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Decoding Individual Investors' Behavior: Unveiling Risk Perception as a Mediator in the Indian Stock Market

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Abstract

The current study examines how overconfidence, herding, underconfidence, and risk perception influence the investment decisions made by individual investors. Additionally, it delves into the mediating role of risk perception in these relationships. The researchers collected 410 responses from individual investors in southern India using a structured questionnaire, and the hypotheses were tested using partial least squares structural equation modeling (PLS-SEM). The results indicate that overconfidence and risk perception significantly influence investors' decision-making. Analyzing how underconfidence, herding, and overconfidence influence investment decisions, in scenarios with and without considering risk perception, revealed that risk perception serves as a partial mediator in the link between overconfidence and investment decision-making. Whereas it fully mediates the link between herding, under confidence, and investors' decision-making. This research provides significant insights to aid in mitigating these biases in decision-making. More importantly, it also enhances an understanding of biases and risk perception in investment decisions, which could be beneficial for individual investors, investment advisors, portfolio managers, and policymakers engaged in the stock market. This study is the first to link the variables of overconfidence, herding, under confidence, and risk perception with investors' decision-making, although numerous studies have examined prominent biases and their impact on investors' decision-making.

Keywords: Herding, Individual Investors, Overconfidence, PLSpredict, Risk Perception, Underconfidence.

Introduction

Traditional finance theories, such as Markowitz's principle of Modern Portfolio Theory, Modigliani and Millar's Arbitrage Pricing process, Sharpe, Lintner, and Black's Capital Asset Pricing Model, and the Option Pricing theory introduced by Black, Scholes, and Merton (1). According to these theories, investors are presumed to make well-informed decisions, and that the financial markets are efficient, indicating that stock prices correctly reflect all relevant information (1, 2). These presumptions are grounded on the expected utility theory and efficient market hypothesis (2). But in reality, investors behave irrationally; they buy stocks without considering their fundamental value, follow the stocks purchased by friends, hold onto losing stocks while selling winning stocks, set their investment decisions on previous performance, and trade excessively (3). Traditional finance theories are incapable of explaining stock market bubbles, crashes, and anomalies (2). An alternative to standard finance theories, a new field emerged called behavioral finance. Prospect theory was developed through a critique of expected utility theory, setting the base for the discipline of behavioral finance (4). Behavioral finance tries to understand investors' psychology and explain how it influences investment decisions (5). Behavioral finance researchers suggest that many behavioral biases have a substantial effect on individual investors' decision-making (6, 7). Bias is a natural tendency to make mistakes in decision-making (8). Research on behavioral finance has shown that investors often make poor investment decisions due to behavioral biases (9, 10). Investors tend to make irrational decisions driven by emotions and feelings (11). Research on investors' decision-making is significant for understanding the behavioural components that influence investment decisions and, consequently, impact the stock market (12). Individual investors are less informed and more prone to making bad investment choices than institutional investors because individual investors are vulnerable to behavioural biases (13). Researchers in behavioural finance have mainly concentrated on

