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Understanding Investor Behavior: Evidence from Individual Investors in Varanasi, India

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Abstract- Behavioral finance challenges the classical idea that investors make rational decisions based on information and options by arguing that psychological biases systematically distort investors' financial judgment. This study examines five behavioral biases: overconfidence, anchoring, herding, representativeness, and regret aversion and their indirect effects on investment decision-making through perceived risk among individual investors in Varanasi, a tier-two city in India. The primary data were obtained from 209 individual investors through a structured, five-point Likert-scale questionnaire and a convenience sampling method; the model was estimated using Partial Least Squares Structural Equation Modeling (PLS-SEM) in SmartPLS. The measurement model demonstrated good internal consistency, convergent validity, and discriminant validity. The structural model was able to support all eleven hypotheses: the effects from anchoring, herding, representativeness and regret aversion were positive and significant in relation to perceived risk, whereas the effects from overconfidence were negative and significant in relation to perceived risk; the effect of perceived risk on investment decision-making was negative and significant, and perceived risk carried significant indirect effects from all five behavioral biases to investment decision-making. The highest positive path coefficient for perceived risk was for regret aversion, and the largest effect size in the model was for the path from perceived risk to decision. The results indicate that perceived risk is a significant pathway between cognitive and emotional biases and financial decisions and provide a valuable set of cues for investor education and advice.

Keywords: behavioral finance; behavioral biases; perceived risk; investment decision-making; individual investors

I. INTRODUCTION

Classical finance theory assumes these investors are rational agents who process the information available to them efficiently and form unbiased expectations. It further assumes that the market price reflects the information available to the investor, and that the investor chooses the portfolio that maximizes expected utility, given the risk level [1]. However, decades of empirical evidence have documented excess stock-price volatility, momentum, and systematic overreaction and subsequent reversal in financial markets, suggesting that a purely rational explanation of investor behavior is incomplete [2], [3], [4]. Behavioral finance arose from this void, building on cognitive psychology and suggesting that investors use mental shortcuts when making investment decisions, that emotion plays a role in their decision-making, and that they are vulnerable to systematic errors in assessing outcomes subject to uncertainty.

Behavioral biases can be particularly important for individual, non-institutional investors, who are usually unable to access advanced analytical tools yet must make important decisions amid uncertainty. Each of these biases is found separately and has been shown to affect how investors process information, assess risk, and choose among investment options [5], [6]. Overconfident investors tend to overestimate the accuracy of their own judgment; anchored investors overestimate the importance of salient reference points, e.g. the price at which they bought the stock or the recent peak of the stock's price;

herding investors make decisions that are more about what they see others doing than based on their own judgement; regret-averse investors overestimate the pain of a bad decision; and representativeness causes investors to extrapolate recent trends as if they reflected underlying probabilities. Despite the many independent studies devoted to each of these biases, very few studies incorporate multiple biases in the same model and structural context, and even fewer investigate investors' own perception of risk as the psychological link between the biases and the observed financial decisions.

Individual investors have been increasingly active in Indian stock markets, especially since the advent of digital brokerage platforms, the rise of financial-influencer content, and changes in household saving behavior during the pandemic, drawing attention from the academic and regulatory communities to the behavioral determinants of retail investment activity [7]. Yet, much of the available evidence in India is based on investor samples from metros or national online samples, and empirical studies of tier-two cities are far more limited in scope. Varanasi is a tier-two urban center where digital retail investment is growing. Still, it may not be as well served by institutional advisory expertise, which is often concentrated in larger metros and less studied in the behavioral finance literature. Understanding how behavioral biases operate can inform investor protection policy in India's rapidly digitizing retail investment ecosystem and extend the external validity of behavioral finance findings.

Another remaining difference is the link between behavioral biases and investment decisions. A psychological construct suggested as a link between more distal cognition and emotion, and an investor's behavior is perceived risk, defined as the investor's subjective estimate of the likelihood and potential severity of loss from an investment [8], [9]. In the same situation, two investors with the same information could make different decisions because one believes he's taking more risk than the other. Their biases may influence that perception. Modeling perceived risk as an intervening variable thus provides a fuller understanding of the bias–decision relationship than modeling only direct effects.

In this context, the present study compares the relationship between five behavioral biases (overconfidence, anchoring, herding, representativeness, regret aversion) with individual investors' perceived risk and, in turn, links perceived risk with investment decision-making and examines the indirect effects of each bias on investment decision-making through perceived risk, based on the survey data of 209 individual investors in the Varanasi district.

The study makes a valuable contribution to the field of behavioral finance in three ways. First, it combines five behavioral biases into a single structural model, rather than studying them separately and analyzing the coefficients estimated for each model side by side. Secondly, it introduces perceived risk as an explicit intervening mechanism, clarifying how biases are linked to financial behavior rather than merely documenting a statistical association. Third, it provides region-specific evidence relevant to retail investors, advisors, educators, and policymakers, and adds to the empirical evidence base in a tier-two city context that is underrepresented in behavioral finance research [10].

