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Behavioral Factors and Risk Perception Affecting Investment Decision in the Context of Nepal

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Abstract

This study investigated the influence of key behavioral biases; overconfidence, herding, mental accounting, and loss aversion on investment decision in Nepal with risk perception as a mediator variable. Approving Prospect Theory and behavioral finance literature, the study used Partial Least Squares Structural Equation Modeling (PLS-SEM) to analyze responses of 420 financial professionals. The findings revealed that while herding is positively influenced with regard to investment decisions, overconfidence, loss aversion and mental accounting found strong negative influences. Furthermore, risk perception has a strong mediating effect between behavior variables and investment decisions, attesting to its crucial role in determining financial judgment. The model showed good descriptive and predictive capacities, as reflected in high R^2 and Q^2 predict values. The study provides good insight to the growing literature on behavioral finance in developing markets and offers practical implications for investor education and strategy making in Nepal.

Keywords: behavioral biases, risk perception, investment decision, PLS-SEM, Nepal

Introduction

Investor behavior in financial markets generally deviates from the rationality that is assumed in mainstream finance. Particularly for emerging economies like Nepal, cognitive and affective biases often subtle but powerful upset better investment decision-making. Despite the theoretical strength of conventional models like Modern Portfolio Theory (Markowitz, 1952), the Capital Asset Pricing Model (Sharpe, 1964), and Efficient Market Hypothesis (Fama, 1970), these models themselves frequently fail to capture actual events like unjustified volatility, asset bubbles, and irrational trading behavior. These limitations have paved the way for the creation of behavioral finance, a framework that merges psychological principles with financial decision-making

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(Kahneman & Tversky, 1979; Thaler, 1985). Behavioral finance argues that investors are not necessarily rational utility-maximizers but that their decisions are influenced by biases such as overconfidence, herding, mental accounting, and loss aversion (Shefrin & Satman, 2000). Overconfidence leads to excessive trading by investors due to their overestimation of intelligence and lack of risk underestimation (Barber & Odean, 2001). Herding results in investors following other people's actions rather than independent thinking, hence reinforcing market inefficiencies (Bikhchandani et al., 1992). Mental accounting leads to people psychologically separating money in an illogical way, affecting diversification of portfolios (Thaler, 1999). Loss aversion, the second key element of Prospect Theory, makes the investors avoid realization of losses, hence resulting in suboptimal asset holding (Tversky & Kahneman, 1991).

The effect of all such biases is even compounded in emerging economies like Nepal, where informational and structural inefficiencies continue to dominate. The financial system is underdeveloped and formal financial instruction is limited. This environment encourages reliance on non-professional advice family members, friends, or social influencers rather than professional financial guidance, thereby consolidating herding behaviors and dismantling analytical rigor (Hong et al., 2023; Shrestha & Rawat, 2023). Under these circumstances, risk perception a subjective assessment of uncertainty and potential loss becomes the most important mediator between behavioral predispositions and investment decision. Slovic (1987) has noted that individuals tend to utilize heuristics and affective, rather than statistical, reasoning when they are measuring risk. In collectivist societies like Nepal, attitudes to risk can be conditioned by cultural norms that do not always correspond with financial logic. Behavioral biases undoubtedly shape investor decisions but are not always clearly expressed; they are risk perception- and internalization-mediated and shaped. For instance, overconfident investors may underestimate risks, leading to aggressive strategies, while loss-averse investors may overestimate negative threats and avoid potentially lucrative investments (Sitaula & Uprety, 2024). Moreover, social conformity-driven herding behavior may distort market signals and amplify perceived risk, limiting individual judgment (Shrestha & Rawat, 2023). Even as appreciation of such dynamics has been heightened worldwide, empirical research from Nepal is limited, particularly in terms of how these behavioral traits play off one another and are shaped by subjective risk perceptions.

Financial literacy is yet another important key in tempering such biases. Financial literacy is associated with improved investment performance and reduced susceptibility to behavioral errors (Lusardi & Mitchell, 2023). However, research also shows that even savvy investors can behave irresponsibly when they are pressured or unsure (Hastings & Craig, 2023). Technical solutions like as robo-advisors offer some relief by decision-making automation but generate new vulnerabilities such as algorithmic over-reliance and absence of instincts. On top of that, emerging fields like neuron-finance (Camerer et al., 2023) and moral investing (Eccles et al., 2023) have stretched the boundaries of financial conduct by incorporating brain functions and ethical inputs into models bypassing the utility-maximization tradition of classical economics.

