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BETWEEN BIAS AND PERCEPTION: UNDERSTANDING INVESTMENT DECISIONS IN THE AGE OF ROBO ADVISORS

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Abstract
Psychological biases have a significant impact on how investors process information perceive risks and assess investment opportunities. Through the mediating function of risk perception this study attempts to investigate the impact of confirmation bias conservatism bias overconfidence bias availability bias and loss aversion bias on investment decision making. Additionally the study looks into how risk perception and investment decision-making are influenced by the perceived usefulness of robo advisors. A self-administered questionnaire was used to gather data from 133 individual investors in Pakistan through purposive sampling. To test the suggested relationships the study used AMOS and SPSS for Structural Equation Modeling (SEM). Prior to assessing the structural relationships the measurement models validity and reliability were evaluated using Confirmatory Factor Analysis (CFA). While confirmation bias conservatism bias overconfidence bias and loss aversion bias did not exhibit significant effects availability bias was found to have a significant impact on risk perception. It was discovered that risk perception significantly improved investment decision-making underscoring the significance of risk perception in influencing investor behavior. The findings imply that investors who rely significantly on current and easily accessible information typically perceive higher levels of investment risk which subsequently influences their investment choices. By combining several cognitive and behavioral biases into a single framework and presenting data from an emerging economy this study adds to the body of literature on behavioral finance. By highlighting the significance of enhancing risk assessment procedures and lessening the impact of behavioral biases on investment decisions the findings provide useful implications for

investors financial advisors fintech companies and policymakers.

INTRODUCTION

Investment decision making directly impacts investors wealth portfolio performance and long term financial well being it has garnered significant attention in the finance literature. Financial markets offer a wide range of investment options such as exchange traded funds stocks bonds mutual funds and other financial assets. As a result it is now crucial for investors financial institutions and policymakers to comprehend the elements that affect investment choices. Conventional theories of finance especially the Efficient Market Hypothesis (EMH) make the assumption that investors act rationally and base their choices on all available information (Fama, 1970). According to this viewpoint investors find it challenging to regularly generate abnormal returns because market prices accurately reflect all pertinent information.

Researchers have consistently noted that investors do not always act logically despite the presumptions of traditional finance. According to Barberis and Thaler (2003) rather than using objective analysis investors often make decisions based on their emotions personal beliefs and cognitive limitations. In a similar vein Pompian (2017) pointed out that psychological variables frequently skew investors assessments and result in systematic mistakes in decision making. Because of this traditional financial theories are insufficient to explain many investment decisions. It is now even more crucial to comprehend investor behavior due to the increasing complexity of financial markets.

The investment landscape has been drastically changed by social media digital trading platforms mobile investment apps and technological advancements. According to Kulkarni et al. (2025) by making financial information and investment opportunities more accessible technological developments have boosted investor participation. However processing and assessing investment options has become more challenging due to the abundance of information. Similarly, Falsetti (2025) contended that although digital platforms make investing easier they do not completely eradicate the behavioral inclinations that affect investors choices.

The field of behavioral finance which integrates psychology and finance to explain how people make financial decisions in everyday life emerged as a result of these constraints. When making investment decisions investors frequently rely on heuristics feelings and subjective assessments according to behavioral finance (Barberis & Thaler, 2003). Pompian (2017) also noted that investors often display predictable behavioral patterns that impair their capacity to assess information impartially. As a result behavioral biases are now a significant topic of study in contemporary finance research.

The way that cognitive and behavioral biases affect investor judgment and decision making processes is explained by behavioral finance theory. Specifically loss aversion is a behavioral bias related to investors responses to gains and losses while confirmation bias conservatism bias overconfidence bias and availability bias are cognitive biases that impact information processing. The inclination of investors to ignore contradicting evidence in favor of information that confirms their preexisting beliefs is known as confirmation bias. The Ahmad et al. (2022) discovered that investors who are impacted by confirmation bias frequently develop excessive confidence in their assessments as a result of their selective attention to positive information. Investors may be unable to properly evaluate investment risks and opportunities as a result of such behavior.

Investors also frequently exhibit conservatism bias. Sharma (2024) asserts that investors with a conservatism bias are frequently hesitant to change their minds when new information becomes available. Rather they rely too much on past events and historical data. Due to this delayed response market conditions and investment risks may be incorrectly assessed. Ahmad et al. (2022) found that investors capacity to adapt to shifting financial environments is impacted by conservatism bias.

Another well known factor influencing investment behavior is overconfidence bias. Overconfident investors tend to overestimate their knowledge and forecasting skills according to Odean (1998). According to a more recent study by Rahmat (2024) overconfident investors often engage in excessive trading activities and underestimate investment risks. Over time such behavior could lower investment performance and increase exposure to financial losses.

When investors heavily rely on information that is readily available or recently encountered this is known as availability bias. Tversky and Kahneman (1973) first proposed that people frequently base their decisions on information that immediately comes to mind rather than carrying out thorough analyses. Chishti et al. (2025) discuss the financial markets. discovered that when making investment decisions investors frequently rely on current news conversations on social media and easily accessible information. As a result availability bias may lead to poor investment decisions and erroneous risk assessments.

One of the most important ideas in behavioral finance is loss aversion bias which is derived from prospect theory. People feel the anguish of losses more strongly than the joy of comparable gains as Kahneman and Tversky (1979) showed. As a result when faced with possible losses investors frequently become overly cautious. Loss averse investors often steer clear of risky investment opportunities and may hold onto losing investments in an effort to prevent suffering losses according to Rahmat (2024) (Farooq & Moon, 2025). These biases have an impact on investors perceptions of risk in addition to their direct influence on investment decisions.

An individuals subjective evaluation of the uncertainty and possible losses connected to an investment opportunity is known as risk perception. Weber et al. (2002) contended that because investors assess possible risks prior to allocating financial resources risk perception is a critical factor in determining financial behavior. Ahmad et al. (2022) added that behavioral biases affect investors perceptions of risk which in turn affects investment decisions indirectly. As a result risk perception could be a crucial link between behavioral biases and the process of making investment decisions.

New tools designed to enhance the quality of financial decisions have been introduced by recent technological advancements. The robo advisor an automated investment platform that employs data analytics machine learning and artificial intelligence to offer tailored investment recommendations is one example of this innovation. According to Eichler and Schwab (2024) robo advisors provide more systematic and objective investment advice than conventional advisory methods. Additionally Kulkarni et al. (2025) found that by using data driven decision making procedures robo advisors can lessen the impact of cognitive and emotional biases.

