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PSYCHOLOGICAL DRIVERS OF INVESTMENT BEHAVIOR: EXAMINING OVERCONFIDENCE, SELF-ATTRIBUTION, AND HERDING

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Abstract
The purpose of the present study is to quantify the effect of instrumental biases of over confidence bias, self-attribution bias and herding behavior on investment decisions of business graduates in Lahore city (a city in Pakistan). This study suggests that psychological factors have a role in the creation of financial inefficiencies, rather than classical finance paradigm that assumes rational (economic) behaviour. The research design used was quantitative, cross sectional and the method used was to have 400 business graduates respond to self-completed questionnaires. The measurement model and the structural model was tested by using Partial Least Squares–Structural Equation Modeling (PLS–SEM). Results show that there is a positive significant effect between overconfidence bias and self-attribution bias and herding behavior on investment decisions. The results point to the broad effects of psychological factors on financial choices, particularly in an emerging market where such actions are likely to be greater. The study makes significant theoretical contributions to the behavioral finance by generalizing it up to an under-studied sample in Pakistan, and practical implications for individual investors, financial advisors, regulators, and educational institutes to promote rational and informed investing decisions.

1. Introduction

Conventional financial theories posit that human beings seek to be rational in maximizing utility through money markets (Joo & Durri, 2015). Instead, behavioral finance claims that human mental attitudes, cognitive prejudices and emotional effects act as a barrier to rational decision-making. These heuristics and biases that result in inefficient financial decisions are the foundation for behavioral finance (KIMEU, 2016). Localized these biases are strong among the youth in Pakistan and that is why merit scrutiny to assess their implications for financial wellbeing. Behavioral finance, an inter-disciplinary field of study, examines how and if various psychological factors such as overconfidence have affected their own investment decisions in the literature. One of the founding works regarding this aspect is Kahneman and Tversky's Prospect Theory, a 1979 work that states that people value gains and losses based on their reference point, with loss aversion being paramount (Tian, 2024; Kahneman & Tversky, 1979).

Despite sufficient education in business and finance, training one to analyze risks and returns, all manner of psychological biases continues to stand in the way of rational decision-making. These are the biases that generally creates a resistance among people, specially students for not to invest across various sectors of economy. Accordingly, this research concentrates on the sources of some obvious behavioral biases preventing investment among business students in both public and private universities. The general goal is to provide insights into how these biases affect investor's decisions and to consequently make a contribution in developing strategies that will help investors build more effective decision-making processes for their financial best interest. More specifically, this study aims to examine the impact of overconfidence bias, herding behavior, and self-attribution bias among business students to predict the ways in which these biases influence investment decisions and help enhance more rational financial decisions.

The study addresses three primary research questions:

Q1: What does herding bias affect investment decisions?

Q2: What does overconfidence influence investment decisions?

Q3: What does self-attribution bias influence investment decision-making?

This research fills the gap in Pakistani literature by exploring the investment behaviors of salaried individuals, which have received relatively less attention from scholars. The study elucidates how income levels, saving habits, and expenditure are intrinsically linked with investment decisions. The study also highlights the crucial role of savings for investment funds in Pakistan. The study highlights a general trend of the salaried individual class in terms of the conventional investment avenues that are safe, liquid, tax friendly and retirement oriented. It also pointed out the main problem areas, such as access to information on investment opportunities through formal channels is significantly limited, and lack of understanding of market instruments among potential investors. The results are of great value to a range of stakeholders. Knowing about these behavioral problems will help investors overcome them, leading to more logical investment strategies. The study would provide a good tool for researchers and academicians to assess the decision-making process in order to uncover bias and minimize its effects, while for regulatory authorities, insights gained from the study would help in developing effective policies to reduce the negative impact of identified behavioral factors and create prosperous and sustainable investment environments.

2. Literature Review

2.1 The Concept of Investment and Investment Decisions

Investment essentially involves the strategic commitment of existing financial capital with an explicit anticipation of reaping better returns in the future, based on Adhikari (2020). In essence, it's forward-looking and deals intrinsically with uncertainties by emphasizing time and future possibilities. Investment depends highly on the availability and access to reliable information to a large extent, which is needed in forecasting outcomes to inform decisions. From an economic perspective, investment differs from saving; whereas saving refers to an income that is not consumed, investment refers to the usage of such unconsumed income with an expectation to generate higher returns from it. An investor bases an investment decision on various determining factors: expected profit rates, levels of risk involved, and cost of finance prevailing in the market, among other things, according to Adhikari (2020). Usually, investors reach an investment decision only in the event that the expected profit adequately compensates for such costs and accounts sufficiently for the incurred risk.