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how biases influence investors' decision-making (6, 7, 14). To the authors' knowledge, no existing research has examined how risk perception mediates the relationships of herding, overconfidence, and underconfidence with investors' decision-making. There is a crucial need to explore the effect of biases on investment decision-making by incorporating mediator variables to gain deeper insights into how psychological factors influence investment decisions, especially in developing markets (3). While a substantial body of literature has focused on investor behavior in developed financial markets, emerging markets remain relatively underexplored (1, 15–17). This research gap is significant because emerging markets often exhibit distinct characteristics, such as higher volatility and evolving regulatory frameworks that can lead to different investment dynamics compared to their developed counterparts. Additionally, factors like cultural nuances, economic instability, and varying levels of financial literacy in these regions may influence investor decision-making processes. Adequate attention should be given to behavioral bias research, particularly in the Indian context (18). Based on past research, most studies were conducted in the northern region of India (19, 20). However, it is observed that very few studies have been carried out in the southern region of India. Therefore, it is imperative to study investors in southern India to comprehend how these biases influence their financial decision-making. Among the various behavioral biases, overconfidence is evidenced as exerting the most substantial impact on the decision-making of individual investors, closely followed by herding, especially in the Indian setting (6). Underconfidence is also an important bias to check the impact on decision-making (21). Therefore, the current study attempts to fill these gaps by analyzing the psychological effects of herding, overconfidence, and underconfidence on the decision-making of individual investors in the Indian stock market. It further investigates the role of risk perception as a mediating variable in the connection between herding, overconfidence, underconfidence, and individual investors' decision-making. Thus, we make a valuable empirical contribution to the existing body of literature by confronting the two research questions: First, how do herding, overconfidence, underconfidence, and risk perception directly influence investors' decision-making? Second, does risk perception serve as a mediator in the relationships between herding, overconfidence, under-confidence, and investors' decision-making? The structure of the present article is as follows: the second section covers the literature review and hypothesis development. Following that, we discuss the methodology, results, discussion, and conclusion of the research. In the end, we address the limitations of the current work and recommend future research avenues.

Conceptual Framework and Hypotheses Development

The concept of behavioral finance theory posits that psychological aspects influence individual investors' investment decision-making processes, which subsequently impact the stock market. This study employed prospect theory, which highlights investors' decision-making based on risk prospects (4). Cognitive biases, which have an impact on decision-making, are the driving force behind this phenomenon (1). Cognitive biases impact investment decisions, resulting in suboptimal investment decisions (22). Herding theory posits that investors often rely on the decisions of others rather than their own judgment (23). This study considers overconfidence, herding, and underconfidence as exogenous variables, with investors' investment decision-making as the endogenous variable. The primary focus, however, is to probe how risk perception mediates the relationship between herding, underconfidence, overconfidence, and investment decisions. The following section discusses relevant studies from previous research.

Overconfidence Bias and Investment Decisions

In behavioral finance research, overconfidence bias is an often-used behavioral bias (24). Many researchers have widely accepted overconfidence as a prominent behavioral bias in the stock market (25, 26). Overconfidence is one of the most impactful criteria affecting equity investors' decision-making (6). Overconfidence bias is defined as "unwarranted faith in their own intuitive reasoning, judgments, and cognitive abilities" (27). It indicates that investors overestimate their knowledge and abilities and underestimate market information when making investment decisions. Overconfident investors are more prone to disregard market information and rely on their own information (28). Previous research has revealed that overconfident investors tend to overvalue their predictive abilities, leading to inaccurate forecasts (29). Overconfident investors trade excessively, leading to lower profits (30). It has been reported that investors in the Chinese market frequently make poor trading decisions as a result of their overconfidence (31). Previous research has also shown that overconfidence bias significantly influences investment decisions (7, 14, 26). Therefore, this study proposes the following hypothesis:

H$_1$: Overconfidence significantly affects the investors' decision-making.

Herding Bias and Investment Decisions

Investors often mimic others' decisions, regardless of their own risk-bearing capacity (32). Investors do not usually follow a fundamental analysis but rather imitate others while making investment decisions. Prior research has observed that investors exhibit herd behavior during extreme market conditions (33). Empirical evidence underscores that herding bias exerts a substantial positive influence on investors' decision-making (34). Individual investors are more susceptible to herd behavior during the bearish market (35). Additionally, investors tend to engage in herd behavior under both bullish and bearish market conditions (36,37). In particular, investors exhibit herd behavior more often in bearish markets (36). Prior research has also revealed that herding bias significantly influences investment decision-making (6,14,38). Therefore, we propose the following hypotheses:

H$_2$: Herding significantly affects the investors' decision-making.