II. LITERATURE REVIEW

2.1 Theoretical Background

Traditional finance theory assumes that the investor is a rational utility maximizer who updates their beliefs according to the Bayesian principle and compares options using risk-adjusted expected returns. [11] prospect theory provided an alternative explanation: People compare gains and losses against a reference point, give even larger weight to losses than to equivalent gains, and use non-linear probability weighting functions that do not fit the predictions of expected utility theory. On this basis, [12] found that people typically use heuristics when dealing with probabilities under uncertainty, including representativeness, availability, and anchoring, which, while efficient, are predictable and systematic. In financial markets, this means that investor mistakes are predictable rather than random [13].

These trends have been subsequently observed directly among market players. Both [5], [6] have documented the negative consequences of overconfidence on investors' trading activity: overconfident investors make excessive trades and end up earning lower net returns, while [6] identified the disposition effect as a persistent phenomenon of retail trading, which manifests itself as a reluctance to take action when the price of a trading asset declines. Based on these results, more recent work has focused on specific biases among retail investors in emerging and developed markets, with an increasing number of studies adopting structural equation modeling to test multi-construct models [14], [15]. The present study follows this tradition, analyzing five common biases (overconfidence, anchoring, herding, representativeness, and regret aversion) and perceived risk as the mechanism to connect these biases to the investment decision-making process.

2.2 Overconfidence Bias and Perceived Risk

Overconfidence is when people are more likely to believe that what they know, how they judge, and their ability to predict will be more accurate than they actually are. In finance, overconfident investors believe they have better information and/or analysis than others, so they trade more often, hold less diversified portfolios, and underestimate the objective risk of their trades. Overconfidence affects investors' subjective sense of security, plausibly lowering rather than raising it: If an investor is highly confident, they will likely think that a given investment is less risky than a less confident investor with the same expertise would. In their extensive study of Japanese investors, [16] reported that overconfidence was correlated with greater tolerance for investment losses and lower subjective risk assessment. In the study, [17] found that investors' risk propensity mediated part of the impact of overconfidence on investment performance, whereas [18], in their systematic review of financial overconfidence, found that inflated self-assessment was one of the most consistently observed overconfidence distortions across the markets. This aligns with the findings of [19], who noted that overconfident investors undervalue the likelihood of negative events. On this basis:

H1: The relationship between Overconfidence Bias and Perceived Risk of individual investors is negative.

2.3 Anchoring Bias and Perceived Risk

Anchoring bias is a phenomenon in which investors' future judgments are unduly influenced by their initial reference point, often the purchase price of a stock or a recent high price reached in the past 52 weeks, and that initial reference has little importance for the current situation. Anchored investors base their decisions on new information on this anchor rather than fully updating their beliefs, which can lead to an improper assessment of the position's riskiness as prices move away from the anchor. The historical benchmark for anchoring ties price risk assessment, making people more likely to feel greater risk when prices move away from the anchor, because the perceived gap between the current price and the anchor is seen as a warning [20]. Consistent with this, [10] also observed that anchoring-prone investors in emerging markets exhibited higher risk perception when prices deviated from their recalled prices. This finding aligns with other research on the reactions of heuristic investors in South Asian markets [14]. Accordingly:

H2: Anchoring Bias is positively associated with Perceived Risk among individual investors.

2.4 Herding Bias and Perceived Risk

Herding bias refers to investors ignoring their own private information or analysis and instead following the observed trading behavior of others. Herding may be motivated by an informational cascade, as the investor rationally believes that others have better information, or by a motive of reputation or social conformity, in which the investor would prefer to conform to the others [21]. Herding is closely linked to risk perception as, for example, collective movements toward or away from a security are often driven, and in turn reinforced, by the prevailing risk perception of the market; an investor who sees others selling out of a position might believe that it is a sign of increasing risk, even when the fundamentals haven't changed. Yet, [22] have shown that younger investors who are herders tend to be more risk-sensitive during periods with high price volatility, and research on disposition effects and crowd behavior has documented that herders' own risk assessments are systematically influenced by the behavior of others in the crowd, rather than by independent analysis [23]. [24], who studied the contributions of overconfidence, excessive optimism, and herd behavior to investor behavior, also found that three of these biases significantly affected investors' risk-related judgments. Therefore:

H3: Herding Bias is positively associated with Perceived Risk among individual investors.

2.5 Representativeness Bias and Perceived Risk

Representativeness bias occurs when investors estimate the likelihood of a given event, such as a stock continuing to outperform, based on how similar it is to a pattern they have observed in the past, rather than on objective statistical likelihood. Investors who suffer from this type of bias tend to carry their recent run in a company's stock price or comparisons with successful companies into their future expectations for the latter, without considering reversion. Representativeness replaces probability-based thinking with pattern matching, which can lead investors to either be misled by recent positive trends into lowering their risk estimates or to change their risk perception when a pattern is broken drastically [25]. [26] noted that pattern-based reasoning using sentiment analysis was correlated with changes in retail investors' investment risk perception. Accordingly:

H4: Representativeness Bias is positively associated with Perceived Risk among individual investors.