The use of robo advisors has grown dramatically in recent years especially among investors who are tech savvy. Falsetti (2025) discovered that robo advisory services promote more disciplined investing behavior and increase investment efficiency. As a result by offering unbiased advice and minimizing behavioral distortions robo advisors may have an impact on the relationship between investors perceptions of risk and their investment choices.

Behavioral finance has become especially significant in developing nations like Pakistan. Investor participation in financial markets has increased due to the quick growth of fintech solutions digital financial services and online trading platforms. Nonetheless many investors still rely on subjective assessments when making investment decisions and financial literacy rates are still comparatively low. As a result in developing financial markets as opposed to more developed ones behavioral biases may have a greater impact on investor behavior.

The relationship between behavioral biases and investment decision making has been the subject of a sizable body of literature but there are still a number of significant research gaps. First rather than investigating several biases concurrently within a thorough framework numerous studies have concentrated on individual behavioral biases separately (Ritika & Kishor, 2021) (Ahmed et al. (2022). Second not much research has looked into how risk perception functions as a mediator in the explanation of how behavioral biases affect investment decisions especially in emerging markets (Ahmed et al., 2022) (Moon, 2026). Third the moderating function of perceived usefulness of robo advisors is still largely unexplored in behavioral finance research particularly in developing nations like Pakistan despite the quick development of financial technology (Back et al., 2023) (Kulkarni et al., 2025). .

Lastly very few studies have combined risk perception and perceived usefulness of robo advisors availability bias loss aversion bias confirmation bias conservatism bias and overconfidence bias into a single framework. These gaps show that in the context of contemporary financial markets a more thorough understanding of investor behavior is required.

Thus using risk perception as a mediating factor the current study investigates the impact of confirmation bias conservatism bias overconfidence bias availability bias and loss aversion bias on investment decision making. The study also looks into whether perceived usefulness of robo advisors have an impact on how risk perception and investment decision making are related. The study aims to add to the body of knowledge and offer useful insights for investors financial institutions fintech companies and policymakers by fusing behavioral finance principles with contemporary financial technology.

Investors often make decisions in uncertain and risky situations investment decision making has long been a topic of interest in finance. According to conventional finance theories investors make decisions that optimize expected returns after processing information rationally (Fama, 1970). Nonetheless researchers studying behavioral finance have consistently maintained that investors dont always act rationally. Psychological biases frequently affect how investors interpret data and assess investment opportunities claim Barberis and Thaler (2003). In a similar vein Pompian (2017) proposed that emotional reactions and cognitive constraints often lead to deviations from logical decision making behavior.

Confirmation bias conservatism bias overconfidence bias availability bias and loss aversion bias are just a few of the behavioral biases that have been found to affect investor behavior in an increasing amount of research. Ahmad et al. (2022) discovered that investors information processing and assessment of investment opportunities are influenced by confirmation bias. Similarly overconfidence and loss aversion have a big impact on investment related decisions according to Rahmat (2024) (Farooq & Moon, 2025). Even though earlier research has demonstrated the significance of these biases the majority of studies have looked at each one separately rather than examining their combined impact within a thorough framework.

The role of risk perception is another area where the literature currently in publication is lacking. The Weber et al. (2002) highlighted that investors do not assess risk objectively but rather subjectively. Recently Ahmad et al. (2022) proposed that risk perception could be a key way that behavioral biases affect investment choices. Despite this finding there are still not many empirical studies looking at risk perceptions mediating function.

Investment decision making now takes into account new factors due to the growing use of financial technology. Automated investment platforms known as robo advisors have become popular offering investors recommendations based on algorithms. According to Eichler and Schwab (2024) robo advisors can enhance decision quality by lessening the impact of cognitive biases and emotions. As a result Kulkarni et al. (2025) discovered that advisory systems powered by technology might promote more impartial investing practices. Nevertheless there is still little empirical data on the moderating function of robo advisors in behavioral finance frameworks especially in developing nations.

The problem is especially pertinent in Pakistan where more investors are participating in financial markets as a result of easier access to digital financial services. Despite these advancements a lot of investors still struggle with issues like behavioral biases market volatility and financial literacy. Thus it is necessary to look into how risk perception is influenced by behavioral biases and whether perceived usefulness of robo advisors can mitigate this relationship. In addition to adding to the body of knowledge on behavioral finance addressing these problems will benefit investors financial institutions fintech companies and legislators.

This study aims to investigate the connections between investor biases risk perception and investment decision making in light of the identified research gaps and the growing significance of comprehending investor behavior in contemporary financial markets. In order to accomplish this goal the following research objectives and questions have been developed..

RO1: To investigate how investor biases affect how risk is perceived.

RO2: To look into how investment decision-making is impacted by risk perception.

RO3: To evaluate how investor biases risk perception and investment decision-making are related.

RQ1: How do investor biases affect how risk is perceived?

RQ2: Does risk perception affect how investors make decisions?

RQ3: How do investor biases perceptions of risk and decision-making about investments interact?

2. Theoretical Background

Behavioral finance theory and prospect theory serve as the main theoretical foundations for this study. These theories offer significant explanations for why investors often stray from logical decision making procedures and how psychological elements affect financial behavior. In order to clarify the role of artificial intelligence in investment decision making the increasing use of robo advisors is also examined from the standpoint of technology enabled decision support.

2.1 Behavioral Finance Theory

In response to the shortcomings of conventional financial theories behavioral finance theory was developed. Conventional methods like the Efficient Market Hypothesis make the assumption that investors act logically process information effectively and make choices that optimize utility (Fama, 1970). Nonetheless a number of studies have shown that investors often make choices that cannot be justified by logical economic hypotheses.

When assessing financial data investors frequently rely on heuristics and psychological shortcuts claim Barberis and Thaler (2003). Pompian (2017) posited that investment decisions are often influenced by emotions personal experiences and cognitive biases. Investors may misinterpret information underestimate risks and make poor financial decisions as a result of these influences.

Because it explains the existence and consequences of confirmation bias conservatism bias overconfidence bias availability bias and loss aversion bias behavioral finance theory thus offers a suitable foundation for the current investigation. The theory provides a helpful viewpoint for comprehending how investors create perceptions and make investment decisions because these behavioral biases make up the independent variables of the suggested framework.

2.2 Prospect Theory

Kahneman and Tversky (1979) created prospect theory to explain how people make decisions when faced with uncertainty. By showing that people assess gains and losses differently the theory refuted the presumptions of Expected Utility Theory. People tend to focus more on possible losses rather than just final results.

Kahneman and Tversky (1979) discovered a phenomenon called loss aversion which states that losses typically have a greater psychological impact than comparable gains. This observation has grown to be one of behavioral finances most important ideas. Loss averse investors are more likely to avoid risk when faced with possible gains and to become risk seeking when trying to recover losses according to later research (Pompian, 2017) (Farooq & Moon, 2025).