Global crises like pandemics and climate change have also increased investor risk sensitivity further, bringing into focus long-termism and psychological resilience (Baker et al., 2023). Although, these have not yet been robustly examined within developing economies where investor education, formal financial deepening, and technological penetration remain low. In Nepal's case, the predominately informal reliance on information networks and low methodological sophistication in existing financial behavior research point to a theoretical and contextual lacuna. Most of the prior studies in Nepal have either focused on aggregate behavioral determinants in isolation or used rudimentary regression analyses that fail to reflect the intricate, interactive character of psychological and affective variables (Karki, 2024). In particular, the mediating role of risk perception allegedly directing and influencing these biases into investment behaviors under researched empirically. Moreover, the structural specificity of Nepalese investors, driven by low trust in financial institutions, social conformity, and low digital adoption, requires locally situated models instead of transposed Western theories.

To fill these empirical and theoretical gaps, this research suggests a behaviorally anchored model that investigates the concurrent impacts of overconfidence, herding, mental accounting, and loss aversion on investment choices, where risk perception serves as a central mediating variable. In contrast to earlier models that utilize a one-dimensional stance, this research employs Structural Equation Modeling (SEM) in order to have access to interdependent, simultaneous, and hidden relations among constructs. SEM allows for testing both direct and indirect effects, hence providing a more subtle understanding of the way investor psychology works under intricate real-life settings. By focusing on Nepal's unique socio-financial context, this research aims to contribute to the broader behavioral finance literature and yield practical insights regarding investor education, policy-making, and financial advisory services in emerging economies. In so doing, it informs a more holistic and culturally aware research strategy to the investigation of investor behavior that transcends conventional rational assumptions and respects the multifaceted nature of decision-making under uncertainty.

Literature Review

Behavioral finance has greatly challenged the assumptions made by mainstream financial theory, particularly that investors are rational maximizers of returns on the basis of objective risk analysis. Mainstream models such as the Capital Asset Pricing Model (Sharpe, 1964) and the Efficient Market Hypothesis (Fama, 1970) rely on rational choice theory and assume that markets are efficient and rational investors use all available information. But a recent outburst of research in behavioral finance reveals that investor decisions are systematically influenced by cognitive heuristics and affective biases, frequently yielding inferior results, especially in situations of uncertainty, ambiguity, or information asymmetry. Prospect Theory, established by Kahneman and Tversky (1979), is a pioneering model describing the psychological foundations of decision-making under risk. As this theory would postulate, individuals evaluate outcomes with respect to a personal benchmark and experience asymmetric responses to gains and losses loss aversion. Investors become risk-averse when confronted with gains and risk-taking when confronted with losses, ending up with irrational behavior such as the holding of down-trading assets in hopes of rebounding. This was developed further by myopic loss aversion theory (Benartzi & Thaler, 1995), which explains why more frequent investment monitoring makes an individual more risk-sensitive and causes overly conservative investment choices. Gal and Rucker (2018) highlighted the variability of loss aversion's degree and direction by context and thus the need for empirical models that consider cultural, economic, and psychological variables, especially in diverse settings such as Nepal.

Herding behavior and other behavioral effects are extensively researched in finance literature, particularly where there is low financial literacy and information availability. Informational cascades model (Bikhchandani et al., 1992) describes how individuals follow the behavior of other people, especially during uncertainty, on the assumption that others possess superior information. The behavior creates bubbles in prices and market crashes since asset prices diverge from intrinsic values. Herding behavior occurs frequently among speculative asset classes like crypto currencies. Although herding can be rational in certain situations because of public signals common to all (Sias, 2004), in underdeveloped markets like in Nepal it generally results from over-reliance on social networks, conformity, and institutions distrust. Non-professional dominance or dominance of financial advice and collectivist culture enhance this phenomenon, leading to inefficient market behavior. Mental accounting, as originally suggested by Thaler (1985), depicts another useful cognitive distortion where individuals mentally compartmentalize money into different accounts based on where it came from or what they will use it for. This results in irrational financial behaviors such as spending excess profits on excessive items or irrational wants of dividends over capital gains. The "house money effect" (Thaler, 1999) demonstrates the tendency of individuals to be more likely to gamble on perceived gains than earned income. While such behavior is so ingrained, studies by Rick and Loewenstein (2021) have shown that its effect could be mitigated by mental accounting and self-awareness. In the Nepalese context in which investment decision is closely entangled with cultural values and traditional norms, mental accounting is therefore particularly relevant and deserving of more empirical research.