2.6 Regret Aversion and Perceived Risk

Regret aversion describes the behavior of investors to make a choice that reduces the expected regret of making a wrong choice rather than to choose what is optimal on purely probabilistic grounds. The regret-averse investor can also hold onto the losing positions very long before finally selling them off, wait to make an entry when a promising investment arises because he's afraid of getting in "too late," or forgo a profitable exit because he associates having a "loss" with the idea of "regret". The feeling of regret aversion is a sensitive response to the prospect of loss and is thus closely related to the riskiness an investor considers a decision to entail: the more emotionally risky a decision is perceived to be, the more aversive the regret will be. As mentioned previously, in their study of regret aversion and information cascades in real-estate investment decision-making, [27] found that regret-averse investors experienced significantly higher risk perceptions, which is one of the most salient psychological factors in their study of subjective risk evaluation among the biases they examined in real-estate investment decisions. Therefore:

H5: Regret Aversion is positively associated with Perceived Risk among individual investors.

2.7 Perceived Risk and Investment Decision-Making

The subjective investor assessment of either the risk of an adverse event or the severity of the event, known as perceived risk, is well known to be a proximate determinant of investors' financial choices, rather than objective, measured market risk. Investors make risk assessments for themselves, and what matters is their perception of risk and how it aligns with their actual risk, as this is not a purely statistical measure but is highly correlated with behavior [8]. A higher perceived risk level is typically associated with slower investment decision-making: investors with a high level of perceived risk to an investment will decrease their position size, delay entering the investment or exit all investments in that position. [9] found significant negative correlations between risk perception and investors' confidence and decisiveness in decision-making; similarly, [28] reported that financial risk tolerance and subjective risk perception were key influences on the relationship between behavioral tendencies and investment decisions. Hence:

H6: Perceived Risk is negatively associated with Investment Decision-Making among individual investors.

2.8 Indirect Role of Perceived Risk

In addition to their direct connections with perceived risk, behavioral biases are theorized to relate to investment decision-making indirectly, through the pathway of perceived risk, which requires

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differentiating biases that affect the decision through the investor's felt sense of danger from those that may affect it through another pathway. This mechanism was empirically supported by [8], who showed that the relationship between various behavioral biases and investment decisions was significantly mediated by risk perception in an emerging-market sample. Likewise, according to [15], risk perception was a significant mediator between behavioral biases and investment decisions, and financial literacy was a moderator in the above-mediated pathway. Similarly, [28] found that behavioral biases in investment decisions are primarily mediated by financial risk tolerance and perceived risk, rather than acting directly. Based on this evidence and consistent with the model that did not identify any direct links between the five behavioral biases and Investment Decision-Making, the present study suggests that each of the five behavioral biases studied has a significant indirect effect on investment decision-making via perceived risk.

H7: Overconfidence Bias has a significant indirect effect on Investment Decision-Making through Perceived Risk.

H8: Regret Aversion has a significant indirect effect on Investment Decision-Making through Perceived Risk.

H9: Representativeness Bias has a significant indirect effect on Investment Decision-Making through Perceived Risk.

H10: Anchoring Bias has a significant indirect effect on Investment Decision-Making through Perceived Risk.

H11: Herding Bias has a significant indirect effect on Investment Decision-Making through Perceived Risk.

2.9 Conceptual Framework

The resulting model is illustrated in Figure 1, showing that Perceived Risk is an endogenous variable influenced by the five behavioral biases, while Investment Decision-Making is predicted by Perceived Risk. Each behavioral bias, therefore, has an indirect effect on Investment Decision-Making through Perceived Risk. The model consists of six direct paths (H1–H6) and five indirect paths (H7–H11), which are estimated in a single structural model and tested empirically in Section 4.