Because prospect theory offers a theoretical explanation for the connection between loss aversion risk perception and investment decision making it is especially pertinent to the current investigation. According to the theory investors sensitivity to possible losses shapes their perceptions of risk which in turn affects how they make investments.

2.3 Robo Advisors and Technology Based Decision Support

Investment practices have undergone a substantial transformation due to the swift progress of financial technology. The rise of robo advisors which use algorithms artificial intelligence and data analytics to make automated investment recommendations is one of the most significant developments (Jung et al., 2018) (Moon, 2026).

Robo advisors in contrast to traditional financial advisors depend on methodical and impartial decision making procedures. According to Eichler and Schwab (2024) these systems promote more logical investment choices and lessen emotional influences. Likewise Kulkarni et al. (2025) found that robo advisors help investors avoid typical behavioral biases and increase the consistency of investment recommendations.

From the standpoint of behavioral finance robo advisors could be a significant tool for curbing irrational investment behavior. As a result robo advisors are included in this study as a moderating factor that could affect how risk perception and investment decision making are related.

2.4 Theoretical Foundation of the Proposed Framework

The suggested framework explains how psychological biases affect investment decision making by combining Prospect Theory and Behavioral Finance Theory. Confirmation bias conservatism bias overconfidence bias availability bias and loss aversion bias are all explained by behavioral finance theory whereas prospect theory explains how investors view risk and react to uncertainty.

The study suggests that behavioral biases impact investors perceptions of risk which in turn impact investment decision making based on these theoretical viewpoints. Additionally in line with current research on fintech (Eichler & Schwab, 2024) (Kulkarni et al., 2025) the study makes the assumption that by lessening the impact of behavioral distortions robo advisors could assist investors in making more objective decisions. As a result it is anticipated that robo advisors will moderate the connection between investment decision making and risk perception.

The current study offers a thorough framework for comprehending investor behavior in modern financial markets by fusing behavioral finance concepts with technology driven investment support systems.

3. Literature Review and Hypothesis Development

3.1 Confirmation Bias and Risk Perception

The propensity for people to look for evaluate and retain information that confirms their preexisting beliefs while disregarding evidence to the contrary is known as confirmation bias (Nickerson, 1998). Investors in the financial markets frequently look for information that supports their prior investment choices and steer clear of information that contradicts them. Investors may consequently form prejudiced opinions about the risk and performance of their investments.

According to behavioral finance research investors perceptions of investment risks and their evaluation of market information may be skewed by confirmation bias. Because they concentrate mostly on data that confirms their expectations investors who suffer from confirmation bias frequently underestimate possible risks. This could result in erroneous risk assessments and bad investment choices (Ahmad et al., 2022) (Moon et al., 2026). According to recent research confirmation bias has a major impact on investor behavior and risk assessment in the financial markets (Sharma, 2024; Chishti et al., 2025) (Moon, 2026). Based on the above discussion, the following hypothesis is proposed:

H1: Confirmation Bias significantly influences Risk Perception.

3.2 Conservatism Bias and Risk Perception

The term conservatism bias describes investors propensity to gradually change their opinions in response to new information. Investors who are impacted by this bias are hesitant to incorporate new market information into their decision making process and instead continue to rely on prior beliefs (Edwards, 1968). Investors may respond slowly to shifting economic conditions and new risks in the financial markets due to conservatism bias. Investors may be unable to accurately assess current investment risks because they rely too much on historical data. According to earlier research conservatism bias impacts how information is processed and how investors perceive risk and uncertainty (Ahmad et al., 2022) (Moon et al., 2026). As a result investors who are biased toward conservatism may view investment risks in a different way than logical investors.Consequently, investors exhibiting conservatism bias may perceive investment risks differently compared to rational investors.

H2: Conservatism Bias significantly influences Risk Perception.

3.3 Overconfidence Bias and Risk Perception

In behavioral finance one of the most researched biases is overconfidence bias. It describes investors propensity to overestimate their expertise aptitude and capacity to forecast future market movements (Odean, 1998). Investors who are overconfident frequently think they have better knowledge and experience. As a result they frequently overestimate anticipated returns and underestimate risks. Because they think their judgments are more accurate than those of other investors these investors often engage in excessive trading and take greater investment risks (Rahmat, 2024). A substantial correlation between risk perception and overconfidence bias has been discovered in a number of empirical investigations. According to Ahmad et al. (2022) investors who exhibit higher levels of overconfidence are more inclined to invest in risky assets and perceive lower levels of investment risk. Therefore, the following hypothesis is proposed:

H3: Overconfidence Bias significantly influences Risk Perception.

3.4 Availability Bias and Risk Perception

According to Tversky and Kahneman (1973) availability bias happens when investors base a large portion of their investment decisions on information that is readily available current or memorable. Investors frequently rely on easily accessible data from social media news outlets financial blogs and market rumors rather than performing in depth analyses. The real state of the market may not always be accurately reflected in such data. As a result investors might have false impressions of investment opportunities and related risks. According to recent research availability bias has a substantial impact on investors assessments of risk. Investors perception of market risk and uncertainty is influenced by their propensity to overestimate the significance of recent events and readily accessible information (Chishti et al., 2025) (Moon et al., 2026). Therefore, the following hypothesis is proposed:

H4: Availability Bias significantly influences Risk Perception.

3.5 Loss Aversion Bias and Risk Perception

The tendency for people to feel losses more strongly than gains of comparable size is known as loss aversion bias which has its roots in prospect theory (Kahneman & Tversky, 1979). Loss aversion affected investors prioritize avoiding losses over making gains. As a result they frequently develop a high level of sensitivity to possible investment risks and may steer clear of opportunities involving uncertainty. Even when logical analysis indicates otherwise investors occasionally hold onto losing investments in order to prevent suffering losses. Loss aversion has been shown to have a consistent impact on investors perceptions of risk and uncertainty. Stronger loss aversion tendencies are typically associated with higher perceived investment risk and more cautious investment behavior (Rahmat 2024) (Ahmad et al. 2022) (Moon et al., 2026). Accordingly, the following hypothesis is proposed:

H5: Loss Aversion Bias significantly influences Risk Perception.