One of the other pervasive themes in behavioral finance is overconfidence, where investors overstate their ability, knowledge, and influence in determining financial results. Empirical work by Odean (1998) and Barber and Odean (2001) documented that overconfident investors trade too much and achieve lower net returns mainly due to poor timing and risk underestimation. This trend is reinforced by self-attribution, wherein success is attributed and failure is externaled, thereby over time reinforcing overconfidence. Findings from a study by Bhandari and Deaves (2006) indicate that overconfidence is prevalent among young investors, while Glaser and Weber (2007) propose that it is context-specific, with individuals tending to be overconfident in familiar financial contexts. The observation calls for context-specific studies, especially in environments like Nepal, where overconfidence might manifest differently due to varying information access and varying cultural self-efficacy constructs. While these determinants of behavior impact decision-making in and of themselves, they more often work in interdependent and intersecting ways. At the nexus of such interaction lies a bridging factor: risk perception. Objective measures of risk are facts, yet risk perception is subjective, based on experience, emotion, and social pressure. Grable and Joo (2004) note that risk perceptions vary widely from statistical projections and may be a better predictor of investor action. This is consistent with the overall result of Prospect Theory, that individuals are more sensitive to framing than to true probability. Subjective risk perception can at times overwhelm rational thinking in investment choice. Contextual variables such as media usage, institutional trust, and social ambiguity are significant. For example, Guiso et al. (2021) showed that media coverage during the COVID-19 crisis significantly changed individuals' perception of financial risk. Similarly, Bălănescu et al. (2021) argue that cultural norms, regulatory transparency, and governance trust significantly influence perception of risk, thereby influencing investors' behavior.

Empirical evidence for these psychological and behavioral mechanisms in Nepal remains limited but growing. Giri and Adhikari (2023) documented cultural conservatism and application of collective norms as propulsive determinants of risk attitudes. Karki (2024) and Dhungana et al. (2022) registered herding behavior among various investor groups and linked it with low financial literacy and limited access to formal advisory services.

Studies by Aryal (2024) and Sitaula and Uprety (2024) examined the effects of affective biases, under which loss aversion and overconfidence were dominant forces, often mediated through subjective risk perceptions. Shrestha and Rawat (2023) also found that Nepalese investor behavior is prominently marked by herding and non-official financial advice during weak financial regulation and investor education. Kandel et al. (2024) complemented that regulatory ambiguity and differential policy communication are to blame for uncertainty and incorrect risk estimations. Financial literacy has ever been a mediating variable that can offset the impact of behavioral biases. Research by Bhattarai (2019) and Nepal et al. (2023) shows that financially well-literate investors are more capable of handling cognitive biases and better able to interpret market signals. Subedi and Silwal (2024) found that not only does financial literacy reduce the direct effect of biases, but also increase the mediating effect of risk perception on investment decisions. However, the majority of earlier research is plagued by methodological shortcomings. Most of the current research employs small samples, cross-sectional data, and bivariate statistical measures that fail to reveal the dynamic, interrelated nature of behavioral constructs. Few of the studies have employed rigorous techniques such as Structural Equation Modeling (SEM) that allow multiple latent variables and mediating pathways to be tested collectively. In addition, the separation of behavioral biases as independent instead of intercorrelated or higher-order factors has limited the explanatory power of current models.

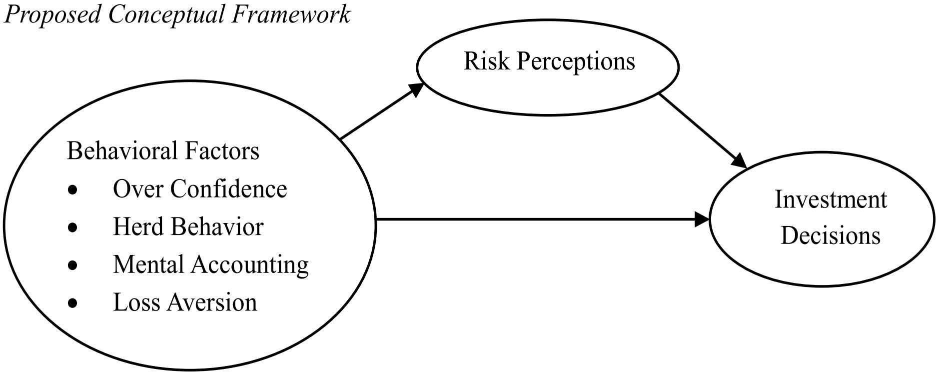
With these gaps, the need is dire for context-appropriate theory-guided empirical work that integrates behavioral bias, mediating factors like risk perception, and moderating factors like financial literacy into one analytical framework. In such poorly researched economies as Nepal, such work can potentially offer not only academic value but also practical insights for investor education, financial policy-making, and regulation of the market.