Underconfidence Bias and Investment Decisions

Underconfidence causes individuals to underestimate their own knowledge and abilities when making investment decisions. Investors often lack confidence in their knowledge and abilities, which makes them doubtful about their decision-making. Underconfident investors typically perceive themselves as less efficient than others do (21). Underconfidence can induce investors to exaggerate their exposure to potential losses, resulting in suboptimal investment choices (21). Therefore, the proposed hypotheses of this study are as follows:

H$_3$: Underconfidence negatively affects the investors' decision-making.

Risk Perception and Investment Decisions

Risk perception refers to how investors evaluate assets based on their experiences and concerns and perceive the risk as either low or high (16). Risk perception is vital when dealing with investment decisions in uncertain situations (39). It is an important cognitive characteristic of financial behavior that influences investment decisions (40). Many behavioral biases induce investors to make poor investment decisions (10). However, investors' risk perception helps them to make an appropriate investment decision under risk. Past literature has also reported that risk perception significantly impacts investors' decision-making (17, 41, 42). Therefore, the hypothesis of this study is formulated as follows:

H$_4$: Risk perception significantly affects the investors' decision-making.

Mediating Role of Risk Perception

The behavioral finance literature provides substantial evidence that behavioral biases significantly influence an individual's perception of risk, often leading to distorted judgments and decision-making (43). Studies have shown that behavioral biases influence the risk perception of individual investors (41,44). Researchers have identified a substantial connection between the perception of risk and investors' decision-making (16,17,45). The studies mentioned above confirm that risk perception acts as both a dependent and independent variable; consequently, this makes it appropriate to consider it as a mediator. Based on these existing studies, we developed the following hypothesis:

H$_5$: Overconfidence significantly influences risk perception in investors' decision-making.

H$_6$: Herding significantly influences risk perception in investors' decision-making.

H$_7$: Underconfidence significantly influences risk perception in investors' decision-making.

H$_8$: The association between overconfidence and investors' decision-making is proposed to be mediated by risk perception.

H$_9$: The association between herding and investors' decision-making is proposed to be mediated by risk perception. **H$_{10}$:** The association between underconfidence and investors' decision-making is proposed to be mediated by risk perception. Figure 1 below demonstrates the proposed research model used in this study.