Investment decisions are thus those types of choices made by an individual or entity that determine the ways in which their resources are distributed across all types of assets. These decisions are primarily targeted at making a profit or meeting certain financial goals and can thus range across many different asset classes, from shares and bonds to even real estate and new business ventures (Nguyen et al., 2024). It is thus essential to understand the various factors affecting these decisions. Empirical evidence continues to show that investors do consider multi-faceted analyses in the form of comprehensive accounting details related to the respective firm, its public image or reputation, its performance trend, impartial market data, and the relevant government regulations and policies surrounding the investment (Dahal, 2022 This detailed analysis further emphasizes a degree of complexity in the development of an appropriate investment decision that may be more in tune with the investor's expectations for returns to be realized from the investment and the amount of risk tolerance he/she possesses.

But, even with the systematic approaches always in place, there are regular disruptions of traditional financial theories that assume rational decision making and efficient markets, all of which are contradicted by behavioral finance. It is a new field that brings in psychological perspectives: Investors have been found to make irrational decisions due to cognitive biases, emotional responses, and the use of heuristic shortcuts (Gurung et al., 2024).These systematic errors give rise to irrational financial decisions and constitute a central tenet of behavioral finance. The discipline recognizes that individuals can make irrational choices. This is outside the models whereby decisions are based only on all available information to maximize utility (Gurung et al., 2024). According to authors emphasize that investors often make irrational decisions led by psychological biases; understanding them is crucial for developing successful risk management strategies and providing recommendations for individual investments (Gurung et al., 2024; Kanapickienė et al., 2024; Kumar & Goyal, 2015). The majority of classifications of behavioral biases divide them into cognitive biases-developed due to errors in information processing-and emotional ones-developed due to affective states rather than due to the lack of some fact (Kanapickienė et al., 2024; Hidajat, 2019; Marocco & Talamo, 2022). Overconfidence, anchoring effects, loss aversion, and psychological accounting theory are just some key points approached by the cognitive frame (Šobić, 2023; Bhatt et al., 2022; Marocco & Talamo, 2022).

2.2 Conceptual Framework and Theoretical Development

The theoretical foundation of this study lies chiefly in Prospect Theory by Kahneman and Tversky and the Theory of Planned Behavior by Singh et al. within the bounds of the year 2025. Prospect Theory by Kahneman and Tversky challenges expected utility theory on the basis that people value outcomes as gains or losses relative to a reference point, rather than as absolute values. One of the core elements of this theory is loss aversion, where the pain associated with a loss is felt more strongly than the satisfaction from a gain of an equivalent magnitude (Kahneman & Tversky, 1979). This is why people make what seem to be irrational financial decisions like hanging onto a losing investment for too long and being more cautious when there's opportunity to make a profit, but riskier when there's a chance of loss (Ahmad, 2022; Ren, 2024). At the same time, the Theory of Planned Behavior an offspring of the Theory of Reasoned Action is one of the most comprehensive theories that predict behavioral intentions. This theory suggests that a person's action is a function of his attitude toward the action, subjective norm, and perceived behavioral control (Bonna & Amoah, 2020; Singh et al., 2025). TPB describes what the internal psychological factors and external social factors are, and how they combine to form an investor's complex decision making process (Hapsari, 2021).

2.2.1 Overconfidence Bias and Hypothesis Formulation

Overconfidence bias refers to a pervasive cognitive distortion wherein people systematically overestimate their competency, knowledge or the accuracy of their beliefs and forecasts concerning investment outcomes. This bias is generally manifested in the form of overestimation of one's personal abilities, a very optimistic view about potential returns, or a predisposition towards higher risk-taking. Overconfident investors normally consider their judgments on financial securities to be better and more accurate than those of others, which creates exaggerated self-confidence. Such attitudes lead to higher trading activities, which have paradoxically tended to generate lower profits than their less confident counterparts, and also result in inadequate portfolio diversification or poor judgment of investment risks. This pattern has been rooted in an exaggerated belief in one's capacity to generate an accurate judgment, which motivates reliance on one's personal information rather than on objective evidence.

H1: Overconfidence bias has a statistically significant positive effect on investment decisions.