3.6 Risk Perception and Investment Decision Making

According to Weber et al. (2002) risk perception is an investors subjective assessment of the uncertainty and possible losses connected to an investment opportunity. Because investors typically assess risks before allocating their financial resources risk perception is crucial to the decision making process. While investors with lower risk perceptions are more likely to invest in risky assets investors with higher risk perceptions typically adopt conservative investment strategies. According to research in behavioral finance investors perceptions of risk have a big impact on their choices. According to a number of studies investment behavior and financial decision making are significantly influenced by risk perception (Ahmad et al. 2022).Therefore, the following hypothesis is proposed:

H6: Risk Perception significantly influences Investment Decision Making.

3.7 Mediating Role of Risk Perception

According to behavioral finance theory investors decisions are indirectly influenced by cognitive biases through psychological processes. Risk perception is one such mechanism. Investors who are impacted by behavioral biases typically view and assess investment risks differently which has an impact on their investment choices. According to recent research risk perception plays a significant mediating role between behavioral biases and investment decision making (Ahmad et al. 2022). Consequently it is anticipated that the relationship between behavioral biases and investment decision making will be mediated by risk perception.

H6a: Risk Perception mediates the relationship between Confirmation Bias and Investment Decision Making.

H6b: Risk Perception mediates the relationship between Conservatism Bias and Investment Decision Making.

H6c: Risk Perception mediates the relationship between Overconfidence Bias and Investment Decision Making.

H6d: Risk Perception mediates the relationship between Availability Bias and Investment Decision Making.

H6e: Risk Perception mediates the relationship between Loss Aversion Bias and Investment Decision Making.

3.8 Moderating Role of Robo Advisor

Robo advisors are technology driven investment platforms that use data analytics algorithms and artificial intelligence to automatically recommend investments (Jung et al., 2018). By providing unbiased data driven investment advice robo advisors have revolutionized contemporary investment practices. In contrast to human investors who are frequently swayed by feelings and cognitive biases robo advisors employ methodical techniques that may lessen irrational decision making. According to recent research robo advisors enhance investment results by assisting investors in making more informed decisions and evaluating risks more objectively. Therefore depending on how much investors rely on robo advisory services risk perceptions ability to influence investment decision making may differ.Accordingly, the following hypothesis is proposed:

H7: Robo Advisor moderates the relationship between Risk Perception and Investment Decision Making

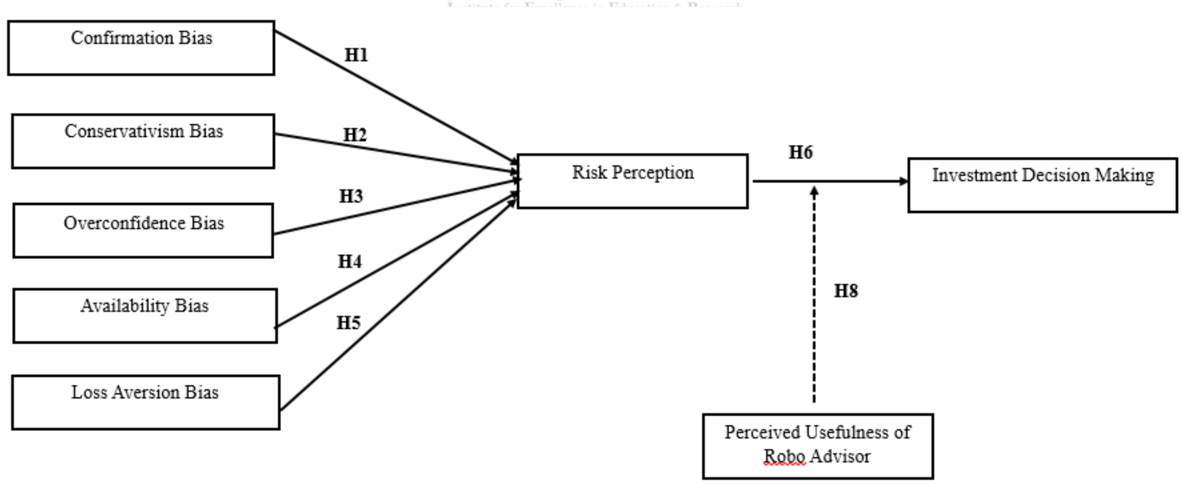

Figure.3.1 Conceptual Framework

4. Methods

4.1 Sample

The studys target population consisted of Pakistani individual investors who had previously made financial market investment decisions. People who invest in stocks mutual funds savings instruments real estate cryptocurrencies and other investment avenues are among these investors. Only respondents with prior investment experience were deemed eligible to participate in the study which focuses on investor behavior and decision-making practices. Studies in behavioral finance that look into how psychological biases affect investment choices have used comparable investor-based samples (Ahmed et al., 2022) (Ritika & Kishor, 2021). Purposive sampling was used to gather information from investors who fit the requirements for selection. An online survey was used to gather data and it was disseminated through personal contacts professional networks investment communities and social media sites. Google Forms was used to administer the questionnaire and participation was completely voluntary. 133 valid responses in all were collected and analyzed. Because prior researchers advise a minimum sample size of 133 observations for trustworthy model estimation and hypothesis testing the sample size is deemed sufficient for Structural Equation Modeling (SEM) (Kline, 2016) (Hair et al. 2019) (Moon et al., 2025). Additionally SEM research in behavioral finance has effectively examined connections between investor biases risk perception and investment decisions using comparable sample sizes (Ahmed et al. (2022).

4.2 Measures

The measurement scales utilized in this research were taken from previously approved tools found in the literature on financial technology investment decision-making and behavioral finance. A five-point Likert scale with 1 denoting strongly disagree and 5 denoting strongly agree was used to gauge each item. Four items that were modified from earlier behavioral finance research that looked at investors propensity to look for information that confirms their preexisting beliefs while ignoring contradicting information were used to measure confirmation bias (Ritika & Kishor, 2021). Five items representing investors reliance on easily accessible information and current events when making investment decisions were used to measure availability bias (Ritika & Kishor, 2021). Four items that captured investors overconfidence in their forecasting and investment expertise were used to measure overconfidence bias (Ritika & Kishor, 2021). Four items measuring investors propensity to retain preexisting beliefs and underreact to new information were used to measure conservatism bias (Ritika & Kishor, 2021). Four items representing investors inclination to avoid losses rather than obtain comparable gains were used to measure loss aversion bias which is consistent with prospect theory (Kahneman & Tversky, 1979) (Ritika & Kishor, 2021) (Moon, 2026). Items modified from Ahmed et al. (2022) were used to gauge risk perception. who examined how risk perception functions as a mediator between investors behavioral biases and investment choices. When making investment decisions investors subjective assessments of uncertainty perceived investment risk and risk-related concerns are captured by this scale. Items modified from recent financial technology and robo-advisory literature were used to gauge the perceived usefulness of robo advisors. According to Abdul Manaf Ismail and Zakaria (2025) the scale assesses the degree to which investors view robo-advisors as helpful dependable effective and advantageous for enhancing financial planning and investment choices. Seven items that were modified from earlier research on investment behavior were used to measure investment decision making. These items evaluate investors capacity to weigh options choose viable investment opportunities and make well-informed decisions (Ahmed et al., 2022) (Moon et al., 2024). The adopted instruments have shown respectable levels of validity and reliability and have been widely used in earlier research. To ensure clarity and appropriateness for the Pakistani investment context while maintaining the items original conceptual meaning minor wording changes were made as needed.

