random sampling method is typically used in behavioral research, especially when specific populations need to be targeted. The current sample consisted of 349 retail investors, which represented a sufficient sample, which allowed the collection of a significant amount of data and further statistical exploration. A sample size of 349 participants to study structural equation modeling (SEM) suits well since a good volume is found to justify strong testing of hypothesized associations between the variables.

Data Collection

A structured questionnaire motivated by the existing literature and designed to assess AI Innovation (IVs), Self-Attribution Bias, Hindsight Bias (MVs) and Investment Decision (DVs) was used to gather the data. Nine questions in total were answered by the respondents with the first section capturing the demographic variables and the remaining parts overview the key constructs being addressed in the questionnaire. The Likert scale (5-point scales, where 1 was strongly-Disagree-(SD) and 5 was strongly-Agree-(SA)) was used in the study because it is a widely used method of measuring attitude and opinion in behavioral science research.

Instrumentation and Scales

The questionnaire was composed using well-established scales in preceding studies:

Table 3.1: Measurement Scales and Sources

Construct	Source	Number of Items	Description
AI Innovation	Parasuraman (2000)	4	The measures quantify the values of the usefulness and newness of the AI tools in making decisions and as everyday integrations.
Self-Attribution Bias	Baker et al. (2019)	6	Assesses how investors attribute investment successes and failures to internal or external factors.
Hindsight Bias	Baker et al. (2019)	3	Evaluates how investors perceive market outcomes as more predictable after the fact.
Investment Decisions	Gill et al. (2018)	3	Focuses on the quality, rationality, and risk level of investment choices made.

A pilot study of 50 investors was used to pretest each scale in terms of its clarity and reliability. Internal consistency was established using "CRONBACH ALPHA" values in each of the scales. The values are as follows:

- AI Innovation: 0.756
- Self-Attribution Bias: 0.722
- Hindsight Bias: 0.806
- Investment Decisions: 0.842

These values signify acceptable to good reliability in all the scales, hence suitable in the main study.

Data Analysis Techniques

The data collected by means of the survey was analyzed using SPSS (Statistical-Packages for Social-Sciences) and the Process Macro designed by Hayes. The Process Macro is the tool that enables the testing of complex mediation arguments, which is highly appropriate to this research because it seeks to understand how self-attribution and hindsight biases mediate the association between AI innovation and decision to invest. The process of the analysis included the following steps:

1. **Descriptive statistics**: To know how responses are divided and whether there is some non-commanding tendency and statistical aberration in the given data.
2. **Correlation Analysis**: To check the relations amongst the variables of interest (AI innovation, Self-attribution biases, hindsight bias, and investments decisions).
3. **Regression Analysis**: To evaluate the relationship between the direct influences of AI innovation in investment decision making, Self-attribution biases and hindsight biases.
4. **Mediation-Analysis**: To determine the possibility of self-attribution and hindsight biases mediating the connection between AI innovation and investment decision as indicated by the hypotheses.

4. RESULTS AND DATA ANALYSIS

Reliability Analysis

It is also important to determine the reliability of the measures used in this research before entering into the hypothesis test and correlation results. Reliability test is important in order to ascertain whether the measures employed to measure AI innovation, self-attribution bias, hindsight bias, and investment decision are apt and they always capture the constructs that are intended to be measured (Park, Kim, & Lee, 2025). Each scale was also computed based on the internal consistency measure, Cronbach's Alpha. The findings are as shown:

Table 4.1: Reliability Statistics for Study Constructs

Construct	Cronbach's Alpha	N of Items	Interpretation
Hindsight bias	0.806	3	Good internal consistency (>0.8).
Self-attribution bias	0.722	6	Acceptable reliability (>0.7).

AI Innovation	0.756	4	Acceptable reliability (>0.7).
Investment Decisions	0.842	3	Good reliability (>0.8).

The scale reliability utilized in this study has been confirmed because all the Cronbach alpha scores have been above the expected value of 0.7. Particularly, AI innovation has a Cronbach's alpha of 0.756, Self-Attribution Bias is 0.722, Hindsight Bias is 0.806, and Investment Decisions is 0.842. These values suggest acceptable to good internal consistency which affirms reliability of the scales and appropriateness in the future statistical analysis.