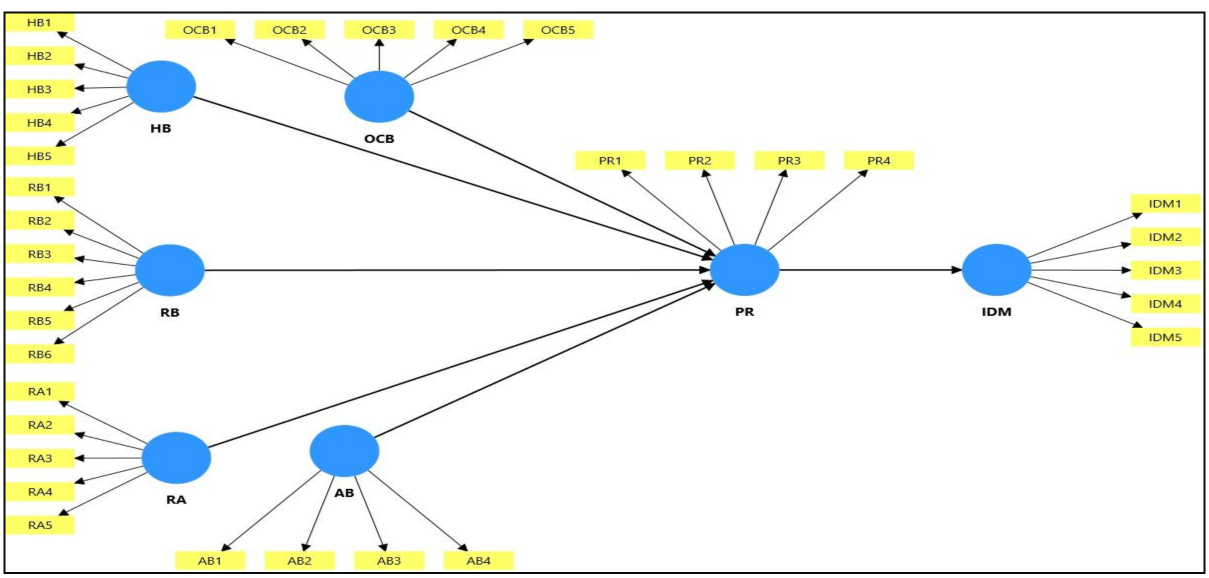

Figure 1. Proposed Conceptual Framework

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III. RESEARCH METHODOLOGY

3.1 Research Design and Study Context

The study is quantitative, descriptive and cross-sectional in design, aimed at revealing behavioral bias and investment decision-making among individual investors in the Varanasi district of Uttar Pradesh. It examines the relationships among five behavioral biases (Anchoring, Herding, Overconfidence, Regret Aversion, and Representativeness), Perceived Risk as the intervening variable, and Investment Decision-Making as the dependent variable. Varanasi was selected as a demographically diverse tier-two city with a high rate of digital retail participation and limited sampling compared to metropolitan samples.

3.2 Population, Sampling, and Data Collection

Individual stock market investors of the Varanasi district were the target population. India does not have a complete sampling frame of individual investors, so the study adopted non-probability convenience sampling, which is widely used in behavioral finance studies when the formal investor register is unavailable to independent researchers [15], [22]. The respondents were contacted both offline and online: offline through face-to-face approaches at brokerage offices and investor meet-ups, and online via structured web-based questionnaires distributed to investors through investor networks and social media groups, to obtain a more diverse spread of investors than a single method would provide. Data collection continued until 209 valid responses were obtained, which is within the minimum sample size requirement for the PLS-SEM model [29]. A priori sample size assessment suggested that at least 92 respondents should be included in a multiple regression model with five predictors, with a medium effect size ($f^2 = 0.15$), $\alpha = 0.05$, and 80% statistical power [30], [31]. The final sample of 209 valid responses thus met this minimum requirement. The study was conducted voluntarily. The purpose of the study, the confidentiality of their responses and their right to withdraw at any time were explained to the respondents. All participants gave informed consent before completing the questionnaire.

3.3 Measurement Instrument

This questionnaire consisted of two parts: demographic information and the seven constructs on five-point Likert scales (1 = Strongly Disagree, 5 = Strongly Agree). All constructs were modeled reflectively and were drawn from validated scales, as shown in Table 1: Overconfidence from [19]; Anchoring and Herding Bias from [19]; Representativeness Bias from [32]; Regret Aversion from [27]; Perceived Risk from established perceived-risk measures consistent with [8]; and Investment Decision-Making from [33].

Table 1. Measurement of Constructs and Sources

Construct	Items	Source
Overconfidence Bias (OCB)	OCB1–OCB5 (5 items)	[19]
Anchoring Bias (AB)	AB1–AB4 (4 items)	[19]
Herding Bias (HB)	HB1–HB5 (5 items)	[19]
Representativeness Bias (RB)	RB1–RB6 (6 items)	[32]
Regret Aversion (RA)	RA1–RA5 (5 items)	[27]
Perceived Risk (PR)	PR1–PR4 (4 items)	[8]
Investment Decision-Making (IDM)	IDM1–IDM5 (5 items)	[33]

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3.4 Demographic Profile of Respondents

The sample of 209 investors was mostly male (58.37%), within the 26-35 age group (42.11%) and were mostly post-graduate (37.80%) and privately employed (29.67%) and earned a monthly income of up to ₹20,000 (41.63%), indicating a heterogeneous cross-section common to a tier-two investing population (Table 2).

Table 2. Demographic Profile of the Respondents

S. No.	Demographic Variable	Categories	Frequency	Percentage
1	Gender	Male	122	58.37
		Female	87	41.63
2	Age (Years)	18–25 years	52	24.88
		26–35 years	88	42.11
		36–50 years	44	21.05
		51 years & above	25	11.96
3	Educational Qualification	Primary Education	22	10.53
		Secondary Education	36	17.22
		Graduation	59	28.23
		Post-Graduation	79	37.80
		Others	13	6.22
4	Occupation	Student	58	27.75
		Government Employee	23	11.00
		Private Employee	62	29.67
		Businessman	29	13.88
		Others	37	17.70
5	Monthly Income (₹)	₹0–₹20,000	87	41.63
		₹20,000–₹50,000	61	29.19
		₹50,000–₹80,000	32	15.31
		₹80,000–₹1,00,000	22	10.53
		₹1,00,000 & above	7	3.35

3.5 Common Method Bias

Since all constructs were assessed using a single self-administered questionnaire, several methodological precautions were taken to minimize common method bias, which is typical in survey-based behavioral finance studies [7]. These included the provision of

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anonymity and confidentiality, randomization of construct order, the use of clear, unambiguous item wording validated in prior research, and the psychometric separation of predictor and outcome constructs within the questionnaire. However, these procedural safeguards do not completely preclude common method variance; the discriminant validity results reported in Section 4.2 provide evidence that the constructs were empirically distinct.