4. 3 Procedure

A self-administered online survey was used to gather data. Respondents were assured that their answers would be kept private and anonymous before taking part in the study. Respondents were free to stop taking the survey at any time and participation was completely voluntary. Studies on investment decision-making involving individual investors and behavioral finance have extensively used similar methods (Ahmed et al., 2022). A variety of online platforms such as professional communities WhatsApp networks investment forums and social media groups were used to disseminate the questionnaire. The survey could only be completed by those who attested to having prior investment experience. A final sample of 133 usable questionnaires was kept for additional analysis after the data was screened and incomplete responses were eliminated.

4.4 Data Analysis Procedures

IBM SPSS Statistics and AMOS were used for data analysis. At first SPSS was utilized for reliability evaluation demographic analysis descriptive statistics and data screening. Before moving on to additional analysis the dataset was checked for missing values outliers and normality. To guarantee the quality and appropriateness of data for multivariate analysis screening processes are crucial (Hair et al. 2019. In accordance with Anderson and Gerbings (1988) recommendations a two-step Structural Equation Modeling (SEM) method was used. First the measurement model and construct validity were assessed using Confirmatory Factor Analysis (CFA) (Byrne 2016). Factor loadings Cronbachs Alpha Composite Reliability (CR) Average Variance Extracted (AVE) and discriminant validity measures were used to assess the constructs validity and reliability in accordance with Hair et al. [2019]. The suggested relationships between the research variables were examined in the second step by evaluating the structural model. The significance and strength of the proposed relationships were assessed using path coefficients critical ratios and significance values. All statistical tests were set to have a significance level of p 0. 05. The results of the measurement and structural models are shown in the next chapter.

5. Results and Discussions

The dataset was checked for outliers missing values and problems with normalcy before the data analysis was done. The answers were reviewed to make sure they were accurate and comprehensive. The dataset did not contain any notable missing values. Skewness and kurtosis values were used to measure normality and they were found to be within the acceptable range suggested by Hair et al. as of 2019. Additionally tolerance values and the Variance Inflation Factor (VIF) were used to evaluate multicollinearity. The findings confirmed that there was no multicollinearity among the study variables since all VIF values were below the suggested threshold of 10 and tolerance values were greater than 0. 10. The potential for common method bias (CMB) was taken into consideration because the study used a self-administered questionnaire. Respondents were guaranteed anonymity and confidentiality in order to minimize this problem and the questionnaires items were thoughtfully arranged to minimize response bias. The results of Harmans single-factor test showed that no single factor could account for the majority of the variance indicating that common method bias was not a significant concern in the study.

5. 1 Sample Demographics.

A total of 133 legitimate responses from Pakistani individual investors were gathered. Gender age education level and investment experience were among the demographic details collected. There were both male and female investors in the sample. A wide range of age groups educational backgrounds and degrees of investment experience were represented among the respondents..

5.2 Structural Equation Modeling

To test the suggested research framework the study used Structural Equation Modeling (SEM) with AMOS. The measurement model was first assessed using Confirmatory Factor Analysis (CFA) to determine the validity and reliability of the constructs in accordance with the two-step procedure suggested by Anderson and Gerbing (1988). Average Variance Extracted (AVE) and factor loadings were used to evaluate convergent validity while Cronbachs Alpha and Composite Reliability (CR) were used to examine internal consistency. The Fornell and Larcker (1981) criterion was utilized to assess discriminant validity. The structural model was evaluated to test the suggested hypotheses after the measurement models suitability was determined. Commonly used fit indices such as Chi-square/df Comparative Fit Index (CFI) Tucker-Lewis Index (TLI) Goodness-of-Fit Index (GFI) and Root Mean sq. Error of Approximation (RMSEA) were used to assess model fit. The relationships between confirmation bias conservatism bias overconfidence bias availability bias loss aversion bias risk perception perceived utility of robo advisors and investment decision making were then investigated using the structural model.

5.2.1 Confirmatory Factor Analysis

Using AMOS Confirmatory Factor Analysis (CFA) was used to analyze the measurement model and determine the constructs validity and reliability. In accordance with Byrnes (2016) and Hair et al. In order to enhance the measurement model items with low factor loadings and poor explanatory power were eliminated (2019). The retained items showed satisfactory representation of their respective constructs as evidenced by acceptable factor loadings and squared multiple correlations (SMC). The CFA results are shown in Table 1. While SMC values varied from 0. 083 to 0. 545 factor loadings varied from 0. 288 to 0. 738. With item loadings ranging from 0. 608 to 0. 738 Risk Perception showed the highest degree of consistency among its measurement items among the retained constructs. In a similar vein Investment Decision Making showed acceptable loadings between 0. 596 and 0. 690. For a later reliability and validity evaluation the indicators that were kept were deemed adequate. in line with Hair et al. s recommendations. (2019) Cronbachs Alpha (α) Composite Reliability (CR) Average Variance Extracted (AVE) and discriminant validity measures were used to further investigate construct reliability and validity.

Convergent and Discriminant Validity (5. 2). According to the recommendations made by Fornell and Larcker (1981) Hair et al. Cronbachs Alpha (α) Composite Reliability (CR) and Average Variance Extracted (AVE) were used to assess construct reliability. (2019) as well as Bernstein and Nunnally

(1994). Table 2 presents the results. The results show strong internal consistency for Risk Perception (α = 0. 81 CR = 0. 80) and Perceived Usefulness of Robo Advisor (α = 0. 94 CR = 0. 93). Additionally Investment Decision Making (α = 0. 72 CR = 0. 72) showed respectable reliability. Confirmation bias availability bias overconfidence bias conservatism bias and loss aversion bias on the other hand had reliability values that were significantly below the suggested thresholds. However because these constructs have been extensively employed in earlier behavioral finance research and represent theoretically significant aspects of investor behavior they were kept (Ritika & Kishor, 2021). Factor loadings and AVE values were used to evaluate convergent validity. Risk Perception (AVE = 0. 45) Investment Decision Making (AVE = 0. 41) and Perceived Usefulness of Robo Advisor (AVE = 0. 68) showed comparatively stronger convergent validity despite several constructs reporting AVE values below the ideal threshold of 0. 50. Similar results have been documented in behavioral finance research where theoretically significant constructs were kept in spite of low AVE values because of their acceptable reliability and conceptual relevance (Hair et al. 2019). Using the Fornell-Larcker criterion discriminant validity was evaluated. The square root of AVE values (diagonal elements) was typically higher than the matching inter-construct correlations as Table 2 illustrates. Additionally Hair et al. s critical threshold of 0. 85 was not met by the correlations between constructs. (2019). Consequently the findings offer plausible proof that the constructs are empirically unique and assess various theoretical ideas.