Correlation Results

The correlation analysis was used to explain the value of the means of the variables. The study used Pearson correlation coefficients to identify the strength as well as direction of the association that exists between AI innovation, self-attribution bias, hindsight bias and investment decisions. The table of correlation analysis results are as follows:

Table 4.2: Pearson Correlation Matrix of Key Variables

Variable	AI Innovation (AiINN)	Hindsight Bias (hindsgh)	Self-Attribution Bias (selfattr)	Investment Decision (INVDECISIO)
AI Innovation	1.000	-0.027 (ns)	-0.016 (ns)	0.165**
Hindsight Bias	-0.027 (ns)	1.000	0.570**	-0.305**
Self-Attribution	-0.016 (ns)	0.570**	1.000	-0.369**
Investment Decision	0.165**	-0.305**	-0.369**	1.000

The current study explains a couple of empirically relevant links between artificial intelligence (AI) innovation and cognitive bias with investment decision-making. To commence with, AI innovation is statistically significant and positively correlated with investment decisions ($r = 0.165$, $p < 0.01$), which shows that adoption of AI technologies can slightly, but not strongly influence the quality of decisions. Cognitive biases on the other hand have significantly larger effects on investments. There is a moderate negatively correlation between hindsight bias and investment decisions ($r = -0.305$, $p < 0.01$) and the reader will find that those investors (who view the past events in market to predictable) make less effective investment choices. Self-attribution bias is also associated with the negative, albeit weak correlation with investment decision ($r = -0.369$, $p < 0.01$), which shows that those investors who are more biases to ascribe successes to their own abilities and failures to external factors tend to make less than optimal decisions. Moreover, there is a moderate positive correlation between hindsight and self-attribution bias ($r = 0.570$, $p < 0.01$), indicating that the two biases often go hand in hand, and together, they may add even more negative consequences into investment behavior. The findings, in aggregate, show that, despite some potential advantages of AI innovation, cognitive biases still remain a serious impediment to rational decision-making in financial markets. Overall, the correlation results provide initial evidence of the relationships between the variables, with AI innovation showing a weak positive correlation with investment decisions and both hindsight and self-attribution biases showing negative correlations with investment outcomes.

HYPOTHESES TESTING (H1 TO H6B)

H1: AI Innovation → Investment Decisions

Table 4.3: Regression Results for H1 – AI Innovation Predicting Investment Decisions

Statistic	Result	Interpretation
R Square	0.027	AI innovation explains 2.7% of variance in investment decisions.
F	9.735, p=0.002	Model is significant.

Coefficient (B)	0.124, p=0.002	Significant positive effect.

The first hypothesis was implemented by performing a regression analysis and the findings reflected that AI innovation has positive effect on investment decision of retail investors, to extremely significant extent. As indicated in the model summary, AI innovation amounted to only 2.7 per cent variance explained in investment decisions (R^2 = 0.027). The F value obtained using ANOVA test shows a significant model (F = 9.735, p = 0.002). The coefficient value of AI innovation is (0.124) (p = 0.002) implying a statistically significant and positives impacts on investment decision-making.
Thus, **H1 is accepted**.

H2: AI Innovation → Self-Attribution Bias

Table 4.4: Regression Results for H2 – AI Innovation Predicting Self-Attribution Bias

Statistic	Result	Interpretation
R Square	0.000	Almost no variance explained.
F	0.085, p=0.771	Model not significant.
Coefficient (B)	-0.013, p=0.771	No significant effect.

The second hypothesis, stating that AI innovation significantly influences self-attribution bias, was tested through regression analysis. The model summary shows that AI innovation explains virtually no variance in self-attribution bias (R^2 = 0.000), and the regression coefficients for AI innovations is -0.013 (p = 0.771), which is not statistically significant.
Thus, **H2 is rejected**.

H3: AI Innovation → Hindsight Bias

Table 4.5: Regression Results for H3 – AI Innovation Predicting Hindsight Bias

Statistic	Result	Interpretation
R Square	0.001	Negligible variance explained.
F	0.248, p=0.619	Model not significant.
Coefficient (B)	-0.029, p=0.619	No significant effect.

In the third hypothesis, which proposed that AI innovation has a serious impact in hindsight bias, the results of regression indicated that AI innovation does not contribute significantly to variance in hindsight bias which is only averagely 0.1 (R^2 = 0.001). The values of regressions coefficients of AI innovation is -0.029 (p = 0.619) and this is also not statistically significant.
Therefore, **H3 is rejected**.