Conceptual Framework

The Behavioral Life Cycle Hypothesis further illustrates the impact of financial literacy on consumption and saving patterns over an individual's lifetime (Carroll, Choi, & Dvorkin, 2009). Financial literacy significantly influences stock market participation and investment decisions (van Rooij et al., 2011), while interventions aimed at improving financial literacy can lead to better financial behaviors and outcomes (Fernandes et al., 2014). The integration of behavioral biases namely overconfidence, herd behavior, mental accounting, and loss aversion into the conceptual framework is grounded in their profound impact on financial decision-making, as established by behavioral finance theories. These biases summarize the cognitive and emotional dimensions of human behavior, addressing the limitations of traditional rational models (Kahneman & Tversky, 1979; Thaler, 1985). This framework emphasizes the interplay between psychological, cognitive, and educational factors in shaping investment behaviors, highlighting the mediating role of risk perceptions and the moderating influence of financial literacy in promoting sound financial decision-making (Nofsinger, 2018).

Figure 1

Proposed Conceptual Framework



Methods

This study takes a quantitative research design under the positivist epistemological paradigm to investigate the influence of behavioral biases and risk perception on investment decision-making among sophisticated investors in Nepal. The research has strong theoretical underpinnings, specifically Prospect Theory (Kahneman & Tversky, 1979) and the Behavioral Asset Pricing Model (Shefrin & Statman, 1994), which both suggest that investors are not always rational agents but are instead motivated by cognitive and emotional heuristics. Based on this theoretical foundation, the study employs Partial Least Squares Structural Equation Modeling (PLS-SEM) to analyze the structural relationships between behavioral biases viz., overconfidence, herding, mental accounting, and loss aversion and rational investment decisions. Risk perception is included as a possible mediating variable.

The study uses a structured, self-administered questionnaire developed from validated measures in the literature of behavioral finance. Seven items on a seven-point Likert scale operationalized each construct, capturing the respondents' subjective preferences for making financial decisions under uncertainty. The instrument was pilot-tested with a sample of the target population prior to administration to determine clarity, content validity, and internal consistency. The population targeted is financial professionals in Nepal, which comprises 1,818 Chartered Accountants (CAs), 3,423 B-class, 1,560 C-class, and 2,251 D-class registered auditors, as of 2022/23. The population was selected based on their presumed financial literacy and rationality, thus being the appropriate environment for determining the extent to which even highly qualified individuals are influenced by behavioral biases in making investment decisions.

Sampling was done using Cochran's formula for statistical representativeness, with a final usable sample of 420 responses. The questionnaire was administered online via Google Forms for accessibility and timeliness in data collection. Descriptive statistics including frequencies, percentages, means, and standard deviations were first used for profiling the respondents' demographic attributes and sketching out a picture of their behavioral proclivities and financial orientations. Harman's single factor test was applied to detect the potential presence of common method bias, and the findings indicated no substantial threat. Internal consistency was established through Cronbach's Alpha and Composite Reliability, both of which exceeded the acceptable figure of 0.70, thereby supporting the reliability of the measures. To further demonstrate construct validity, Average Variance Extracted (AVE) values were checked to ascertain convergent validity, while discriminant validity was established through the Fornell-Larcker criterion. These procedures guaranteed that every latent construct was statistically different and conceptually consistent. Then, the measurement model was evaluated with the use of PLS-SEM version 4.0, in which direct and indirect relationships among variables could be estimated. Collinearity diagnostics were performed with the Variance Inflation Factor (VIF), where it was confirmed that there was no multicollinearity. Path coefficients were examined via bootstrapping, which improved the stability of the results. The coefficient of determination (R^2) was also calculated to evaluate the explanatory power of the model, that is, the extent to which risk perception and behavioral biases cumulatively account for variance in investment decision-making.

The application of PLS-SEM over covariance-based SEM was theoretically and empirically justified. As the current research was of an exploratory nature and the latent constructs being investigated were complex, PLS-SEM was applied as it was found to be more appropriate due to its flexibility in handling non-normal data distributions and representing both reflective and formative constructs simultaneously. Besides, the approach allows for the estimation of direct and indirect effects, enabling mediation analysis to test whether risk perception is one of the channels through which behavioral biases influence investment decision. The mediation model provides an insight into how psychological biases may distort perceived risk, leading to decision-making behavior.