Table 1. Results of Confirmatory Analysis

SN	Items	Factor Loadings	SMC	Mean	SD
Confirmation Bias(CB)					
CB1	I am not selective in collecting information about my investments.	0.288**	0.08	2.85	**1.2**
CB2	I value positive information more than negative information regarding my investment choices.	0.719**	0.52		
CB4	I ignore information that does not match my beliefs regarding my investment decisions.	0.534**	0.29		
Availability Bias (AB)					
AB1	Information from my close friends and relatives is a reliable reference for my investment decisions.	0.455**	0.21	3.49	**0.9**
AB2	While considering an investment, I put more weight on its recent performance.	0.616**	0.38		
AB4	I consider the recent performance of a security before investing.	0.472**	0.22		
Overconfidence Bias (OCB)					
OCB1	I cannot predict future prices of my investments better than others.	0.599**	0.31	3.02	1
OCB3	I am confident in my ability to make investment decisions better than others.	0.387**	0.15		
OCB4	I have complete knowledge of various investment opportunities.	0.58**	0.34		
Conservatism Bias (CON)					
CON1	I do not easily change my investment decisions once they are made.	0.677**	0.46	3.61	1
CON2	I stick to old information because future outcomes are uncertain.	0.604**	0.37		
CON4	I prefer relying on previously formed opinions rather than immediately accepting new information.	0.581**	0.34		
Loss Aversion Bias (LAB)					
LAB1	I do not avoid an investment when I fear a loss.	0.291**	0.09	3.42	**0.6**
LAB2	I never sell an investment at a loss because I expect it will improve eventually.	0.435**	0.19		
LAB3	Losing Rs. 1,000 is more painful than the happiness gained from earning Rs. 1,000.	0.648**	0.42		
Risk Perception (RP)					
RP1	I believe investments with higher returns usually involve higher levels of risk.	0.698**	0.49	3.96	**0.7**
RP2	I perceive investment risks as an important factor when making investment decisions.	0.714**	0.51		
RP3	I carefully assess the potential risks and rewards before investing.	0.608**	0.37		
RP4	The possibility of financial loss influences my investment decisions.	0.661**	0.44		

RP5	I consider the uncertainty of future returns before making investment decisions.	0.738**	0.55		
Investment Decision Making (ID)					
ID2	I study the risks before making investment choices.	0.69**	0.48	3.51	**0.8**
ID4	I look for the most favourable return from investments.	0.624**	0.39		
ID5	My investment decisions are in accordance with my investment objectives.	0.624**	0.39		
ID6	Expected return and risk are considered together when making	0.596**	0.36		
	.				

Note: SMC = squared multiple correlation, SD = standard deviation

Table 2. Results for convergent and discriminant validity

Variables	α	CR	AVE	1	2	3	4	5	6	7	8
1. Confirmation Bias	0.48	0.54	0.30	**0.55**							
2. Avaliablity Bias	0.48	0.54	0.28	0.588	**0.53**						
3. Overconfidence Bias	0.54	0.55	0.27	0.017	-0.118	**0.52**					
4. Consertavism Bias	0.66	0.66	0.39	-0.220	-0.321	0.496	**0.62**				
5. Loss Aversion Bias	0.46	0.46	0.23	0.047	0.159	0.131	0.113	**0.48**			
6. Risk Perception	0.81	0.80	0.45	0.024	0.204	-0.287	0.032	0.418	**0.67**		
7. Perceived Usefulness of Robo Advisor	0.94	0.93	0.68	0.357	0.388	-0.088	-0.258	-0.119	-0.089	**0.82**	
8. Investment Decision Making	0.72	0.72	0.41	0.389	0.422	-0.143	-0.115	-0.080	0.62	0.69	**0.82**

Note: Diagonal entries (bold) represent the square root of Average Variance Extracted (AVE), while off-diagonal entries indicate the correlations among constructs. The results satisfy the Fornell and Larcker (1981) criterion for discriminant validity. CR = Composite Reliability; α = Cronbach's Alpha; AVE = Average Variance Extracted.

5.2.2 Testing hypotheses and structural models.

The structural model was assessed to look at the suggested relationships between the study variables after determining the measurement models suitability. The structural model results are shown in Figure 1 and the structural model analysis summarizes the regression coefficients. Moderate explanatory power was demonstrated by the models ability to explain roughly 60% of the variance in risk perception (R2 = 0. 60) and 30% of the variance in investment decision making (R2 = 0. 30). In line with Hair et al. (2019) R2 values of this size indicate that the models ability to predict investor behavior is adequate. The findings show that Risk Perception was significantly improved by Availability Bias (β = 1. 644 p). 0. 05) supporting the hypothesis that investors who rely heavily on recent information and readily available information tend to perceive higher levels of investment risk. This finding is consistent with behavioral finance literature which suggests that easily accessible information disproportionately influences investor judgments and risk assessments (Tversky & Kahneman 1974) (Moon et al., 2024). In contrast Confirmation Bias (β = -1. 186 p Risk perception was not significantly affected by Overconfidence Bias (β = 0. 343 p 0. 05) Conservatism Bias (β = 0. 038 p 0. 05) or Loss Aversion Bias (β = -0. 219 p 0. 05). The current findings imply that these biases may have a limited or context-dependent impact on Pakistani investors perceptions of risk despite the fact that prior research has documented significant effects of these biases on investor behavior. Similar discrepancies have been noted in research on emerging markets where a variety of informational cultural and economic factors impact investor behavior (Ahmed et al., 2022). The findings also show that investment decision-making was significantly improved by risk perception (β = 0. 550 p 0. 001). This finding implies that investors are more likely to make well-informed and logical investment decisions if they carefully consider uncertainty potential losses and investment risks. The outcome is consistent with earlier studies that highlight how important risk perception is in influencing investment behavior and financial decision-making processes (Ahmed et al. (2022)) (Moon et al., 2024). All things considered the results only partially validate the suggested framework. Only Availability Bias had a significant impact on Risk Perception out of all the behavioral biases that were looked at and Risk Perception turned out to be a significant predictor of Investment Decision Making. These results emphasize how crucial information accessibility and perceived risk are to comprehending investor decision-making in the Pakistani setting.