3.6 Data Analysis Technique

Partial Least Squares Structural Equation Modeling (PLS-SEM) was used to analyze the data, as it is more predictive and exploratory in nature, can handle multiple predictors, mediators, and terminal constructs in one model in moderate sample sizes, and does not require any multivariate normal distribution, which is suitable for data collected in a Likert Scale [29]. The measurement model, reliability and validity (Sections 4.1–4.2) and a standard model evaluation procedure were tested before evaluating the structural model, multicollinearity, effect size, path coefficients, indirect effects, R^2, model fit, Importance–Performance Map Analysis and PLSpredict (Sections 4.3–4.10).

IV. DATA ANALYSIS AND RESULTS

The measurement and structural model results are reported in this section. The constructs used are represented by behavioral constructs (abbreviated as OCB, AB, HB, RB, RA) and endogenous constructs (Perceived Risk (PR) and Investment Decision-Making (IDM)). All values are directly taken from the output of SmartPLS and are not modified.

4.1 Outer Loadings and Reliability

Table 3. Outer Loadings, Cronbach's Alpha, Composite Reliability, and AVE

Construct	Outer Loading Range	Cronbach's α	Composite Reliability (ρc)	AVE
Anchoring Bias (AB)	0.820–0.874	0.87	0.91	0.717
Herding Bias (HB)	0.784–0.869	0.892	0.92	0.698
Investment Decision-Making (IDM)	0.716–0.776	0.799	0.861	0.554
Overconfidence Bias (OCB)	0.861–0.906	0.926	0.944	0.772
Perceived Risk (PR)	0.736–0.820	0.804	0.872	0.63
Regret Aversion (RA)	0.826–0.882	0.91	0.933	0.736
Representativeness Bias (RB)	0.788–0.876	0.905	0.926	0.676

As reported in Table 3, outer loadings ranged from 0.716 to 0.906, exceeding the recommended threshold of 0.708 and indicating satisfactory indicator reliability. The internal consistency reliability for all items was good, with Cronbach's alpha values ranging from 0.799 to 0.926 and composite reliability values (ρc) ranging from 0.861 to 0.944. The Average variance extracted (AVE) ranged from 0.554 to 0.772, exceeding the acceptable threshold of 0.50 and indicating reasonable convergent validity for all constructs. Overall, the measurement model demonstrates good psychometric properties for measuring the constructs.

4.2 Discriminant Validity (HTMT)

Table 4. Discriminant Validity: Heterotrait–Monotrait (HTMT) Ratios

Constructs	AB	HB	IDM	OCB	PR	RA	RB
AB	—						
HB	0.079	—					
IDM	0.226	0.178	—				
OCB	0.200	0.070	0.21	—			
PR	0.250	0.209	0.641	0.414	—		
RA	0.117	0.103	0.238	0.05	0.479	—	
RB	0.058	0.080	0.088	0.061	0.212	0.062	—

The HTMT ratios used to assess discriminant validity among the seven constructs. A criterion recommended as being more sensitive than the traditional Fornell-Larcker approach was the Heterotrait–Monotrait (HTMT) ratio of correlations used as a tool to assess discriminant validity. The results reported in Table 4 indicate that all HTMT values were between 0.050 and 0.641, with the highest, 0.641, for the Perceived Risk-Investment Decision-Making pair, well below the conservative cut-off of 0.85. The seven constructs appear to be empirically distinct from each other in these results.

4.3 Multicollinearity (VIF)

Table 5. Multicollinearity Assessment (VIF)

Structural Relationship	VIF
Anchoring Bias → Perceived Risk	1.052
Herding Bias → Perceived Risk	1.015
Overconfidence Bias → Perceived Risk	1.041
Regret Aversion → Perceived Risk	1.021
Representativeness Bias → Perceived Risk	1.006
Perceived Risk → Investment Decision-Making	1

The Variance Inflation Factor (VIF) was calculated for the inner model to assess multicollinearity among the predictor constructs in the structural model. The VIF values reported in Table 5 ranged from 1.006 to 1.052, well below the usual cut-off value of 5. This means multicollinearity among the predictors Constructs are not problematic and are unlikely to adversely affect estimates of the structural paths.