By following a deductive approach, in which hypotheses are derived from existing theoretical propositions and empirically tested using rigorous statistical techniques, this study presents a comprehensive and context-specific exploration of behavioral finance in Nepal. The application of descriptive, causal, and inferential statistical techniques enables the testing of both the prevalence and causal mechanisms of behavioral biases and risk perceptions. Such methodological rigor not only enhances the internal and external validity of the study but also contributes meaningfully to the cumulative body of knowledge on behavioral finance in developing economies. Last but not least, the results are likely to illuminate policymakers, educators, and financial professionals with the cognitive and affective underpinnings of investment behavior and suggest solutions for averting irrational decision-making in Nepal's evolving financial landscape

Results

Demographic Information

Table 1

Profile of Respondents

	Respondents	Count	Total	Proportion
Gender	Male	146	420	0.347
	Female	274	420	0.653
Experience (Years)	1 to 5	144	420	0.342
	5 to 10	140	420	0.335
	Above 10	136	420	0.323
Categories	C-class Auditors	72	420	0.171
	Chartered Accountants (CAs)	84	420	0.200
	D-class Auditors	104	420	0.248
	B-class Auditors	160	420	0.381

Table 1 illustrates the demographic profile of the respondents in this study (N = 420), stratifying their gender, professional experience, and auditor category. In terms of gender composition, the sample comprises 34.7% male. This indicates a greater presence of females among the respondents that may reflect the change in gender dynamics within the auditing and financial profession in Nepal. In terms of professional experience, the respondents were proportionally well-balanced among three categories: 1 to 5 years (34.2%), 5 to 10 years (33.5%), and more than 10 years (32.3%). The balanced distribution improves the reliability of results among different levels of exposure at work and enables strong interpretations with regard to behavioral trends and risk perception in investment choices. The sample was also classified based on professional title, such as the various categories of auditors. The highest group consisted of B-class auditors (38.1%), followed by D-class auditors (24.8%), Chartered Accountants (CAs) (20.0%), and C-class auditors (17.1%). It is this classification that can harness the heterogeneity in Nepalese auditing in terms of knowledge, regulation exposure, and behavioral patterns.

Common Method Bias

The table 2 represent common method biases, because data measurements for independent, mediating, and dependent variables all came from the same respondents under one measurement context, common method bias (CMB) has a risk of occurring. Common method bias distorts or deflates observed relationships due to method-based systematic error rather than in the constructs that are being measured (Podsakoff et al., 2003). To satisfy this requirement, Harman's single-factor test was used, a widely used diagnostic method for the identification of CMB in cross-sectional self-reported survey data (Podsakoff & Organ, 1986).

Table 2

Harman's Common Factor Test

Item	Principal axis Factoring
Sum of Squire Loadings	43.247%
Proportion Variance	10.461%

Specifically, Principal Axis Factoring with no rotation was conducted, and the un-rotated factor solution was examined for the purpose of determining the extent to which one factor was able to account for the variance of the items. The test also showed that the first factor explained only 10.461% of the variance, which is much below the commonly accepted cut-off of 50%, only beyond which CMB can be considered to be a potential threat (Fuller et al., 2016). The ratio of explained variance by a single factor thus very much suggests that common method bias is no cause for concern in this study, contributing to the internal validity of the findings.

Model Fit Assessment

As reported in Table 3, the SRMR for the model is 0.072, below the conventional cutoff of 0.08, indicating a good model fit (Hu & Bentler, 1999). Furthermore, the NFI is 0.875, slightly lower than the ideal threshold of 0.90. While this is a slight deviation from the perfect fit, it is acceptable within the framework of exploratory modeling, especially with support from a low SRMR (Henseler et al., 2016). Overall, the model perceives an adequate level of fit, therefore validating the structural relation suggested in the robustness of the theoretical model.

Table 3

Model fit Assessment

Chi_square	7336.982
Chi_square_df	2.854
NFI	0.875
SRMR	0.072

Measurement Model

Convergent Validity. As evident in Table 4, the majority of HTMT values are sufficiently below the conservative threshold of 0.85 recommended for achieving discriminant validity. For instance, correlations such as HB–ID (0.814), HB–LA (0.735), HB–MA (0.719), HB–OC (0.778), and HB–RP (0.717) capture similar levels of discriminant validity between Habit and the other constructs. Similarly, ID–LA (0.698), ID–MA (0.725), ID–RP (0.779), LA–RP (0.668), MA–RP (0.611), and OC–RP (0.716) are well below the threshold, confirming construct distinctiveness. However, the HTMT ratio of ID–OC (0.841) is close to the ceiling, and therefore conceptual confounding and the necessity for testing by bootstrapping techniques are present.