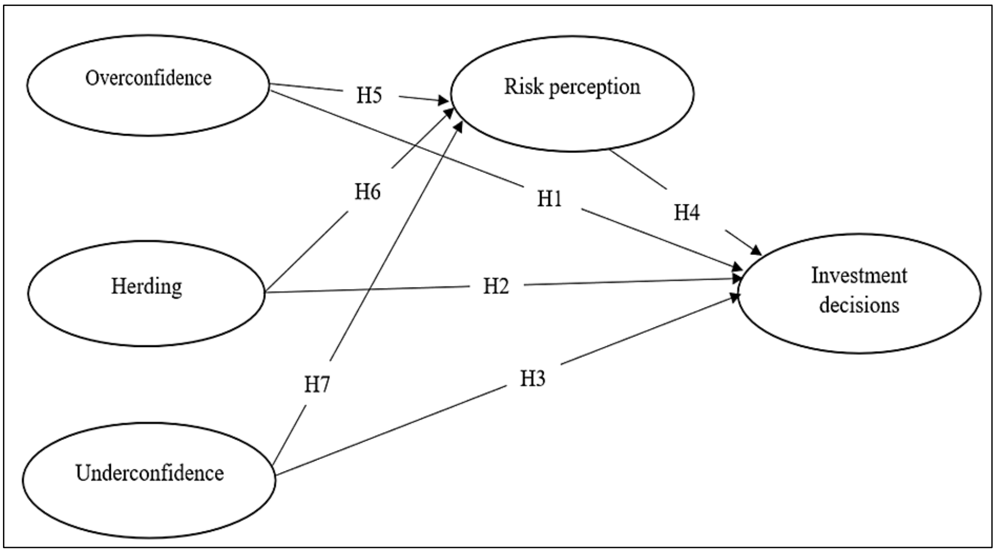

Figure 1: Research Model

Methodology

The current study adopted a quantitative research approach, utilizing a survey method in which a structured questionnaire was circulated to respondents to obtain data from individual investors in the southern region of India, namely Tamil Nadu, Kerala, Karnataka, Telangana, and Andhra Pradesh, using snowball sampling. Investor details are unavailable, and brokers hesitate to share information owing to internal policies (24). Due to this significant challenge in obtaining the data, we employed snowball sampling (46). We assessed and confirmed the questionnaire's reliability and validity through a pilot study with 80 investors. As no further adjustments were necessary, the finalized version of the instrument was subsequently distributed to investors for the final data collection. The data was collected between April 2024 and August 2024. The questionnaire was distributed across various social media platforms, including Instagram, Facebook, and WhatsApp. We obtained 410 valid responses from participants, which were subsequently used to analyze the data and evaluate the stated research hypotheses. The current study employed the G*power software to determine the sample size (47), which suggested a minimum required sample size of 129. This calculation relied on the inclusion of four predictors, with an alpha level set at 0.05. Subsequently, we used a medium effect size of 0.15 for our analysis, accompanied by a power level of 0.95. G*power was chosen because of its high precision in conducting power analyses for statistical techniques such as SEM (48). To measure latent constructs, this study adopted measurement scales from the existing literature. The seven-item scale was adopted for investment decisions from previous research (49). The questions include, "I am confident that I can take investment decisions accurately". Both overconfidence bias and herding were measured with four items each, adopted from (50). The questions for overconfidence include, "I trade more frequently than other people". The questions for herding include, "Other investors' decisions on buying and selling stocks have an impact on my investment decisions". The underconfidence scale, comprising three items, was adopted from prior research (21). The questions include, "I feel my skills and knowledge of the stock market are not enough for excessively trading in the stock market". The five-item scale measures risk perception, adopted from existing literature (17). The questions include, "I am cautious about stocks which show sudden changes in price or trading activity". The questionnaire is structured into two sections. The first section covers demographic details, including gender, age, occupation, annual income, and investment experience in stocks. The second section comprises 18 items related to the study's constructs: herding, overconfidence, under confidence, risk perception, and investment decisions. A 5-point Likert scale was used to measure all constructs, where 1 = 'strongly disagree' and 5 = 'strongly agree'. The proposed research hypotheses of the study were rigorously tested using a "partial least squares structural equation modeling" (PLS-SEM) with SmartPLS 4, a method known for its effectiveness in addressing multiple constructs and intricate relationships (51).

Results

Demographic Profile of the Respondents

Out of the 410 respondents, 321 were male, and the remaining 89 were female. A significant portion, specifically 50.49% of the total participants, fell within the 26–35 age group. Additionally, 30.24% of the participants were in the 36-45 age group, while 10% were aged 25 or younger, and 9.27% were above 46 years old. About annual income, most respondents, 35.37%, reported earning between Rs. 2.5–5 lakhs. Notably, 53.17% of the respondents had 2-5 years of experience in the stock market. Table 1 below presents the key information highlighting the respondents' demographic details.

Common Method Bias

Common method bias (CMB) in PLS-SEM is a serious issue, especially in behavioral studies (52). CMB arises when data is obtained using a single instrument; therefore, it is essential to ensure that CMB issues are absent (53). In this study, we assessed CMB using Harman's one-factor test. The results highlight that a single factor explains 46.35% of the total variance, which is below the standard threshold limit of 50% (54). Thus, the present research concludes that CMB is not an issue.