2.2.2 Self-Attribution Bias and Hypothesis Formation

According to research (Athota et al., 2022; Priyadarsini & Prithi, 2023) Self-attribution bias is a type of psychological bias that refers to the attribution of positive outcomes to intrinsic abilities, diligent effort or personal traits and unfavorable ones to factors beyond one's control. For example, when an investor makes a successful stock selection, they may attribute the success to their astute market analysis, while a losing trade is due to unforeseen market volatility or misfortune (Athota et al., 2022). This concept is usually referred to as self-serving bias in psychology. The motive behind this bias is the need to protect self-esteem by externalizing the blame for failures (Athota et al., 2022). In investment situations, these biases compel investors to give credence selectively to information supporting their desired outcomes (Priyadarsini & Prithi, 2023). Whenever investments in various assets happen to lead to failure or financial losses, such situations are often justified as a consequence of uncontrollable external conditions (Anggini et al., 2021). Such distorted perception contributes to confronting difficulties with the objective reevaluation of past decisions and thus to problems in drawing conclusions from errors, further complicating effective self-regulation (Anggini et al., 2021; Naveed & Taib, 2021). Eventually, self-attribution bias may lead to the persistence of flawed patterns of decision-making and an increase in excessive trading or risk-taking behaviors (Wang, 2023).

H2: Self-attribution bias has a statistically significant positive effect on investment decisions.

2.2.3 Herding Behavior and Hypothesis Development

Herding behavior in financial markets is best described as the tendency of individuals to imitate the actions and decisions of a larger group or the majority without conducting independent analysis or checking the rationality of such actions. This is more prevalent in periods of uncertainty in the market, whereby individuals always want to move with the tide rather than their independent judgment impelled by some "fear of missing out" or perceived safety in numbers. In finance, this happens when investors make investment decisions based on the actions of other investors, instead of their own research or fundamental analysis. In the end, there are major inefficiencies in the market, and major price distortions as artificial demand or supply causes the price of assets to fluctuate much from their intrinsic or fundamental value. The two most prevalent forms of herding behaviour are the exclusion of independent evaluation and due diligence and where investors focus more on collective sentiment. It causes overreaction to news in the market, more volatility in the market and poor market performance individually.

H3: Herding Behavior is positively related to investment decisions with strong significance.

3. Methodology

3.1 Sampling and Data Collection

The research design used in this study was quantitative cross-sectional design to investigate the association between behavioral bias and investment decision making of the business graduates in Lahore. The cross-sectional approach was appropriate for this study because data was gathered from many different investors at a single time and was designed to reflect investor behavior at a single point in time. In this respect, the method is an empirically based investigative approach. The population targeted were business graduates of all public and private universities in Lahore, Pakistan who were investors. They have a basic understanding of business and finance and are a vital population to understand the pertinent behavioral factors in their decisions. The sample size was 400 investors and self-administered questionnaires were used for primary data collection. Ethical considerations, such as obtaining prior consent, ensuring confidentiality, and guaranteeing anonymity, were of essence, with the guarantee that all the data collected was solely for academic purposes

3.2 Measures

The research had a structured questionnaire with some constructs each of which was measured using the 5point Likert scale (where '1' indicated Strongly Disagree and '5' indicated Strongly Agree).The use of the ordinal scaling technique in measuring attitudes, perceptions, and behaviors in social sciences has long been recognized (Jebb et al., 2021). In the process of developing constructs and measuring the items, the study adopted the use of items that had been recognized within the pre-existing literature to ensure content validity and reliability, as recommended in the process of measuring scale constructs (Ghalayini & Alkees, 2021), (Jebb et al., 2021). In the table that follows, the details of the variables, number of items, the scaling they used, and the source of the items, are all outlined.

The reliability and validation of the variables within the study had been determined using the necessary and appropriate statistical methods, including the Cronbach Alpha coefficient for the reliability of the constructs and the use of the convergent and discriminant values within the Confirmatory Factor Analysis (Leguina, 2015), (Cheung et al., 2023), (Alfalla-Luque, 2019).