Table 4

HTMT Results

	HB	ID	LA	MA	OC
HB					
ID	.814				
LA	.735	.698			
MA	.719	.725	.8051		
OC	.778	.841	.711	.616	
RP	.717	.779	.668	.611	.716

HTMT estimates for LA–MA (0.805) and MA–OC (0.616) are also in acceptable ranges, supporting discriminant validity. According to Sarstedt et al. (2020), bootstrapped confidence interval analysis must be conducted by the researchers when HTMT ratios draw close to or equal 0.85 levels to confirm that the intervals do not cross over with 1.0, indicating discriminant validity absence. Given that most HTMT ratios in the current study are significantly less than 0.85, these findings confirm the sufficiency of the measurement model and demonstrate that the constructs have strong discriminant validity, ensuring they have conceptual distinctiveness.

Internal Consistency. In a bid to establish the internal consistency reliability of the measurement model, the study examined Cronbach's alpha, composite reliability (rho_c), and reliability coefficients (rho_a) as presented in Table 5. Internal consistency is the degree to which items that measure a specific construct are intercorrelated, thereby ensuring that they manage to measure the same theoretical dimension consistently (Hair et al., 2017). According to widely applied benchmarks, internal consistency ranging from above 0.70 for Cronbach's alpha and composite reliability is good to excellent (Hair et al., 2021). According to Table 6, Cronbach's alpha for all constructs ranges from 0.702 (Mental Accounting) to 0.861 (Herding Bias), denoting good to excellent item consistency. Similarly, rho_c measures between 0.787 and 0.900, while rho-a measures are also considerably in excess of threshold 0.70, again supporting internal consistency of the measurement scales.

Finally, Average Variance Extracted (AVE) was calculated to test convergent validity, which is concerned with how much the indicators of a construct share a high proportion of variance (Table 5). All the constructs met the critical AVE criterion of 0.50, ranging from 0.575 (Overconfidence) to 0.747 (Investment Decision), indicating that more than 50% of the indicators' variance is explained by the corresponding latent construct (Fornell & Larcker, 1981). Collectively, the above findings confirm that the constructs possess not only high internal reliability but also adequate convergent validity. This is in line with the recommendations by Henseler et al. (2016) and Sarstedt et al. (2020), who note that several measures of reliability and validity reinforce the overall psychometric soundness of the measurement model of PLS-SEM analysis.

Table 5

Constructs Reliability

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	AVE
HB	0.861	0.863	0.9	0.643
ID	0.736	0.721	0.787	0.747
LA	0.768	0.769	0.866	0.683
MA	0.702	0.728	0.831	0.622
OC	0.818	0.828	0.871	0.575
RP	0.809	0.815	0.875	0.637

Coefficient of determination (R^2) and Variance Inflation Factor (VIF)

Chin (1998) considers R^2 values of 0.67, 0.33, and 0.19 as indicative of high, moderate, and low predictability. R^2 for Investment Decision (ID) in the present study is 0.742 and for Risk Perception (RP) is 0.892, which indicates high predictive power. The adjusted R^2 (0.739 for ID and 0.891 for RP) is somewhat lower, suggesting model stability without over fitting (Hair et al., 2021). Collinearity was considered as well using VIF, where percentage of all predictors Herding Bias (1.863), Overconfidence (2.621), Mental Accounting (2.359), and Loss Aversion (2.826) were in proper bounds (Hair et al., 2021). This confirms there are no issues with multicollinearity and confirms the reliability of path coefficients. Despite these predictors having moderate collinearity, the model estimates are statistically reliable. The model as a whole presents great explanatory and theoretical validity.

Analysis of the Predictive Power of the Model: PLS-Predict

Table 6

Prediction Summary

	Q^2predict	RMSE	MAE
ID	0.688	0.558	0.415
RP	0.889	0.335	0.225

Table 6 shows, out-of-sample predictive validity of the model was assessed using PLS-Predict as suggested by Shmueli et al. (2019), to investigate the strength of the model to forecast behavior beyond the estimation sample. The model's Q^2predict values for Investment Decision (ID) = 0.688 and Risk Perception (RP) = 0.889, shows a strong degree of predictive accuracy, above the zero hurdle value. The model also demonstrated low levels of RMSE (ID = 0.558; RP = 0.335) and MAE (ID = 0.415; RP = 0.225), suggesting that it made very few prediction errors, supporting the model's accuracy (Shmueli et al., 2019; Hair et al., 2021). These results confirm that the model offers considerable predictability and external validity for investment behavior.