H4: Self-Attribution Bias → Investment Decisions

Table 4.6: Regression Results for H4 – Self-Attribution Bias Predicting Investment Decisions

Statistic	Result	Interpretation
R Square	0.136	Self-attribution bias explains 13.6% variance.
F	54.576, p=0.000	Model significant.
Coefficient (B)	-0.328, p=0.000	Significant negative effect.

The fourth hypothesis, stating that self-attribution bias significantly affects investment decisions, was tested with regression analysis. The model summary shows that self-attribution bias explains 13.6% of the variance in investments decisions (R^2 = 0.136). The regression coefficients for Self-attribution bias is -0.328 (p = 0.000), which is statistically significant and negative.
Thus, **H4 is accepted**.

H5: Hindsight Bias → Investment Decisions

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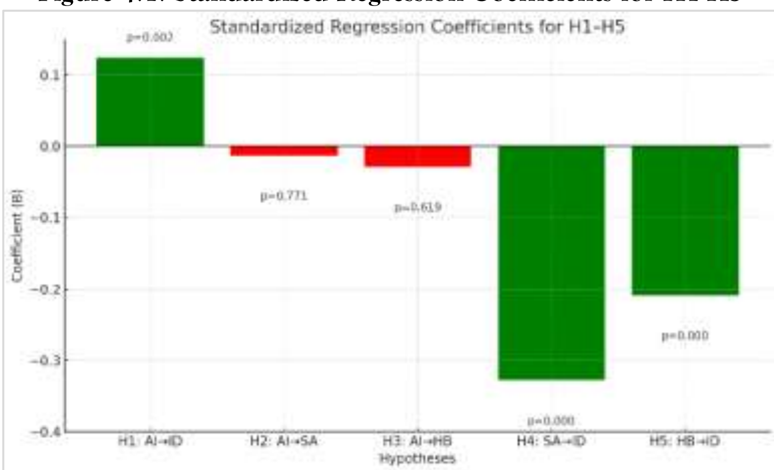
Table 4.7: Regression Results for H5 – Hindsight Bias Predicting Investment Decisions

Statistic	Result	Interpretation
R Square	0.093	Hindsight bias explains 9.3% variance.
F	35.611, p=0.000	Model significant.
Coefficient (B)	-0.209, p=0.000	Significant negative effect.

For the fifth hypothesis, which states that the hindsight bias plays a significant role in affecting the investment decisions, the regression analysis presents that the hindsight bias contributes to 9.3 % variance in the investment decisions (R^2 = 0.093). The regression coefficient of hindsight bias is -.209 (p = .000) and is statistically significant and negative.
Thus, **H5 is accepted**.

Figure 4.1: Standardized Regression Coefficients for H1-H5



Mediation Analysis (PROCESS Model 4)
H6a: Hindsight Bias Mediates AI Innovation → Investment Decisions

Table 4.8: Mediation Results for H6a – Hindsight Bias as Mediator

Step	Coefficients	Result
AI innovation → Hindsight bias (a path)	-0.029, p=0.619 (ns)	Not significant
Hindsight bias → Investment decisions (b path)	-0.2058, p=0.000	Significant negative
Indirect effect	0.0060, BootLLCI=-0.0210, BootULCI=0.0328	CI includes zero → ns
Direct effect (c')	0.1176, p=0.002	Significant positive

Likewise, hypothesis H6a which referred to the fact that hindsight bias mediates the connections between AI innovation and investment decisions was checked through mediation analysis. The hindsight bias does not mediate the association between AI innovation and practices (path is not significantly; B = -0.029, p = 0.619) nor the indirect effect of AI innovation on practices (indirect effect is not significant; B = 0.0060, BootLLCI = -0.0210, BootULCI = 0.0328).
Thus, **H6a is rejected**.