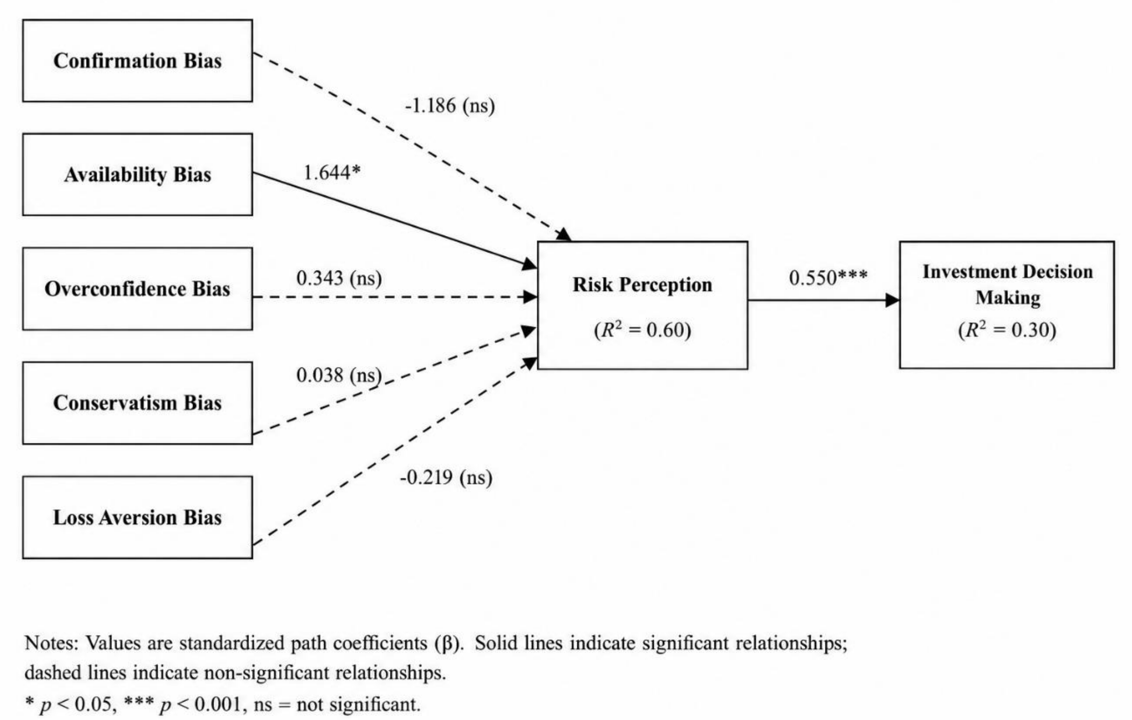

Figure 2. Structure Model

Testing the direct relationships suggested by the framework was the main goal of the current investigation. Future research is advised to address the mediating role of risk perception and the moderating role of perceived usefulness of robo advisors which were not considered in the structural model.

6. Implications

6.1 Theoretical Implications

By analyzing the impact of several investor biases on risk perception and investment decision making within a single framework the current study adds to the body of research on behavioral finance. This study incorporates confirmation bias availability bias overconfidence bias conservatism bias and loss aversion bias to provide a more thorough understanding of investor behavior in contrast to earlier research that concentrated on individual biases separately. The results emphasize how crucial risk perception is as a major factor in making investment decisions. Availability bias was found to have a significant impact on risk perception among the biases examined indicating that investors frequently rely heavily on recent and easily accessible information when assessing investment risks. This result validates the premises of behavioral finance theory which contends that investors frequently make irrational decisions because of psychological biases and cognitive shortcuts. Additionally by offering data from Pakistan a setting that is still understudied in behavioral finance research the study adds to the expanding body of literature on investor behavior in emerging economies. The results advance knowledge of how investors evaluate risk process information and decide which investments to make in emerging financial markets. Therefore by combining investor biases risk perception and investment decision making into a single empirical framework this study enhances the body of behavioral finance literature already in existence.

6.2 Managerial Implications

Investors financial advisors investment firms and fintech companies can all benefit from the studys conclusions. Investment professionals should make sure that investors receive comprehensive impartial and balanced information instead of depending only on current market trends or easily accessible information as availability bias greatly affects risk perception. Investors should be informed by financial advisors about the possible impact of behavioral and cognitive biases on investment choices. Financial literacy campaigns investor awareness programs and educational campaigns may help people identify their prejudices and make better decisions. Additionally brokerage houses and investment firms may create analytical tools and decision-support systems that encourage investors to assess investment opportunities methodically rather than depending on gut feeling or recent experiences. These programs have the potential to lessen prejudice and encourage better-informed investing practices. The findings also show that risk perception has a big impact on how investors make decisions. Financial institutions should therefore create investment products and advisory services that make it easier for investors to comprehend possible risks and returns. Businesses can help investors make more logical and knowledgeable investment decisions by enhancing their ability to assess risk.

6.3 Policymaker Implications

The studys conclusions have significant ramifications for financial market organizations regulators and legislators. Regulators should support investor education and financial literacy initiatives that improve investors comprehension of financial markets and investment risks since investor biases and risk perception affect investment behavior. Organizations like the Pakistan Stock Exchange (PSX) the Securities and Exchange Commission of Pakistan (SECP) and other financial regulatory bodies may create awareness campaigns that highlight common behavioral biases and how they affect investment choices. These programs can assist investors in making more objective and knowledgeable financial decisions. Policymakers should also encourage the responsible use of digital investment platforms and financial technologies that give investors clear accurate and objective information. Enhancing access to trustworthy financial information and fortifying investor protection measures can further improve the caliber of investment choices and help Pakistans financial markets become more effective.

7. Conclusion

This study looked at how Pakistani investors perceived risk and made investment decisions in relation to confirmation bias availability bias overconfidence bias conservatism bias and loss aversion bias. Within the context of behavioral finance the study also examined the connection between risk perception and investment decision making. The results showed that while confirmation bias overconfidence bias conservatism bias and loss aversion bias did not significantly affect risk perception availability bias did. The findings also showed that risk perception has a major impact on investment decision-making emphasizing how crucial it is for investors to evaluate uncertainty and possible losses. All things considered the study offers empirical proof of behavioral finances applicability in explaining investor behavior in developing markets. The results provide valuable insights for investors financial advisors investment firms and policymakers while also advancing knowledge of how psychological biases and risk perception influence investment decisions. By offering evidence from the Pakistani context where research on investor biases and investment behavior is still comparatively scarce the study also contributes to the body of literature on behavioral finance.