Hypotheses Testing

The structural model was then analyzed to evaluate direct relationships between selected behavioral biases Herding Bias (HB), Loss Aversion (LA), Mental Accounting (MA), and Overconfidence (OC) and the dependent construct Investment Decision (ID). The results of this path analysis, as bootstrapped with 5,000 resamples, are presented in Table 7. The estimates are described by sample mean (M), standard deviation, T-statistics, and p-values. The validity of hypothesized paths is determined based on a T-statistic greater than 1.96 and p-values below 0.05, indicating statistical significance at the 5% level (Henseler et al., 2016). The research discovers that Herding Bias has a positive and statistically significant influence on investment decisions ($\beta = 0.028$, $p = .002$), consistent with existing literature revealing that people are likely to follow others' actions in the financial market, especially in the context of uncertainty (Bikhchandani & Sharma, 2001). This agrees with herding theory that claims social conformity pressures significantly affect investment behavior. Conversely, Loss Aversion negatively affects investment decisions ($\beta = -0.061$, $p = .016$), as Prospect Theory predictions of individuals being more concerned with losses than equal gains are supported (Kahneman & Tversky, 1979). This suggests that heightened responsiveness to potential losses deters investors from more risky or rational asset investments. Similarly, Mental Accounting also demonstrates a significant negative impact on ID ($\beta = -0.057$, $p = .006$), indicating that investors who mentally divide their money into "accounts" may not view investments as an entire package and thus make worse decisions (Thaler, 1999). This is also in agreement with prior studies emphasizing the disruptive role of compartmental thinking in financial decision making (Ricciardi & Simon, 2000). Most saliently, Overconfidence exerts a strong and highly significant negative influence on ID ($\beta = -0.355$, $p < .001$), capturing the overconfident investors' tendency to exaggerate their information and downplay risk that typically results in poor investment performance (Barber & Odean, 2001; Glaser & Weber, 2007). The extremely large T-statistic value of 3.572 confirming OC once again highlights its influential role in deterring rational investment behavior. Overall, statistically significant results validate the hypothesized direct relationships and reinforce the behavioral finance theoretical framework, demonstrating that cognitive and emotional biases significantly impair rational investment decisions. Such studies validate theoretical hypotheses in addition to empirical research (Statman, 2014), endorsing the pivotal impact of investor psychology in financial decision-making processes.

Table 7

Direct Effect between Variables

	Sample mean	Standard deviation	T statistics	P values
HB – ID	0.028	0.012	2.327	.002
LA – ID	-0.061	0.025	2.401	.016
MA – ID	-0.057	0.021	2.734	.006
OC – ID	-0.355	0.098	3.572	.000

Indirect Effect

To evaluate the indirect effects of behavioral biases on investment selection, the research used mediation analysis using bootstrapped confidence intervals where the mediating variable was Risk Perception (RP). The method adheres to guidelines by Preacher and Hayes (2008) for establishing if an intervening construct significantly passes the effect of independent variables to a dependent outcome. All the postulated mediation paths are statistically significant with p-values of less than 0.05 and t-statistics greater than the 1.96 threshold, hence establishing the mediating role of RP. The statistically significant positive indirect effect of Herding Bias (HB) on Investment Decision (ID) through RP ($\beta = 0.028$, $p = .020$) affirms the hypothesis that perceived risk serves to direct socially influenced behavior toward more active investment options a finding consistent with Herding Theory dynamics (Bikhchandani & Sharma, 2001). On the other hand, Loss Aversion (LA) ($\beta = -0.061$, $p = .016$), Mental Accounting (MA) ($\beta = -0.057$, $p = .006$), and Overconfidence (OC) ($\beta = -0.355$, $p < .001$) show negative and statistically significant indirect effects, suggesting that RP intensifies the negative influence of these biases on investment decisions. These results support the behavioral finance paradigm that cognitive biases not only exert direct influence, but also indirectly affect decision-making through shaping the way individuals view and react to risk (Kahneman & Tversky, 1979; Statman, 2014). Among the mediated effects, Overconfidence exhibits the strongest indirect effect with the largest t-statistic (3.572), furthering previous literature that overly confident investors misjudge risk and therefore make irrational investment choices in the face of perceived uncertainty (Barber & Odean, 2001; Glaser & Weber, 2007). Overall, the mediation analysis identifies Risk Perception as an important psychological process through which behavioral biases affect rational investment outcomes. These findings empirically verify the conceptual model and highlight the importance of mediating variable control when estimating investor behavior in such emerging markets as Nepal.