Table 1: Demographic Profile of the Respondents

Variables	Category	Frequency	Percentage (%)
Gender	Male	321	78.29
	Female	89	21.71
Age	≤ 25	41	10
	26 - 35	207	50.49
	36 - 45	124	30.24
	Above 46	38	9.27
Income	≤ 2,50,000	121	29.51
	2,50,001– 5,00,000	145	35.37
	5,00,001–7,50,000	84	20.49
	7,50,001 –10,00,000	34	8.29
	Above 10,00,000	25	6.09
Investment experience (in years)	2 - 5	218	53.17
	5 - 10	101	24.63
	Above 10	91	22.19

Assessment of the Measurement Model

This study encompasses five latent variables: herding, overconfidence, underconfidence, risk perception, and investors' investment decision-making. Using SmartPLS 4, we assessed the measurement model by evaluating the validity and reliability of the independent and dependent variables. "This evaluation consists of indicator reliability, internal consistency reliability, convergent validity, and discriminant validity" (55). If the outer loadings of all items exceed the recommended value of 0.708 (55,56), this indicates a satisfactory level of item reliability. From Table 2, it is observed that indicator reliability is achieved. Next, we assessed Cronbach's alpha along with composite reliability, which were subsequently employed to gauge internal consistency. An acceptable threshold for both should fall between the range of 0.7 and 0.95 (57). As shown in Table 2, both values were within the suggested range, thereby affirming the internal consistency reliability. The average variance extracted (AVE) was evaluated to determine convergent validity, using the mean value of the squared loadings for each indicator of the construct. The AVE should be 0.50 or higher, indicating that the construct accounts for 50% or more of the variance in its items (55). Thus, the present study confirmed that the AVE for all constructs surpassed 0.5; hence, convergent validity was also established. Furthermore, we assessed the model's discriminant validity by employing two criteria. The traditional metric, referred to as the Fornell-Larcker criterion, serves as the first criterion for evaluation (58). In this method, each construct's square root of the AVE should exceed its correlations with other constructs in the model (55). This criterion was fulfilled, as indicated in Table 3. Consequently, discriminant validity was established for all the constructs. The second criterion involved assessing the heterotrait-monotrait (HTMT) ratio, which must fall below 0.9 for every single construct (59). Table 4 depicts HTMT ratio values that are less than 0.9 for all constructs. Hence, it is concluded that there are no issues of discriminant validity in the model.

Table 2: Measurement Model Results

Constructs	Items	Outer Loadings	Cronbach's Alpha	rho a	CR	AVE
Overconfidence	OV 1	0.730	0.799	0.800	0.869	0.624
	OV 2	0.797				
	OV 3	0.836				
	OV 4	0.792				
Herding	HERD 1	0.816	0.847	0.847	0.897	0.686
	HERD 2	0.873				
	HERD 3	0.841				
	HERD 4	0.779				
Underconfidence	UC 1	0.882	0.859	0.920	0.910	0.772
	UC 2	0.866				
	UC 3	0.888				
Investment decisions	ID 1	0.806	0.885	0.887	0.910	0.593
	ID 2	0.783				
	ID 3	0.780				
	ID 4	0.805				
	ID 5	0.702				
	ID 6	0.706				
	ID 7	0.801				
Risk perception	RP 1	0.762	0.835	0.841	0.884	0.605
	RP 2	0.771				
	RP 3	0.783				
	RP 4	0.833				
	RP 5	0.813				

Table 3: Discriminant Validity (Fornell and Larcker Criterion)

	HERD	ID	OV	RP	UC
HERD	**0.828**				
ID	0.484	**0.769**			
OV	0.492	0.614	**0.768**		
RP	0.561	0.525	0.629	**0.766**	
UC	0.262	0.441	0.339	0.466	**0.880**

Notes: The square root of AVE is depicted in bold values

Table 4: Discriminant Validity (HTMT ratio)