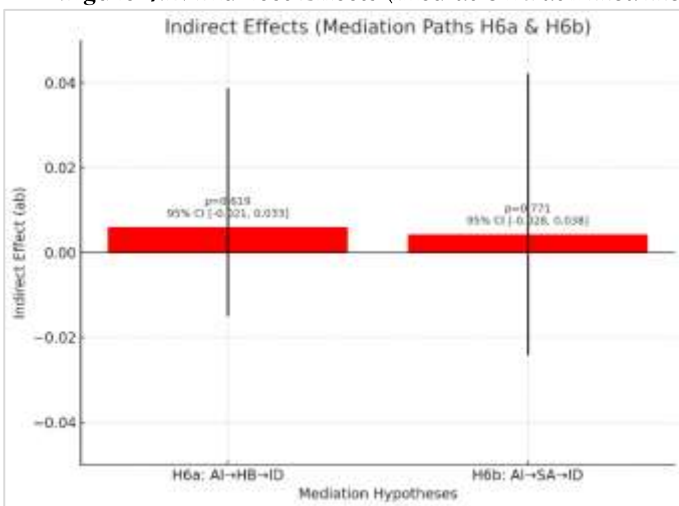
H6b: Self-Attribution Bias Mediates AI Innovation → Investment Decisions

Table 4.9: Mediation Results for H6b – Self-Attribution Bias as Mediator

Step	Coefficients	Result
AI innovation → Self-attribution bias (a path)	-0.0132, p=0.7709 (ns)	Not significant
Self-attribution bias → Investment decisions (b path)	-0.3254, p=0.000	Significant negative
Indirect effect	0.0043, BootLLCI=-0.0284, BootULCI=0.0379	CI includes zero → ns
Direct effect (c')	0.1194, p=0.0013	Significant positive

The sixth hypothesis (H6b), stating that self-attribution bias mediates the relationships between AI innovation and investments decisions, was tested using mediation analysis. The results show that the path from AI innovation to self-attribution bias is not-significant (B = -0.013, p = 0.7709). Therefore, the indirect effect of AI innovation through self-attribution bias on investment decisions is not significant (B = 0.0043, BootLLCI = -0.0284, BootULCI = 0.0379).
Thus, **H6b is rejected**.

Figure 4.2: Indirect Effects (Mediation Path H6a-H6b)



5.4 Summary of Results

The regression and mediation models assist in finding the correlation between the variables:

Table 4.10: Summary of Hypothesis Testing Results

Hypothesis	Path	Result
H1	AI Innovation → Investment Decisions	Accepted
H2	AI Innovation → Self-Attribution Bias	Rejected
H3	AI Innovation → Hindsight Bias	Rejected
H4	Self-Attribution Bias → Investment Decisions	Accepted
H5	Hindsight Bias → Investment Decisions	Accepted
H6a	AI → HB → ID (Indirect)	Rejected
H6b	AI → SA → ID (Indirect)	Rejected

5. DISCUSSION AND CONCLUSION

Interpretation of Findings

This paper set out to find out how AI innovation impacts the decision-making process of retail investors, focusing on the mediating roles of self-attribution bias and hindsight bias. The findings depicted the anticipated and unanticipated results, the distribution of interaction between AI tools and cognitive biases in investment behavior. The hypothesis that AI innovation positively affects investment decisions (H1) was supported. This finding aligns with the existing literature, which suggests that AI tools, particularly those offering predictive insights, can be used to improve the decision-making process through data-based suggestions. The power of AI to handle large volumes of information and generate real-time insights can significantly aid retail investors in making more informed, objective choices. Although the effect size is modest (r = 0.165), the positive relationship demonstrates that AI tools do, to some extent, improve investment decisions. This finding supports the notion that AI can reduce human error and cognitive overload, thus helping investors navigate complex financial environments more effectively. Contrary to expectations, the study found no significant influence of AI innovation on self-attribution bias (H2) and hindsight bias (H3). These results suggest that, while AI tools may enhance decision-making in terms of providing data-driven insights, they do not seem to significantly alter investors' psychological tendencies toward these biases. In other words, AI innovation does not appear to mitigate or exacerbate these biases in the retail investors in this study. This finding may have several reasons; one of these reasons could be that, in line with the advanced capabilities of the AI tool, investors might intensively base their interpretations of AI suggestions on their own decision-making skills and past experiences. Moreover, investors are unlikely to trust the technology yet, and when implemented, they might view AI-based results, as yet another component in the tower of factors that affect their decision analysis and not a game-changer. The results of Self-attribution biases (H4) and hindsight biases (H5) are similar with the findings mentioned in previous studies, indicating that the two biases adversely affect the quality of investment decisions. It was also demonstrated that Self-attribution bias harms investment decisions and that the bias is confirmed, as those investors/retailers who attributes a success to their own abilities and failures to the outside world make worse decisions. This result is in line with those of the earlier studies, which have noted that this bias results in such issues as overconfidence and taking more risks (Dawson, 2020). An analogous effect, that is, a negative effect on investment decisions has also been observed as to the hindsight bias and this was also in conformity with the literature that underlines that the hindsight bias distorts the perception of risk of investors and hinders the likelihood of investors to learn on the basis of their errors (Hussain et al., 2013). The findings of non-support of the mediation hypothesis (H6a and H6b) is substantial. The mediators of the relationships between AI innovation and investments decisions (Self-attribution and hindsight biases) did not prove significant. To put simply, the self-attribution and hindsight bias analyses as mediators in the correlation between AI innovation, and investment choices do not show a statistically significant effect. That is to say that as much as these biases can work to influence the manner in which individuals perceive and respond to new technological applications, they do not in any organized manner work to alter the general distribution of capital. It can be supposed that although AI innovation directly affects investment decision, its relationship is not significantly mediated by cognitive biases of self-attribution and hindsight bias. One of the interpretations would be that AI innovation is mainly an instrument to offer objective data and investor bias, although affecting their judgement, don't have a significant effect overall impacts of AIs on decision-making. This is to say, the investors can still follow AI suggestions but their psychological biases will still continue to inform how the investors make of interpretation the suggestions given by AI.