4.4 Direct Hypothesis Testing

Table 6. Bootstrapping Results: Direct Effects (H1–H6)

Hypothesis	Path	Β	t-value	p-value	Decision
H1	AB → PR	0.184	3.647	<0.001	Supported
H2	HB → PR	0.148	2.840	<0.005	Supported
H3	OCB → PR	-0.350	6.499	<0.001	Supported
H4	RA → PR	0.427	8.425	<0.001	Supported
H5	RB → PR	0.213	4.450	<0.001	Supported
H6	PR → IDM	-0.516	11.435	<0.001	Supported

The bootstrapping results in Table 6 show statistically significant support for all six hypotheses ($p < 0.05$). H1 was supported as the path coefficient for Anchoring Bias to Perceived Risk was significant and positive ($\beta = 0.184$, $t = 3.647$, $p < 0.001$). Herding Bias had a significant positive path coefficient ($\beta = 0.148$, $t = 2.840$, $p < 0.005$), supporting H2. The results supported H3, with a significant negative path coefficient ($\beta = -0.350$; $t = 6.499$; $p < 0.001$) between Overconfidence Bias and perceived risk. Among the five biases, the highest positive estimated path coefficient for Perceived Risk was for Regret Aversion ($\beta = 0.427$, $t = 8.425$, $p < 0.001$), supporting H4. Representativeness Bias had a significant positive path coefficient ($\beta = 0.213$, $t = 4.450$, $p < 0.001$), supporting H5. Finally, Investment Decision-Making was negatively and significantly related to Perceived Risk ($\beta = -0.516$, $t = 11.435$, $p < 0.001$), thereby confirming H6 and yielding the largest path coefficient in absolute value in the structural model. The five biases were found to be significantly related to the investors' perceived risk, and investors' investment decisions were significantly related to their perceived risk.

4.5 Coefficient of Determination

Table 7. R^2 and Adjusted R^2 of Endogenous Constructs

Endogenous Construct	R^2	Adjusted R^2	Interpretation
Perceived Risk (PR)	0.411	0.396	Moderate explanatory power
Investment Decision-Making (IDM)	0.266	0.262	Weak to moderate explanatory power

The R^2 results shown in Table 7 indicate that Perceived Risk had an R^2 value of 0.411 (adjusted $R^2 = 0.396$), indicating a moderate level of explanatory power. In both situations, the adjusted R^2 is close to the unadjusted R^2, indicating that these estimates of the variance explained are reasonably stable given the number of predictors and the sample size.

4.6 Effect Size (f^2)

Table 8. Effect Size (f^2) of Structural Relationships

Structural Relationship	f^2 Value	Effect Size	Interpretation
AB → PR	0.054	Small	Modest contribution to Perceived Risk
HB → PR	0.037	Small	Weak contribution to Perceived Risk
OCB → PR	0.2	Medium	Meaningful contribution to Perceived Risk
RA → PR	0.303	Medium	Largest bias-level effect size on Perceived Risk

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Structural Relationship	f^2 Value	Effect Size	Interpretation
RB → PR	0.076	Small	Limited contribution to Perceived Risk
PR → IDM	0.362	Large	Strong Influence on Investment Decision- Making

The effect-size results in Table 8 show that Perceived Risk was moderately affected by Regret Aversion (f^2 = 0.303) and Overconfidence Bias (f^2 = 0.200), while Representativeness Bias (f^2 = 0.076), Anchoring Bias (f^2 = 0.054), and Herding Bias (f^2 = 0.037) had small effects on Perceived Risk. The largest effect size in the model was observed for Perceived Risk → Investment Decision-Making (f^2 = 0.362), indicating a large effect. Across all bias-level predictors, Perceived Risk, Regret Aversion, and Overconfidence Bias showed the largest effect sizes, with the largest observed for the Perceived Risk-to-Investment Decision-Making path.

4.7 Indirect Effects Analysis

Table 9. Bootstrapping Results: Indirect Effects via Perceived Risk (H7–H11)

Hypothesis	Indirect Path	B	t-value	p-value	Decision
H7	OCB → PR → IDM	0.180	5.533	<0.001	Supported
H8	RA → PR → IDM	-0.220	6.677	<0.001	Supported
H9	RB → PR → IDM	-0.110	4.086	<0.001	Supported
H10	AB → PR → IDM	-0.095	3.250	<0.001	Supported
H11	HB → PR → IDM	-0.076	2.660	0.008	Supported

The indirect-effect results reported in Table 9 show that the indirect effect of each of the five biases was significant ($p < 0.05$). No direct paths from the five biases to Investment Decision-Making were suggested in the model, and the results indicate a significant indirect path from each bias to Investment Decision-Making, though not necessarily a specific type or degree of mediation. Overconfidence Bias had an indirect effect on Investment Decision-Making through Perceived Risk ($\beta = 0.180$, $t = 5.533$, $p < 0.001$; H7 supported). The total indirect effect of Overconfidence Bias is positive because Overconfidence Bias is negatively related to

Perceived Risk, and Perceived Risk is negatively related to Investment Decision-Making; the product of these two negative path coefficients yields a positive indirect effect. Perceived Risk likewise carried significant indirect effects from Regret Aversion ($\beta = -0.220$, $t = 6.677$, $p < 0.001$; H8, the largest indirect effect in the model), Representativeness Bias ($\beta = -0.110$, $t = 4.086$, $p < 0.001$; H9), Anchoring Bias ($\beta = -0.095$, $t = 3.250$, $p < 0.001$; H10), and Herding Bias ($\beta = -0.076$, $t = 2.660$, $p = 0.008$; H11, the smallest though still significant indirect effect). As proposed, the indirect effect of each of the five biases discussed above on investors' decisions is significant when combined with Perceived Risk.