Table 8
Mediating Effect

Variables	Beta coefficient	Standard deviation	t- statistics	P values
HB -> RP -> ID	0.028	0.012	2.327	.020
LA -> RP -> ID	-0.061	0.025	2.401	.016
MA -> RP -> ID	-0.057	0.021	2.734	.006
OC -> RP -> ID	-0.355	0.098	3.572	.000

Discussion

This study finds that behavioral biases herding, loss aversion, overconfidence, and mental accounting are influential in investment decisions of professional investors in Nepal, with risk perception being a primary mediating variable. The study confirms Prospect Theory and theory of behavioral finance by finding that even financially competent individuals are susceptible to mental distortions that affect their investment choices systematically. Herding behavior was also observed to have a positive effect on investment choices, stressing social conformity in Nepal's collectivistic society, while overconfidence, mental accounting, and loss aversion had adverse effects on investment choices by inducing risk misperception and poor asset allocation. The strong predictive power of the structural model, as evidenced by high R^2 values for investment choices and risk perception, confirms that these behavioral measures as a set provide a robust account of how investors perceive financial risk and make investment choices, extending previous research and closing an important empirical gap in developing market settings.

The implications of findings are considerable. They demonstrate the urgent requirement for investor education programs that define technical financial literacy and combat cognitive and affective biases that undermine rational investment conduct. Regulatory bodies and financial planners should include behavioral finance theory in professional studies and client advisory processes to help mitigate overconfidence and mental accounting biases. Moreover, policy at the Nepalese social and cultural level should encourage behavioral risk awareness and construct tools that enable investors to reflect upon their view of risk prior to investment choices. By referring to the pivotal part of psychological factors in investment behavior, the present study provides real-world implications for instructors, policymakers, and economic institutions aiming at improving market stability and investor performance in emerging economies like Nepal.

Conclusion

The study analyzed the influence of some of the most prevalent behavioral biases overconfidence, herding, mental accounting, and loss aversion on investment decision-making with risk perception as a mediator in the context of Nepal's evolving financial landscape. Founded on Prospect Theory and recent behavioral finance theory, the findings reveal that while herding behavior exerts a positive but marginal influence on investment decision-making, overconfidence, loss aversion, and mental accounting exert significant negative impacts. These results point out that even finance professionals such as chartered accountants and auditors are not immune to the influence of behavioral biases, thereby challenging the assumption of full rational decision-making in professional investor communities. Notably, risk perception performs a critical mediating function between behavioral biases and investment decision-making, pointing to its central role in interpreting and processing behavioral preferences into actual investment behavior. The study contributes both theoretically and practically. Theoretically, it improves the behavioral finance body of literature in emerging economies through the empirical examination of a multi-path model comprising cognitive and emotional biases and a core psychological mediator. Practically, it offers suggestions for financial educators, policymakers, and advisory institutions in Nepal to create more targeted behavioral interventions and investor education programs that go beyond financial literacy and incorporate cognitive-behavioral principles. The use of Partial Least Squares Structural Equation Modeling (PLS-SEM) provided a rigorous methodological framework for modeling complex relationships and estimating both direct and indirect effects with good predictive ability, as indicated by the high R^2 and Q^2 predict values.

The research is however plagued by several limitations. First, being cross-sectional in nature, it constrains the degree to which causality can be assumed. Behavioral biases and risk attitudes may not be stable and may shift over time or in response to economic shocks trends an experimental or longitudinal design would more likely pick up. Second, while the sample of 420 financially sophisticated practitioners ensures internal validity, the findings may not generalize to retail investors or less financially sophisticated individuals, who may have different behavioral profiles. Third, though the constructs were represented correctly, the study did not incorporate higher-order behavioral constructs (e.g., classifying biases as cognitive vs. emotional), nor did it incorporate financial literacy as a moderating variable, which the current body of research shows can buffer or intensify the impact of biases on investment decision. Also, the impact of cultural and contextual factors, i.e., collectivism, social trust, media, or family-induced financial behavior factors highly relevant in the Nepali context—was not explicitly modeled but would need to be taken into account for future research. Finally, while PLS-SEM offers predictive power, future research can benefit by combining quantitative SEM with qualitative or experimental methods to derive more incisive conclusions regarding the underlying dynamics of irrational investment decision-making behaviors.

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