Constructs	No. Of items	Measures	Adoption
Herding Bias	5	5-point Likert scale (1=Strongly Disagree, 5=Strongly Agree)	Adapted from established literature, consistent with best practices in scale development (Ghalayini & Alkees, 2021), (Jebb et al., 2021)
Investment Decision	5	5-point Likert scale (1=Strongly Disagree, 5=Strongly Agree)	Adapted from established literature, consistent with best practices in scale development (Ghalayini & Alkees, 2021), (Jebb et al., 2021)
Overconfidence Bias	5	5-point Likert scale (1=Strongly Disagree, 5=Strongly Agree)	Adapted from established literature, consistent with best practices in scale development (Ghalayini & Alkees, 2021), (Jebb et al., 2021)
Self-Attribution Bias	5	5-point Likert scale (1=Strongly Disagree, 5=Strongly Agree)	Adapted from established literature, consistent with best practices in scale development (Ghalayini & Alkees, 2021), (Jebb et al., 2021)

4. Empirical Finding

This section discusses the overall empirical results extracted from the Partial Least Squares Structural Equation Modeling technique performed using the SmartPLS 3 tool. As is the best practice in PLS-SEM studies, the procedure began with the evaluation of the measurement model for constructing the constructs in terms of reliability and validity, followed by the testing of the structural model for examining the proposed relationships among the constructs. The proper and intensive utilization of the above-cited methodologies enables an in-depth investigation of the role of overconfidence bias, self-attribution bias, and herding in the investment decisions among the targeted business graduates in Lahore. The findings of this study provide important empirical support that contradicts the general assumption of rational choice in financial markets and helps in achieving an in-depth understanding of the psychology of the investors in an emerging country like Lahore, Punjab, Pakistan.

4.1 Common Method Bias

"Common method bias is a potential problem in studies that use self-reported data via questionnaires because correlated constructs could be spuriously prone to inflation due to common method variances attributable to the methodological source rather than the underlying construct relationships (per se) (Cervellati et al., 2024), (Greenleaf et al., 2017). In order to address the problem and check the degree to which CMB could affect the findings, certain methodological and statistical techniques are generally applied. These methodological processes involve checking anonymity in collecting data, using distinct predictor and criterion variables, and varying response formats. These factors are considered in the data collection method to eliminate the possibility of biased outcomes (Greenleaf et al., 2017), (Leguina et al., 2015). Statistically speaking, Harman's single factor test or the entire collinearity test is usually applied in the PLS-SEM method. Although the test outcomes related to CMB will not be separately outlined in the present documentation, the scrupulous use of stringent evaluation criteria related to the measurement model contributes to the methodical diminution of the CMB effect in the findings (Alfalla-Luque et al., 2019), (Henseler et al., 2016). The successful demonstration of distinct constructs through these rigorous tests suggests that CMB is not a significant confounding factor in the reported relationships.

4.2 Measurement Model Assessment

An examination of the measurement model is a fundamental starting point within the context of PLS-SEM, providing assurance on whether the theoretical constructs are properly captured by their respective items (Henseler et al., 2016). This subsequent task entails a careful consideration in regard to individual item reliability, internal consistency reliability, convergent validity, and discriminant validity. Positive findings in this phase offer assurance on the fact that the measured constructs are reliable and a proper reflector of their respective constructs, thus forming a proper platform for analysis in regard to the structural relationships. The subsequent subsections present the findings in this phase, using information communicated in the tables and figures.

