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COGNITIVE BIASES, RISK PERCEPTION, AND IRRATIONAL INVESTMENT DECISION-MAKING: A MULTI-GROUP ANALYSIS

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ABSTRACT

Behavioral biases impact investment choices in addition to financial analysis. This study examines how risk perception serves as a moderating factor in the relationship between availability bias and loss aversion bias, influencing investment decision-making. Using a quantitative approach, data were collected from 390 Nepalese investors through a structured questionnaire and analyzed using structural equation modelling and a multi-group analysis. Availability bias, where investors rely on readily accessible information rather than conducting in-depth analysis, was found to have a significant positive effect on irrational investment decisions. However, there was no discernible direct effect of loss aversion bias, which is the propensity to avoid losses more than to pursue comparable benefits. Risk perception played a crucial role, significantly influencing investment decisions and moderating the effect of loss aversion bias by reducing its impact on irrational decision-making. However, risk perception did not moderate the association between availability bias and investment choices. The findings suggest that investor behavior in Nepal is influenced by cognitive shortcuts and risk perception, underscoring the importance of financial education and awareness in promoting rational decision-making. Future research should explore other behavioral biases and investigate the role of digital investment platforms in shaping investor psychology.

Keywords: *Availability Bias, Loss Aversion Bias, Risk Perception, Irrationality, Investment Decision-making*

1. Introduction

Investment behavior is influenced not only by economic conditions and financial data but also by the psychological tendencies of decision-makers (Davis, 2001). While traditional perspectives, such as the Efficient Market Hypothesis (Fama, 1970), assume that investors act rationally, behavioral finance demonstrates that decisions are often shaped by mental shortcuts and emotions (Kahneman & Tversky, 1979; Shefrin, 2001). Two important biases—availability bias and loss aversion bias- have been widely recognized as influencing the way individuals make financial choices.

Although prior studies have examined these biases, several issues remain unresolved. First, the majority of research has focused on developed economies, resulting in a limited understanding of how these biases operate in developing markets like Nepal, where limited financial literacy and reliance on informal information sources may exacerbate irrational behavior (Dhakal & Lamsal, 2023). Second, although risk perception is acknowledged as a significant determinant of financial decisions, its moderating role in the relationship between cognitive biases and investment choices has not been systematically tested in this setting. Third, little is known about whether demographic characteristics, such as gender, age, or investment experience, alter the influence of these biases on decision-making.

This study aims to address these shortcomings by examining the impact of availability bias and loss aversion bias on investment decision-making in Nepal, while also investigating the moderating role of risk perception. By applying structural equation modeling and multi-group analysis, this research contributes to theory by extending Prospect Theory and the Heuristics and Biases framework to an underexplored context, and to practice by offering guidance for investors, advisors, and regulators on how to encourage more rational decision-making in volatile financial environments.

2. Literature Review

2.1 Investment Decision Making

Investment involves allocating capital to assets or projects to earn returns that exceed the initial outlay (Sabatimy & Nur, 2023). Typically, higher risks are associated with higher potential returns (Hedegaard & Hodrick, 2014). Investment decisions require strategic thinking and often depend on financial literacy, as individuals with greater financial knowledge are more likely to make rational choices (Merton, 1987; Nagaeva, 2024; Subedi et al., 2025).

Over the past two decades, researchers have increasingly focused on the psychological aspects of investing, particularly the concept of "cognitive unconsciousness," which explains how investors may hold certain perceptions and make decisions without being fully aware of them (Hilton, 2001). Emotional and cognitive biases can lead even informed investors to act irrationally (Baker & Nofsinger, 2002). Behavioral finance, therefore, seeks to connect financial models with actual investor behavior (Barber & Odean, 1999). Ritter (2003) challenged the Efficient Market Hypothesis (EMH), arguing that market inefficiencies stem from behavioral influences, and highlighted that investor decisions are often shaped by biases rather than pure rationality.

2.2 Availability Bias and Investment Decision Making

Availability bias, where individuals rely on easily recalled information instead of thorough analysis, significantly influences investment decisions (Javed et al., 2017). This bias skews investors' perceptions of risk and opportunity, causing them to overestimate the likelihood of certain events based on limited data (Folkes, 1988; Shah et al., 2018). Market pressures further amplify this tendency, as rapid environments encourage reliance on mental shortcuts, often leading to suboptimal outcomes (Bowers et al., 2014; Rasheed et al., 2018; Salman et al., 2020).

Recent studies reinforce these findings across various contexts. For instance, Wang (2023) demonstrated that investors tend to focus on recent news or trends rather than conducting a comprehensive analysis. Sadeeq and Butt (2024) confirmed a strong link between availability bias and irrational investment behavior in the Delhi-NCR region of India, challenging the assumption that investors always act rationally.

As a result, it is assumed that:

> H_1: Availability bias is significantly associated with the degree of irrationality in investment decision-making.

2.3 Loss Aversion and Investment Decision Making

Loss aversion, a key concept in behavioral finance, describes investors' greater sensitivity to losses than to equivalent gains. Kahneman and Tversky (1979) demonstrated through Prospect Theory that losses weigh nearly twice as heavily as gains, often causing investors to prioritize avoiding losses over maximizing profits. This bias leads to behaviors such as holding onto losing stocks for too long and selling winners prematurely, a phenomenon known as the "disposition effect" (Kahneman et al., 1991; Bailey et al., 2011).