4.8 Model fit

As shown in Table 10, SRMR values were 0.054 (saturated model) and 0.056 (estimated model), both less than the 0.08 cutoff for a good approximate fit. The discrepancy indices d_ULS (1.734/1.836 saturated/estimated) and d_G (0.600/0.603 saturated/estimated) and the chi-square statistics (711.843/714.750) are reported as supplementary fit information along with SRMR. A modest (NFI = 0.837, 0.836), but not strong, comparative fit.

Table 10. Model Fit Indices

Fit Index	Saturated Model	Estimated Model	Interpretation
SRMR	0.054	0.056	Good model fit
d_ULS	1.734	1.836	Acceptable
d_G	0.6	0.603	Acceptable
Chi-square	711.843	714.75	Acceptable
NFI	0.837	0.836	Moderate fit

Overall, the SRMR values do not indicate a major fit concern, but the NFI values suggest a moderate fit.

4.9 Importance–Performance Map Analysis (IPMA)

Table 11. Importance–Performance Map Analysis (IPMA) Results for Perceived Risk

Bias	Path coefficient (β)	Performance	Interpretation
Anchoring Bias (AB)	0.184	48.67	Positive but relatively modest influence
Herding Bias (HB)	0.148	50.44	Positive influence; moderate performance
Overconfidence Bias (OCB)	−0.350	51.256	Strong negative influence; highest performance
Regret Aversion (RA)	0.427	50.43	Strongest positive influence
Representativeness Bias (RB)	0.213	47.954	Positive influence; relatively lower performance

The IPMA results in Table 11 show that Regret Aversion had the highest positive path coefficient ($\beta = 0.427$), although its performance score (50.43) was the third-highest among the five bias constructs. Representativeness Bias ($\beta = 0.213$), Anchoring Bias ($\beta = 0.184$), and Herding Bias ($\beta = 0.148$) had comparatively smaller path coefficients, with performance scores of 47.954, 48.67, and 50.44, respectively. Overconfidence Bias had the second largest absolute path coefficient in the model ($|\beta| = 0.350$), and its relationship with Perceived Risk was negative. It also recorded the highest performance score (51.256) among the five bias constructs.

4.10 Out-of-Sample Predictive Assessment (PLSpredict)

Table 12. PLSpredict Out-of-Sample Predictive Assessment

Endogenous Construct	PLS Loss	IA Loss	Average Loss Difference	t-value	p-value
Perceived Risk (PR)	0.303	0.39	−0.087	4.896	<0.001
Investment Decision-Making (IDM)	0.392	0.415	−0.023	2.222	0.027
Overall	0.353	0.404	−0.051	4.384	<0.001

The PLSpredict results in Table 12 show a lower prediction loss in the PLS compared to the IA in both endogenous constructs, namely: Perceived Risk (0.303 versus 0.390, difference of −0.087, $t = 4.896$, $p < 0.001$) and Investment Decision-Making (0.392 versus 0.415, difference of −0.023, $t = 2.222$, $p = 0.027$). The overall PLS loss was also lower (0.353) than the overall IA loss (0.404), which was also statistically significant ($t = 4.384$, $p < 0.001$). The results showed that the model outperformed the indicator-average model in predicting the endogenous constructs, indicating predictive performance beyond the in-sample explanatory results.

V. DISCUSSION

The proposed model was supported by all eleven hypotheses, thereby enhancing confidence in it. The relationships between each bias and Perceived Risk were estimated as individual paths and not formally tested against one another. However, a definite pattern emerges when the individual paths are read side by side. A pattern consistent with previous research identifying overconfidence as an exaggerated perception of risk that causes investors to undervalue the actual risk [16], [17] exists with the other constructs: Anchoring, Herding, Representativeness, and Regret Aversion, each appears tied to an increase in risk perception ($\beta > 0$) while Overconfidence appears to be significantly tied to a decrease ($\beta = -0.350$). This also helps explain the positive indirect effect of Overconfidence Bias on Investment Decision-Making ($\beta = 0.180$): because perceived risk is negatively related to investment decision-making, a reduction in perceived risk associated with overconfidence produces a positive indirect effect.

This by itself isn't proof that overconfidence is good; it is a documented hazard of overconfident investing: When investors underestimate risk, they may trade more frequently and make less-calibrated investment decisions [5], [18].