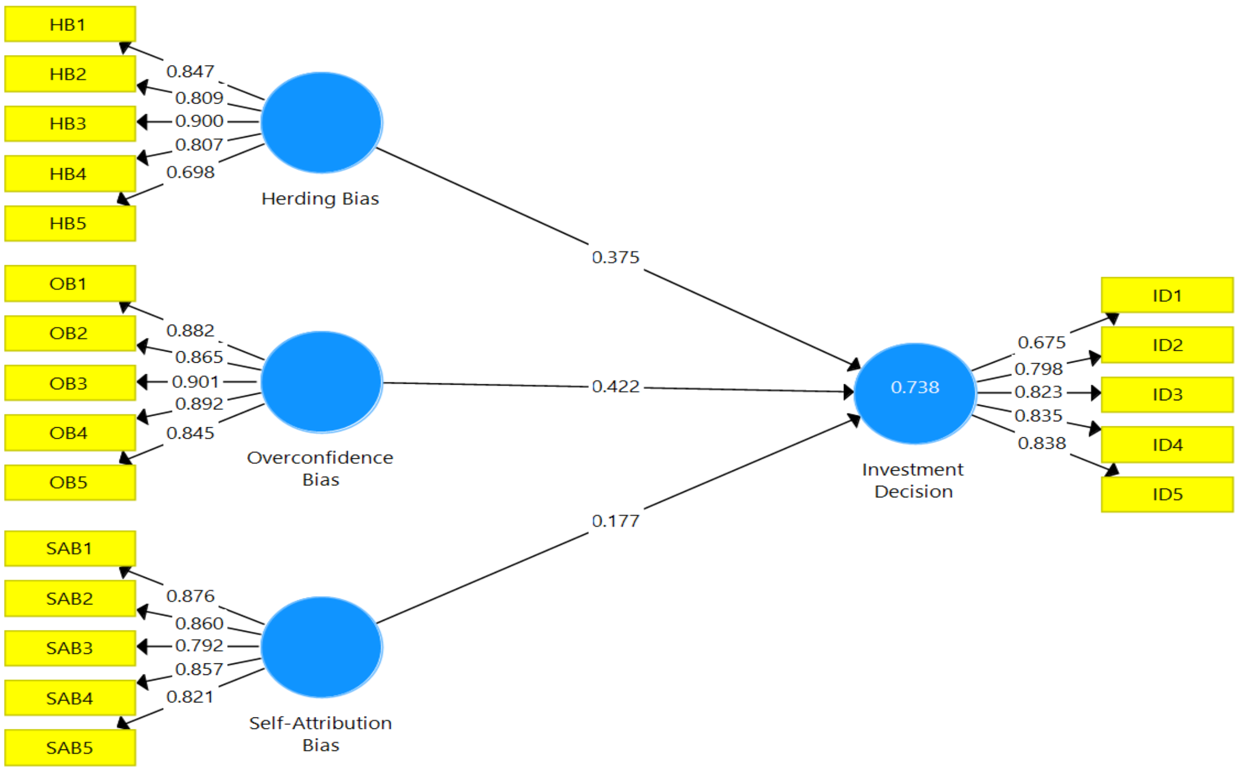

Figure 1. Measurement Model developed by Smart PLS Software

Figure 1 graphically displays the complete measurement model, showing the relationships among the latent variables and their various observed indicators. Each latent construct is represented by arrows pointing to its multiple measurement items, meaning that different facets of the latent concept are shown within each measure. Figure clearly illustrates visually how the theoretical constructs are operationalized through questionnaire items. It serves as a comprehensive overview of constructs and their indicators, offering a clear conceptual map of the variables to be investigated before the statistical results are presented. The visual view enables researchers to rapidly assimilate how the model is designed and how the data collection instrument is structured.

Table 2: Convergent Validity

Construct	Cronbach's Alpha	rho_A	CR	AVE
Herding Bias	0.872	0.879	0.908	0.664
Investment Decision	0.854	0.857	0.896	0.634
Overconfidence Bias	0.925	0.927	0.943	0.770
Self-Attribution Bias	0.897	0.901	0.924	0.708

Table 2 "Construct Reliability and Validity" reports the key statistics for the internal consistency reliability and convergent validity of constructs. Internal consistency was measured using Cronbach's Alpha and Composite Reliability. Results reveal that Cronbach's Alpha and CR values of all constructs were well above the conventional threshold of 0.70, reflecting excellent internal consistency. It therefore implies that items measuring the same construct are highly inter-correlated and consistently indicate one and the same underlying concept. Convergent validity was checked by using the Average Variance Extracted. The AVE values of all the constructs exceeded the cut-off threshold of 0.50, which indicates that more than 50% of the variance of the items of each construct is explained by the construct itself. These strong results for reliability and convergent validity confirm that the measurement items are reliable and consistently reflect their intended constructs.

Table 3: Discriminant Validity

	Herding Bias	Investment Decision	Overconfidence Bias	Self-Attribution Bias
Herding Bias	0.815			
Investment Decision	0.769	0.796		
Overconfidence Bias	0.631	0.768	0.877	
Self-Attribution Bias	0.722	0.710	0.623	0.842

In the "Discriminant Validity: Fornell-Larcker Criterion" given in Table 3, it is seen what the empirical uniqueness of the given constructs stands. According to the Fornell-Larcker criterion, the square root of the AVE of the constructs should be greater than the largest correlation among the constructs. In this case, the diagonal elements are the square root of the AVE, and the other elements are the correlations among the constructs. The result has shown that the diagonal elements are greater than the other elements in the rows and columns of all the constructs. This result is an indication that the discriminant validity of the model is highly supported, and it is clear that the given latent constructs are unique.