Empirical studies support its influence globally: Mahina et al. (2017) observed strong loss aversion on the Rwanda Stock Exchange, while Kumar and Babu (2018) found demographic differences in India, with women exhibiting stronger loss aversion than men. Jain et al. (2019) also confirmed the tendency to sell winners prematurely and hold losers. However, some research challenges the universality of loss aversion. Budiman and Patricia (2021) and Dhakal and Lamsal (2023) reported no significant effects, suggesting that cultural or market factors may moderate its impact. Conversely, Dita et al. (2023) and Kumar and Chaurasia (2024) found that loss aversion leads to overly cautious strategies, limiting capital growth opportunities.

Based on these, the following hypothesis is proposed:

> H_2: Loss Aversion bias is significantly associated with the degree of irrationality in investment decision-making.

2.4 Moderating Role of Risk Perception

Risk perception plays a key role in investment decisions, shaping whether individuals take bold risks or act cautiously. Biases often influence these perceptions, sometimes leading to irrational choices. Sitkin and Weingart (1995) found that engaging in risky situations can shift people's risk mindset, affecting future decisions. Similarly, Weber and Hsee (1998) demonstrated that how investors perceive risk, whether as an opportunity or a threat, significantly influences their choices.

Empirical studies confirm this link. Shindu and Kumar (2014) found that when investors perceive high risk, they tend to reassess their choices before committing. Khan (2017) found that risk perception weakens the effect of availability bias, making investors less likely to rely only on familiar information.

Research also highlights the moderating role of risk perception in behavioral biases, especially loss aversion. Siew et al. (2015) demonstrated that when risk perception is high, loss aversion becomes stronger, rendering investors more sensitive to losses than to gains. Khan (2017) supported this, arguing that higher risk perception intensifies this bias when weighing investment risks.

Shafqat and Malik (2021) found that people with higher risk perception often avoid trading due to loss aversion. Ahmed et al. (2022) expanded on this, suggesting that risk perception can amplify or reduce the impact of availability bias on decisions. Sugianto et al. (2024) noted that initial reference points significantly influence risk assessment, often leading to systematic errors that are exacerbated by availability bias, as easily recalled information can distort judgment.

Based on these insights, the following hypotheses are proposed:

H_3: Risk Perception moderates the relationship between availability bias and investment decision-making.

H_4: Risk Perception moderates the relationship between loss aversion bias and investment decision-making.

3. Theoretical Foundation

This study draws on theories from behavioral finance. Prospect Theory (Kahneman & Tversky, 1979) emphasizes a greater sensitivity to losses than to gains, which supports Hypothesis 2 on loss aversion and irrational investment decisions. The Heuristics and Biases framework (Tversky & Kahneman, 1974) explains the reliance on readily available information, which underpins Hypothesis 1 on the availability bias. Risk perception further shapes responses to uncertainty (Slovic, 1987; Khan, 2017), potentially amplifying loss aversion or reducing the use of heuristics through careful evaluation. Thus, Hypotheses 3 and 4 propose their moderating role. Collectively, these theories ensure the model's conceptual and empirical grounding.

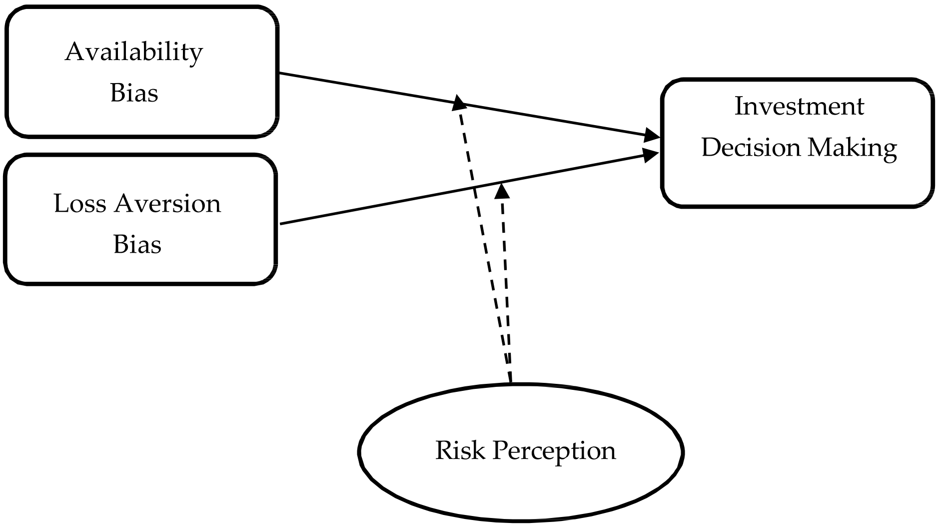

Figure 01: Theoretical Framework

4. Research Methodology

4.1 Instruments Construct

The study uses a structured questionnaire with three sections. The first collects demographic information, including age, gender, occupation, and education, to provide context for analysis. The second covers investment experience and risk attitudes to assess how personal experience influences financial choices. The third section examines cognitive biases, risk perception, and decision-making. A 5-point Likert scale measures availability bias, loss aversion bias, and their impact on investment decisions, using items drawn from validated scales to ensure reliability and alignment with the study's aims.