	HERD	ID	OV	RP	UC
ID	0.558				
OV	0.613	0.745			
RP	0.665	0.724	0.779		
UC	0.291	0.496	0.410	0.539	

Assessment of the Structural Model

The first step is to assess the collinearity issues of predictor variables in the model before measuring the structural model. This study utilized the variance inflation factor (VIF), a widely accepted approach for identifying collinearity problems in the model (49). The main cause of the collinearity issues is the high intercorrelation among variables in any model (60). The VIF values should be less than 5, signifying the absence of collinearity issues in the model (61). In this study, VIF values below 5 indicate that collinearity is not a concern for the model. The next phase is to test the proposed hypotheses through bootstrapping to evaluate the significance and relevance of the path coefficients. Table 5 highlights the beta values, t-statistics, and p-values from the hypothesis testing results, and the study's structural model is displayed in Figure 2. The results reveal that among the behavioral biases, only overconfidence bias (OC) (β = 0.111, t = 2.739) significantly affects investment decisions (ID), supporting H1. However, herding (HERD) (β = 0.038, t =1.204) and underconfidence (UC) (β = 0.035, t = 1.029) show no direct association with investment decisions, thus rejecting H2 and H3. Next, the mediating variable, risk perception (RP) (β = 0.828, t =22.602) significantly impacts investment decisions, supporting H4. Furthermore, OC, HERD, and UC positively influence risk perception. Among these three biases, OC (β = 0.450, t = 12.317) exhibited the strongest influence on risk perception, subsequently influenced by HERD (β = 0.280, t = 7.317), and UC (β = 0.256, t = 7.386), hence confirming H5, H6, and H7.

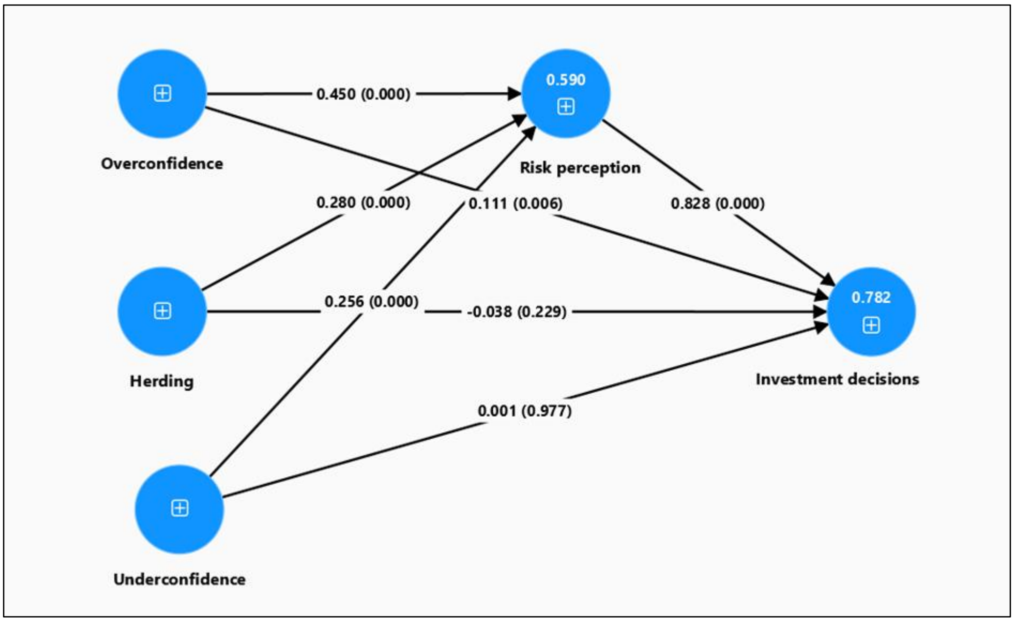

Figure 2: Structural Model Obtained from the PLS-SEM

Table 5: Hypothesis Testing Results

Hypothesis	Path	Beta	T- statistics	P Values	VAF	Decision
H1	OV -> ID	0.111	2.739	0.006	-	Supported
H2	HERD -> ID	0.038	1.204	0.229	-	Not supported
H3	UC -> ID	0.035	1.029	0.677	-	Not supported
H4	RP -> ID	0.828	22.602	0.000	-	Supported
H5	OV -> RP	0.450	12.317	0.000	-	Supported