4: Discriminant Validity

	Herding Bias	Investment Decision	Overconfidence Bias	Self-Attribution Bias
Herding Bias				
Investment Decision	0.890			
Overconfidence Bias	0.708	0.863		
Self-Attribution Bias	0.815	0.810	0.679	

Table 4, entitled "Discriminant Validity: Heterotrait-Monotrait Ratio" provides a much more meaningful interpretation regarding discriminant validity than the traditional Fornell-Larcker test. The HTMT ratio measures the ratio of average heterotrait-heteromethod correlations to average monotrait-heteromethod correlations. To provide satisfactory discriminant validity, it is ideal if all HTMT ratios are less than 0.90, preferably all less than 0.85 (Henseler et al., 2014), (Alfalla-Luque, 2019). Examining Table 4, it appears that all ratios are significantly lower than the measure of 0.90. Again, this indicates, in a most persuasive fashion, that all constructs in this research framework are decidedly different, measuring nothing in common. Both the discriminant validity measures, therefore, point conclusively toward a high quality measurement framework.

Table 5: Cross Loadings

	Herding Bias	Investment Decision	Overconfidence Bias	Self-Attribution Bias
HB1	0.847	0.591	0.493	0.636
HB2	0.809	0.654	0.435	0.575
HB3	0.900	0.685	0.550	0.643
HB4	0.807	0.656	0.528	0.561
HB5	0.698	0.529	0.581	0.522
ID1	0.624	0.675	0.495	0.542
ID2	0.638	0.798	0.567	0.673
ID3	0.558	0.823	0.657	0.498
ID4	0.669	0.835	0.632	0.592
ID5	0.568	0.838	0.698	0.518
OB1	0.548	0.713	0.882	0.540
OB2	0.523	0.691	0.865	0.562
OB3	0.585	0.668	0.901	0.565
OB4	0.605	0.676	0.892	0.592
OB5	0.504	0.617	0.845	0.468
SAB1	0.624	0.644	0.548	0.876
SAB2	0.635	0.639	0.573	0.860
SAB3	0.471	0.535	0.427	0.792
SAB4	0.663	0.603	0.567	0.857
SAB5	0.634	0.557	0.493	0.821

Table 5, showing the "Cross Loadings," serves as an excellent basis for evaluating individual item reliability and contributing to overall discriminant validity. This table shows the outer loadings of each indicator on its own theoretically assigned latent variable and, at the same time, its loadings on all other latent variables in the model. For strong individual item reliability, loading on the construct of an indicator should be 0.708 or higher. This means the item explains more than 50% of the variance in its construct (Alfalla-Luque, 2019). Importantly, an indicator loading on its construct must become significantly higher compared to its cross-loadings with other constructs. As can be seen from the results in Table 5, all indicators demonstrate outer loadings above the threshold of 0.708 on their respective constructs, while these loadings are consistently higher than the respective cross-loadings. This pattern indicates excellent individual item reliability and further reinforces the discriminant validity that each item works well in effectively measuring its intended construct rather than other constructs in the model.

4.3 Structural Model Assessment

After the confirmation of the measurement model, the next procedure in PLS-SEM analysis is the evaluation of the structural model. This entails examining the proposed relationships between the latent variables and estimating the overall predictive relevance of the structural model (Mahat & Hanafiah, 2020), (Subhaktiyasa, 2024). The evaluation of the structural model is essentially concerned with examining the significance of the path coefficients, which portray the strength and direction of the relationships between the variables. However, bootstrapping, a non-parametric resampling method utilizing 5,000 resamples, was used in this research to estimate the T-statistics and p-values for testing the significance of those path coefficients in the structural model

(Rasoolimanesh & Ali, 2018), (Solmaz et al., 2024). The path coefficients in the structural model would be significant if their T-statistic values exceed 1.96 and the accompanying p-values are less than 0.05.