For Perceived Risk, the highest positive estimated path coefficient was with Regret Aversion ($\beta = 0.427$). The highest indirect effect was from Regret Aversion to decisions ($\beta = -0.220$), reflecting the anticipatory emotional reaction concept of regret aversion, in which the anticipated cost of a wrong decision is also perceived as a risk factor. The impact on investors is that those with high regret aversion tend to be more cautious and risk-averse, which can manifest as avoiding some of the best opportunities or being overly cautious.

The path from Perceived Risk to Investment Decision-Making ($\beta = -0.516$) had the highest absolute value and the largest effect size ($f^2 = 0.362$) in the model. This indicates that higher perceived risk is associated with lower investment decision-making, consistent with previous studies that identify perceived risk as a more immediate predictor of financial behavior than behavioral biases alone. This is similar to previous studies in which perceived risk has been used as a more immediate predictor of financial behavior than biases would be [8], [9], [15], and supports the hypothesis that biases are linked to decisions less directly through cognitive short-circuits and more so through the risk perception they engender.

Each of Anchoring, Herding, and Representativeness had smaller but statistically significant effects on Perceived Risk, and these effects are likely secondary and stem from their appearing to be more information-processing heuristics than emotional responses. Despite these, their importance suggests that none of these biases predominates, with perceived risk being influenced by a cluster of overlapping factors, consistent with the literature which focuses on multi-bias models of investor psychology [21], [34].

Taken together, the five biases explain a significant proportion of the variance ($R^2 = 0.411$ for Perceived Risk and $R^2 = 0.266$ for Investment Decision-Making). However, additional factors beyond the scope of this model, such as financial literacy, income, experience and macroeconomic conditions, also play a role and could be incorporated in future research.

VI. THEORETICAL AND PRACTICAL IMPLICATIONS

These biases do not operate uniformly as suggested by the theory; as shown in the present study, most lead to an increase in perceived risk, except Overconfidence, which leads to a decrease in perceived risk, thus necessitating bias-specific, not generic, theorizing. The findings also extend evidence on subjective risk perception beyond predominantly metropolitan or tier-one Indian samples by providing evidence from a tier-two Indian city [8], [15].

Now, in practice, an investor's own unawareness of their predominant biases could facilitate the identification of mismatches between how they feel about taking risks and the reality of the situation. Advisors should consider the different counseling that will be required for each of these types of clients, tailored to their individual bias profile: if a client is regret-averse, they will likely benefit from structured decision frameworks that pre-commit them to entry and exit rules; if a client is overconfident, they will likely benefit from decision aids that make objective risk metrics more difficult to discount. The findings provide support for investor-education programs grounded in psychological mechanisms rather than information gaps, for educators and policymakers in tier-two markets where the advisory infrastructure is relatively weak. Platform designers might include behavioral nudges, for example, a cooling-off notice during trading that appears to be herding, to lessen the negative bias impact on retail results.

VII. LIMITATIONS AND DIRECTIONS FOR FUTURE RESEARCH

There are several caveats to be noted. The absence of a complete investor sampling frame limits generalisability and has restricted the use of non-probability convenience sampling. The cross-sectional design is unable to determine the precedence of relationships or track their evolution over time or in response to market conditions. Likert-type measures still exhibit social desirability biases that apply in cases of overconfidence. The model tested five biases and one mediator. At the same time, constructs such as financial literacy, prior experience and loss aversion were not included and may account for some unexplained variance in Investment Decision-Making ($R^2 = 0.266$).

Researchers could use probability-based sampling and follow-up designs to assess and track the bias–risk–decision relationships over time and examine moderating variables, such as financial literacy and platform use, that theory suggests shape these relationships in future studies [15], [21]. Comparative studies across other tier-two and tier-three cities in India would help identify whether the observed pattern here – whereby regret aversion has the strongest positive estimated association and overconfidence the strongest negative estimated association with perceived risk – can be generalized to locations outside Varanasi.

VIII. CONCLUSION

The present study investigated the relationship between behavioral biases and individual investors' decision-making in the Varanasi district, with perceived risk as an intervening mechanism. Anchoring, Herding, Representativeness, and Regret Aversion were significantly and positively related to perceived risk, and Overconfidence was significantly and negatively related to perceived risk. In contrast, perceived risk was significantly and negatively related to investment decision-making and carried significant indirect effects from all five behavioral biases to investment decision-making. Regret Aversion had the largest positive path coefficient to Perceived Risk ($\beta = 0.427$), representing the strongest positive bias-to-risk relationship in the model.

The findings indicate that investment decision-making cannot be fully understood through rational assumptions alone; the role of perceived risk in translating behavioral biases into investment decisions must also be considered. This study, which combines five behavioral biases and perceived risk into a single PLS-SEM model and analyzes them in a regionally under-researched tier-two Indian city, provides a regionally specific evidence base for the global behavioral finance literature, with important implications for investor education, investment advice, and retail investor protection policy. These implications suggest that investor education, investment advice, and retail-investor protection policies should account for investors' perceived risk, especially the roles of regret aversion and overconfidence, to support better-calibrated investment decisions.

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