8. Limitations

This research has certain limitations just like all empirical studies. First the study used a cross-sectional research design which makes it more difficult to determine how the variables relate to one another. Future research may use longitudinal designs to look at how investor behavior has changed over time. Second only 133 respondents made up the studys comparatively small sample. Even though the sample size was adequate for this analysis larger and more varied samples should be used in future research to increase the findings generalizability. Third self-reported questionnaires were used to gather the data which could lead to response bias and social desirability bias. To gain more unbiased insights into investor behavior future researchers might integrate survey techniques with experimental designs or behavioral data. Fourth because of data and analytical limitations the current study mostly concentrated on direct relationships even though the conceptual framework suggested risk perception as a mediating mechanism and perceived utility of robo advisors as a moderating variable. Future research is encouraged to use larger samples and sophisticated analytical methods like multi-group SEM and bootstrapping to empirically investigate mediation and moderation effects. In order to gain a more thorough understanding of investment decision making in emerging economies future research may examine additional behavioral biases financial literacy investor personality traits technological adoption factors and market conditions.

Future studies could specifically look into whether the relationship between investor biases and investment decision making is mediated by risk perception and whether this relationship is strengthened or weakened by the perceived usefulness of robo advisors. The current study mainly examined the direct relationships between the study variables even though the conceptual framework suggested Risk Perception as a mediating variable and Perceived Usefulness of Robo Advisor as a moderating variable. Mediation and moderation effects were not empirically tested because of sample size and analytical limitations. As a result only direct effects should be considered when interpreting the results. To more thoroughly investigate the mediating role of Risk Perception and the moderating role of Perceived Usefulness of Robo Advisors future research is encouraged to use larger samples and sophisticated SEM techniques like bootstrapping and multi-group analysis.

REFERENCES

Abdul Manaf, S. M., Ismail, M. K. A., & Zakaria, S. (2025). Measuring the use of robo-advisors: A validated scale for Malaysian investors.

Ahmed, Z., Rasool, S., Saleem, Q., Khan, M. A., & Kanwal, S. (2022). Mediating role of risk perception between behavioral biases and investor's investment decisions. SAGE Open, 12(2). https://doi.org/10.1177/21582440221097394

Barberis, N., & Thaler, R. (2003). A survey of behavioral finance. In G. M. Constantinides, M. Harris, & R. M. Stulz (Eds.), Handbook of the economics of finance (Vol. 1, pp. 1053–1128). Elsevier. https://doi.org/10.1016/S1574-0102(03)01027-6

Byrne, B. M. (2016). Structural equation modeling with AMOS: Basic concepts, applications, and programming (3rd ed.). Routledge.

Eichler, K. S., & Schwab, E. (2024). Evaluating robo-advisors through behavioral finance: A critical review of technology potential, rationality, and investor expectations. Frontiers in Behavioral Economics, 3. https://doi.org/10.3389/frbhe.2024.1489159

Falsetti, G. (2025). The impact of AI-driven robo-advisors on decision-making process and personalization of investors (Bachelor's thesis, University of Twente). University of Twente Repository. https://essay.utwente.nl/105120/

Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. The Journal of Finance, 25(2), 383–417. https://doi.org/10.2307/2325486

Farooq, A., & Moon, M. A. (2025). Addicted to the fake: Coaction theory and the psychology behind counterfeit consumption. Pakistan Journal of Commerce and Social Sciences, 19(3), 648–672.

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. Journal of Marketing Research, 18(1), 39–50. https://doi.org/10.2307/3151312

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2019). Multivariate data analysis (8th ed.). Cengage Learning.

Hu, L. T., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. Structural Equation Modeling: A Multidisciplinary Journal, 6(1), 1–55. https://doi.org/10.1080/10705519909540118

Jung, D., Dorner, V., Glaser, F., & Morana, S. (2018). Robo-advisory. Business & Information Systems Engineering, 60(1), 81–86. https://doi.org/10.1007/s12599-018-0521-9

Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. Econometrica, 47(2), 263–291. https://doi.org/10.2307/1914185

Kline, R. B. (2016). Principles and practice of structural equation modeling (4th ed.). Guilford Press.

Kulkarni, M. S., Patil, K. P., & Pramod, D. (2025). The role of robo-advisors in behavioural finance: Shaping investment decisions. Cogent Economics & Finance, 13(1). https://doi.org/10.1080/23322039.2025.2571403

Moon, M. A. (2026). The dark pull of virtual aisles: How interactivity fuels compulsive buying in immersive shopping worlds. Journal of Consumer Behaviour, 25(3), 1414–1431.

Moon, M. A., Majeed, J., & Attiq, S. (2024). Enigma unveiled: Decoding trust and relationship dynamics in the mobile banking sector of an emerging economy. Pakistan Journal of Commerce and Social Sciences, 18(2), 380–407.

Moon, M. A., Malik, M. H., Moin, G., & Abbas, A. (2025). Impact of consumer trust on e-commerce purchase intentions: The role of influencer marketing. Journal of Management Science Research Review, 4(4), 1920–1940.

Moon, M. A., Sajid, A., Bashir, S. S., Saddiqi, A., & Zeeshan, M. (2026). The emotional cost of greenwashing: Airline sustainability advertising and consumer–brand relationships. Journal of Management & Social Science, 3(1), 1–20.

Nickerson, R. S. (1998). Confirmation bias: A ubiquitous phenomenon in many guises. Review of General Psychology, 2(2), 175–220. https://doi.org/10.1037/1089-2680.2.2.175

Odean, T. (1998). Volume, volatility, price, and profit when all traders are above average. The Journal of Finance, 53(6), 1887–1934. https://doi.org/10.1111/0022-1082.00078

Pompian, M. M. (2017). Behavioral finance and wealth management: How to build investment strategies that account for investor biases (2nd ed.). Wiley.

Ritika, & Kishor, N. (2022). Development and validation of behavioral biases scale: A SEM approach. Review of Behavioral Finance, 14(2), 237–259. https://doi.org/10.1108/RBF-05-2020-0087

Tversky, A., & Kahneman, D. (1973). Availability: A heuristic for judging frequency and probability. Cognitive Psychology, 5(2), 207–232. https://doi.org/10.1016/0010-0285(73)90033-9

Weber, E. U., Blais, A. R., & Betz, N. E. (2002). A domain-specific risk-attitude scale: Measuring risk perceptions and risk behaviors. Journal of Behavioral Decision Making, 15(4), 263–290. https://doi.org/10.1002/bdm.414