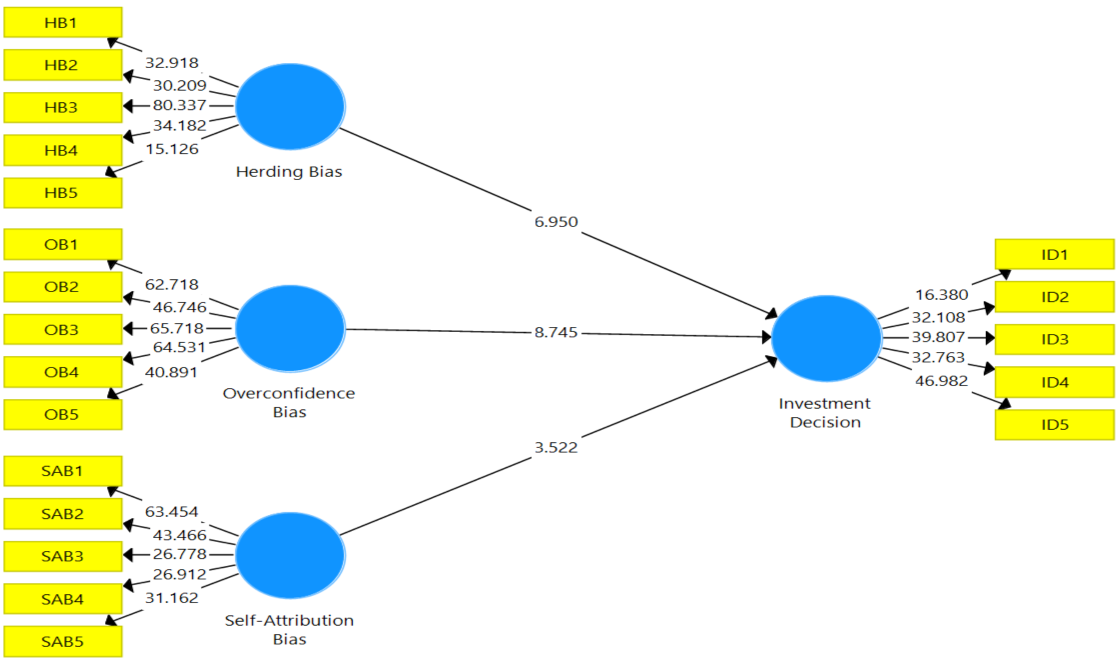

Figure 2. Structural Model developed by Smart PLS Software

Figure 2 gives a pictorial presentation of the hypothesized structural relationships between the behavioral biases and Investment Decisions. From this figure, one sees that latent constructs appear as nodes, while the arrows show the hypothesized directional paths from the predictor biases to the Investment Decision. Each arrow in this structural model has a path coefficient attached to it, normally a beta value, which indicates the estimated strength and direction of a specific relationship and its statistical significance, usually represented by asterisks or numerical p-values. This figure also includes the R-squared value for the endogenous variable, which is a visual display of the amount of variance explained by the predictor variables. This figure is a comprehensive visual summary of both the theoretical framework and the empirical findings from the structural analysis, thus allowing the reader to obtain an overview of the main findings with just one glance.

Table 6: Path Coefficients

Hypothesis	Beta	Standard Deviation	T Value	P Values	LL	UL	Remarks
Herding Bias -> Investment Decision	0.376	0.054	6.950	0.000	0.275	0.481	Significant
Overconfidence Bias -> Investment Decision	0.419	0.048	8.745	0.000	0.326	0.516	Significant
Self-Attribution Bias -> Investment Decision	0.178	0.050	3.522	0.000	0.081	0.268	Significant

Table 6, with the title "Path Coefficients," displays the main results of the test of the hypotheses using the structural model. This table describes the values of the path coefficients, standard deviation, T-value, and p-value for each assumption, with the last column bearing the title "Remarks" that describes the significance of the results. For H1, Overconfidence Bias positively influences investment decisions, and the result for the path coefficient is 0.419, the T-value is 8.745, and the p-value is 0.000. There is no doubt that the result supports the hypothesis since the p-value is well below 0.05.

For H2: Self Attraction Bias is positively influencing the investment decisions, the path coefficient is 0.178, the T-value is 3.522, and the p-value is 0.000. This further reveals the great support for H2 and shows the positive impact on the investment decisions. Finally, for H3: Herding Behavior is also positively influencing the investment decisions, the path coefficient is 0.376, the T-value is 6.950, and the p-value is 0.000. As the p-value is 0.000, H3 is also highly supported. This reveals the positive impact on the investment decisions.

All the abovementioned results have shown that there is a statistically significant positive impact of all three hypothesized behavioral biases.

5. Discussion and Implications

This study explores the significant impact of overconfidence bias, self-attribution bias, and herding behavior on investment decisions made by business graduates in Lahore, Pakistan. The empirical analysis, carried out through Partial Least Squares Structural Equation Modeling, provides valuable insight into how these various psychological factors intrinsically mold individual investment behavior, thus invalidating the traditional assumption of rational decision-making in financial markets. The results strongly suggest a significant positive influence of each bias on the investment decisions of those surveyed, further emphasizing the pervasive role of psychological phenomena in financial contexts (Karki et al., 2024; Priyadarsini & Prithi, 2023; Robin & Angelina, 2020).