H6	HERD -> RP	0.280	7.317	0.000	-	Supported
H7	UC -> RP	0.256	7.386	0.000	-	Supported
H8	OV -> RP -> ID	0.112	4.148	0.000	77.23%	Supported
H9	HERD -> RP -> ID	0.131	3.540	0.000	67.88%	Supported
H10	UC -> RP -> ID	0.373	12.305	0.000	52.83%	Supported

Furthermore, mediation effects were evaluated in line with established guidelines (61–63). Accordingly, the mediating role of RP in the relationships between OC, HERD, UC, and ID was rigorously examined. The analysis revealed that the indirect effects of OC, HERD, and UC were statistically supported, as specified in Table 5. Next, we analyzed the total effect of these relationships and found to be statistically significant for all three behavioral biases, indicating that the total effects of HERD (β = 0.193, t = 4.419), OC (β = 0.483, t = 11.775), and UC (β = 0.212, t = 5.904) were significant. Additionally, to determine the strength of the mediation effect, the Variance Accounted For (VAF) was utilized, following the procedures outlined in a previous study (62). In Table 5, VAF values are shown, computed by dividing the indirect effect by the overall effect for all relationships. A VAF of less than 20% indicates zero mediation; a VAF between 20% and 80% suggests partial mediation; and a VAF exceeding 80% signifies full mediation (62). The study showed that the VAF values indicate partial mediation for OC, HERD, and UC, as the VAF values were greater than 20% but less than 80%, as shown in Table 5. For OC, the direct and indirect effects were both positive, whereas for HERD and UC, the direct effects were insignificant, but the indirect effects were significant. Hence, it is concluded that complementary partial mediation exists in the relationship of RP between OC and ID. On the other hand, indirect-only (full mediation) was observed in the connection of RP between HERD, UC, and ID. The researchers analyzed the impact of OC, HERD, and UC on ID without including RP as a mediator, and the R^2 value was found to be 59%. When RP was introduced as a mediator, the R^2 increased to 78.2%, demonstrating that 78.2% of the variance in ID is accounted for by OC, HERD, UC, and RP. This demonstrates the model's high explanatory power (51). Further, the present study measured the model's predictive relevance using the Q^2 value and PLSpredict (64). Q^2 predict values for all investment decision items are greater than zero, as illustrated in Table 6. Regarding the PLSpredict procedure, if the endogenous constructs of PLS MV prediction errors are non-symmetric, it is necessary to compare the partial least squares mean absolute error (PLS MAE) values with the linear regression model mean absolute error (LM MAE) values for each indicator to assess the model's predictive relevance (64). In this study, non-symmetric PLS MV prediction errors were observed. Consequently, we compared the values of PLS MAE with the LM MAE values across all investment decision indicators, as reported in Table 6. The results indicated that, for most indicators, the values of PLS MAE were lower than those of LM MAE, suggesting that the model exhibits medium predictive relevance (64).

Table 6: Results of PLS predict

Indicator	PLS Q^2predict	PLS-SEM MAE	LM MAE
ID 1	0.452	0.759	0.715
ID 2	0.127	0.785	0.774
ID 3	0.557	0.578	0.589
ID 4	0.067	0.852	0.873
ID 5	0.266	0.786	0.792
ID 6	0.036	0.713	0.702
ID 7	0.059	0.783	0.788