Link to Literature

The study is conclusive in giving evidence to develop the literature of the study of AI innovation, behavioral finance and investment cognition biases. The question of AI as an aid to decision-making has been explored in multiple key aspects (Rastogi et al., 2020) and the given research outcome is an elaboration of the findings of the studies above with the implementation of the relationship within AI tools and psychological priorities. It can also be added that the paper provides an addition to literature on the self-attribution and hindsight bias in making financial decisions and assists in proving the premise that both mentioned biases can distort the rationality in investment decision-making (Yuksel & Metin, 2025; Tariq, 2025). Further, the findings of this study must show that, although AI applications can contribute to improvement in decision-making, the latter does not suggest that there would be reduced cognitive biases on the part of the retail investors. This contradiction highlights the whole perception of human to AI interaction and declares that there is a necessity to know more about the ways how AI systems can be created to deliver not only data driven decision making but also the psychology of the investors.

Conclusion

The paper has served as an eye opener in not only the domain of AI innovation but also, the biases in investment decisions. The use of AI tools can enhance better investment decisions, they do not seem to target cognitive biases like self-attribution bias and hindsight bias directly. Even with comprehensive AI-based tools in their line-up, retail investors still make trading decisions based on their psychological dispositions. The fact demonstrates the complexity of the human behavior in personal financial decision-making and implies that AI cannot be provided as a single tool that will move biases away. These results also highlight the significance of including psychological factors and technological advancements in the decision-making processes. Although the AI innovation is capable of extend useful data and information, the human-psychology aspect remains at the center stage of investment choice. Future studies ought to examine ways in which AI tools can be advanced to take into consideration such biases, maybe by focusing on more transmissible AI versions or by integrating mitigation of cognitive biases into tools that advance AI.

Implications of the Study

The theoretical implications of the study take into account the significance of AI innovation in the development of cognitive bias in behavioral finance, where reality of the human psychology is of the essence. The practical implications illustrated that creators of AI are expected to create the instruments that not only provide data-driven insights but also resolve the predispositions or pre-conceptions through explainable AI and continuous feedback streams thereof, and promote sanity and bias-free investment on the part of the investors (Rana et al., 2023).

Recommendations

Based on the findings of the current research, the AI developers and retail investors are recommended the following in order to enhance their investment decisions and alleviate the effects of self-attribution biases and hindsight biases.

I. To minimize biases like self-attribution and hindsight bias, AI systems are to be made as explainable and transparent as possible.
II. The developers are recommended to develop AI models that will be able to identify cognitive errors in the users (e.g. overconfidence) and make corrective proposals.
III. The behavioral insights need to be integrated into AI tools to determine the patterns of investor behavior modification, as well as determine how to influence more rational decisions.
IV. To understand how cognitive biases such as self-attribution and hindsight bias affect the decision-making process, retail customers need to be trained on such biases.
V. The investors should make a personal decision based on personal goals, risk tolerance, and market knowledge, though they are wanted to apply AI as one of the trader assisting tools, which cannot be fully trusted.

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