It proves that Overconfidence Bias significantly influences investment decisions positively; its prevalence underlines the need for investors to increase their self-awareness. This also corresponds with previous findings that overconfident investors are often observed to trade more actively and make higher levels of risk, impelled by an inflated confidence in one's judgment of self-ability (Pramita et al., 2023; Nkukpornu et al., 2020). In line with the literature, the study finds a significant positive impact of Self-Attribution Bias on investment decisions. It has been suggested in the literature that such bias impedes objective learning from failures because it links failures to external causes rather than internal accountability (Athota et al., 2022; Anggini et al., 2021; Naveed & Taib, 2021). The consequence is an erroneous persistence of decision-making patterns.

Moreover, from the analysis, it can be seen that the Herding Behavior significantly influences investment decisions. Strong statistical significance of herding behavior underlines the omnipresent influence in the investment environment, which often leads to market inefficiencies and increased price movements, especially in situations with information asymmetry (Awuor, 2017; Robin & Angelina, 2020; Xia & Madni, 2024). In emerging economies like Pakistan, access to transparent and reliable market information may not be adequate; hence, there will be more bias towards collective sentiment, leading to stronger herd influences. The overall predictive power of Investment Decision by the model indicates that the three behavioral biases together explain a major portion of variance in investment decisions and further support the predictive relevance of the model for out-of-sample data.

The above collective findings underscore the significance of the fact that investment choice is not altogether a rational process, and this is particularly true in the case of business graduates who have basic sector knowledge. The results of this research offer conclusive evidence of the postulate of the significance of psychological factors in reaching financial decisions in an emerging market. The mechanisms by which overconfidence, self-Attribution, and Herd behavior affect investment decisions have helped this research shed a new light on the subject of psychological factors and their universality in reaching financial decisions.

5.1 Theoretical Contributions

This research extends the theoretical frontier in behavioral finance by explaining investor behavior in emerging markets. By empirically verifying the significant impacts of overconfidence bias, self-attribution bias, and herding behavior on investment decisions among business graduates in Lahore, the study widens the applicability and generalizability of the theories of behavioral finance to a demographic and geographic context that has remained comparatively underexplored until now (Singh et al., 2024). These findings further solidify the central propositions of Prospect Theory (Kahneman & Tversky, 1979) and the Theory of Planned Behaviour (Singh et al., 2025) by demonstrating precisely how cognitive and emotional biases, as described by these theoretical frameworks, impact real investment decisions. The research thus provides basic empirical support about the nature of subjective risk and return perceptions, and perceived behavioral control, which influences financial decision-making and provides a better theoretical lens for future research.

5.2 Practical Implications

The findings of this study have several implications for a wide range of stakeholders in the financial system. Individual investors, particularly new graduates of business studies, are better able to recognize and actively overcome these biases, which will help them be more disciplined and evidence-based in their approaches to investing (Sachdeva & Lehal, 2023; Athota et al., 2022). The insights gained could also be used by financial advisors and financial institutions in devising selective programs in financial literacy and tailored advice, considering the psychological makeup of their clients, thus promoting more rational and well-informed decision-making. Interventions by regulators and policymakers to enhance market transparency and improve financial literacy could further reduce reliance on herding behavior and enhance the investor base (Ahmed et al., 2022).

5.3 Limitations and Directions for Future Research

The study has several limitations, which also delineate some productive avenues for future research. First, the cross-sectional design constrains causal inferences and the examination of how behavioral biases and investment decisions evolve over time; hence, longitudinal studies are recommended. Second, the sample consists exclusively of business graduates living in Lahore, Pakistan, which inhibits the scope of generalizing findings to wider populations, other investor segments, or other emerging markets. Future studies should expand the scope to include respondents from different educational backgrounds, income levels, and professional experiences. Finally, the study relies on self-reported data collected through questionnaires. Even though there was an effort to minimize the common method bias, such data might still be prone to social desirability bias or mistakes in self-perception, hinting at the potential value of incorporating objective measures of investment decisions in the future (Hair et al., 2018).

5.4 Concluding Remarks

This present study presents strong empirical support for overconfidence bias, self-attribution bias, and herding behavior as having significant positive effects on the investment decisions of business graduates in Lahore, Pakistan. The findings reveal an urgent need to include psychological insights within financial decision-making frameworks beyond the traditional paradigm of the rational agent, based on complete rationality. By fully explaining the omnipresence of these behavioral biases, this study makes valuable theoretical contributions to views about investor behavior in emerging markets and provides actionable implications for individual investors, financial practitioners, policymakers, and educators. Ultimately, heightened awareness and systematic mitigation of these biases can yield more informed and rational investment outcomes, contributing to improved financial well-being across the investment landscape.

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