Discussion

The study examines how overconfidence, herding, underconfidence, and risk perception affect individual investors' decision-making. Although previous research has predominantly concentrate -ed on the direct influence of biases on investment decisions, this study further advances the field by investigating RP's role as a mediator in the connection of herding, overconfidence, and underconfidence with investors' decision-making. The findings reveal that overconfidence and risk perception significantly impact the investors' decision-making. Overconfidence bias leads investors to engage in excessive trading, overestimating their skills, abilities, and knowledge, and underestimating market information. Overconfident investors believe that they can accurately determine the optimal moments to enter or exit the stock market (20). As a result, overconfident investors incur significant losses. This finding is consistent with those of earlier studies (17,41). Regarding the concept of risk perception, the study participants believed that when it comes to buying stocks, their risk perception helps them make the best investment decisions. This tendency leads individuals to evaluate before investing in a specific stock. This finding aligns with previous research studies (17,41,44). While the impact of herding and underconfidence has not. Notably, the study demonstrated that overconfidence bias exerts a significant influence on investment decision-making, even without accounting for risk perception. Interestingly, the inclusion of risk perception in the model leads to a significant increase in the influence of herding, overconfidence, and underconfidence on decision-making. The reason behind this finding is that overconfident investors are naturally inclined to perceive less risk, making riskier investment choices. They tend to believe that their skills and knowledge surpass those of other investors, which leads them to pick up the more volatile stocks in their portfolio, potentially resulting in negative returns. As far as herding is concerned, the respondents indicated that investors do not base their decisions solely on the actions of others. However, through the indirect effect of risk perception, herding reduces their perception of risk, which in turn influences their investment decisions. This suggests that individual investors follow the crowd to generate profits, and they also believe that tends to reduce risks, which ultimately adversely affects their investments. Furthermore, underconfident investors often overestimate the risks associated with investment opportunities because they underestimate their skills and abilities. As a result, underconfidence amplifies risk perception, which impairs decision-making quality and creates low trading volume. The study's findings provide numerous practical implications pertinent to individual investors, investment advisors, portfolio managers, and policymakers. The findings suggest that individual investors should remain mindful of avoiding biases in their decision-making to select more appropriate stocks that are sound both fundamentally and technically for their portfolios. Second, financial advisors should comprehend their clients' mindsets to mitigate the effects of bias on their investment decision-making. Consequently, they can make optimal investment decisions and potentially generate higher returns by selecting the best stocks. Additionally, financial advisors can gain professional recognition by addressing clients' behavioral biases. Third, if portfolio managers recognize investor psychology, they can enhance portfolio management and improve their risk control. Fourth, individual investors are more inclined to errors in judgment due to behavioral biases; therefore, policymakers should conduct financial education programs to elucidate behavioral biases and their implications.

Conclusion

The current research substantiates the significant influence of risk perception and overconfidence on investors' decision-making. However, the effects of herding and underconfidence on investors' investment decisions were found to be insignificant. Furthermore, this research examines how RP mediates the connection among herding, overconfidence, underconfidence, and investment decisions. Notably, the findings show that the presence of risk perception significantly amplifies the effects of herding, overconfidence, and underconfidence on investors' decision-making.

Limitations and Future Research Avenues

The current research investigates how the proposed biases influence investment decisions. Further, the study evaluates the mediating role of risk perception, particularly in the Indian context. The current study collects data exclusively from the southern region of India. Further research would focus on the entire country of India to validate the study's results with a great diversity of respondents. In this study, risk perception is taken into account. Future research would analyze the connection between potential behavioral biases and investment decisions by incorporating different mediators and moderators to provide deeper insights into the effect of these biases on decision-making. Furthermore, this study focuses exclusively on individual investors as the unit of analysis. Future studies would examine whether retail and institutional investors are equally susceptible to behavioral biases.

Abbreviations
LM MAE: Linear regression model mean absolute error, PLS MAE: Partial least squares mean absolute error.

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Author Contributions
All authors made equal contributions to each section of this study.

Conflict of Interest
The authors state that there is no conflict of interest.

Ethics Approval
Ethical approval was deemed unnecessary, as all participants provided informed consent, and the data collected was completely anonymized.

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