The availability bias items come from a 10-item scale by Kudryavtsev et al. (2013) (items 1–2), Luong and Thu Ha (2011) (items 3–4), and Waweru et al. (2008) (item 5). Loss aversion bias is measured using five items from Khan (2017). Risk perception is assessed using five items from Khan (2017), which cover fear of uncertainty, caution with volatile stocks, trust in brokers, and confidence in stocks with strong past performance. Finally, decision-making is measured using scales from Scott and Bruce (1995) and Rasheed et al. (2018), including intuitiveness as a proxy for illogical behavior in investment decisions.

4.2 Population, Sample, and Sampling Technique

The study employed purposive sampling to ensure that participants had at least five years of investment experience, guaranteeing adequate familiarity with financial decision-making. The convenience sampling technique was also applied to access respondents through online forums and investment workshops, a practical solution in Nepal where comprehensive investor databases are not readily available. While this approach has some limitations, it is consistent with the objectives of explanatory behavioral finance research in emerging markets (Kudryavtsev et al., 2013; Waweru et al., 2008; Sharma & Pyati, 2022; Sharma et al., 2022, 2023).

The sample size was calculated using Cochran's (1997) formula, ensuring a 95% confidence level and a 5% margin of error. With 390 valid responses collected, the study exceeds the minimum requirement, enhancing the reliability of the findings.

To address potential multicollinearity and common method bias (CMB, variance inflation factor (VIF) values were examined for all indicators. As shown in Table 5, all VIF values were below 2, which is well under the conservative threshold of 3.3 suggested by Diamantopoulos and Siguaw (2006). This indicates that multicollinearity is not a concern in this study. While Harman's single-factor test showed that no single factor explained the majority of variance, therefore, there is no issue of CBM in this study.

The study employed a questionnaire survey to gather both dependent and independent variables from a single source, hence introducing the potential for common method bias. Common Method Bias is frequently associated with self-reported data and may exaggerate correlations among variables (Conway & Lance, 2010). To mitigate this, the respondents were assured of confidentiality (Kraus et al., 2020), and Harman's single-factor analysis was performed. The findings revealed that a single-factor accounted for 37.21% of the variance, falling short of the 50% standard; therefore, it suggested that common method bias was not an issue in this study.

4.3 Methods of Data Analysis

The data analysis followed three steps: verification, model development, and evaluation. Descriptive analysis was conducted using IBM SPSS 22, while Smart-PLS was used for advanced statistical modeling. Reliability and validity were assessed through Cronbach's alpha, Average Variance Extracted (AVE), and discriminant validity tests, including the HTMT and Fornell-Larcker Criterion. Structural Equation Modeling was used to test the hypotheses and examine variable relationships, ensuring robust results despite the non-normal data. The sample's demographic details are shown in Table 1.

Table 1 summarizes the responses from 390 participants. The majority are male (62.1%), reflecting greater male involvement in investment decisions. Most respondents are aged 25–35 (52.8%), showing that young professionals are the most active investors.

In terms of education, most hold a bachelor's degree (36.7%) or a master's degree (56.4%), indicating that higher education levels are associated with greater investment participation. Half of the respondents work in private jobs (50%), followed by students (21.3%) and government employees (12.6%). Low representation of retirees and the unemployed suggests that active income supports investing.

Regarding experience, 35.1% have invested for 10–14 years, and another 35.1% for 15 years or more, showing a strong base of experienced investors. Meanwhile, 29.7% have 5–9 years of experience, indicating a steady flow of newer investors joining the market.

Table 1: Socio-demographic Profile of Respondents

Factors	Demographic Variables	Frequencies	Percentage (%)
Gender	Male	242	62.1
	Female	148	37.9
	Total	390	100.00
Age Group	Below 25	57	14.6
	25 to 35 years	206	52.8
	36 to 45 years	81	20.8
	Above 45	46	11.8
	Total	390	100
Qualification	SLC/SEE	2	0.5
	Intermediate	9	2.3
	Bachelor level	143	36.7
	Master's degree	220	56.4
	M. Phill.	12	3.1
	PhD	4	1
	Total	390	100.00
Occupation	Student	83	21.3
	Self-employed	47	12.1
	Government job	49	12.6
	Private job	195	50
	Retired	3	0.8
	Unemployed	13	3.3
	Total	390	100.00
Investment Experience	5-9 years	116	29.7
	10-14 years	137	35.1
	15 and above	137	35.1
	Total	390	100.00

Source: Survey data

In this study, availability bias is measured using five items (AB1–AB5), but AB5 was excluded due to low outer loading. Loss Aversion Bias is assessed with five indicators (LA1–LA5). Risk Perception is measured with five items (RP1–RP5), with RP1 removed for low loading. Investment Decision Making is represented by five items (IDM1–IDM5). The measurement model is shown in Figure 2.

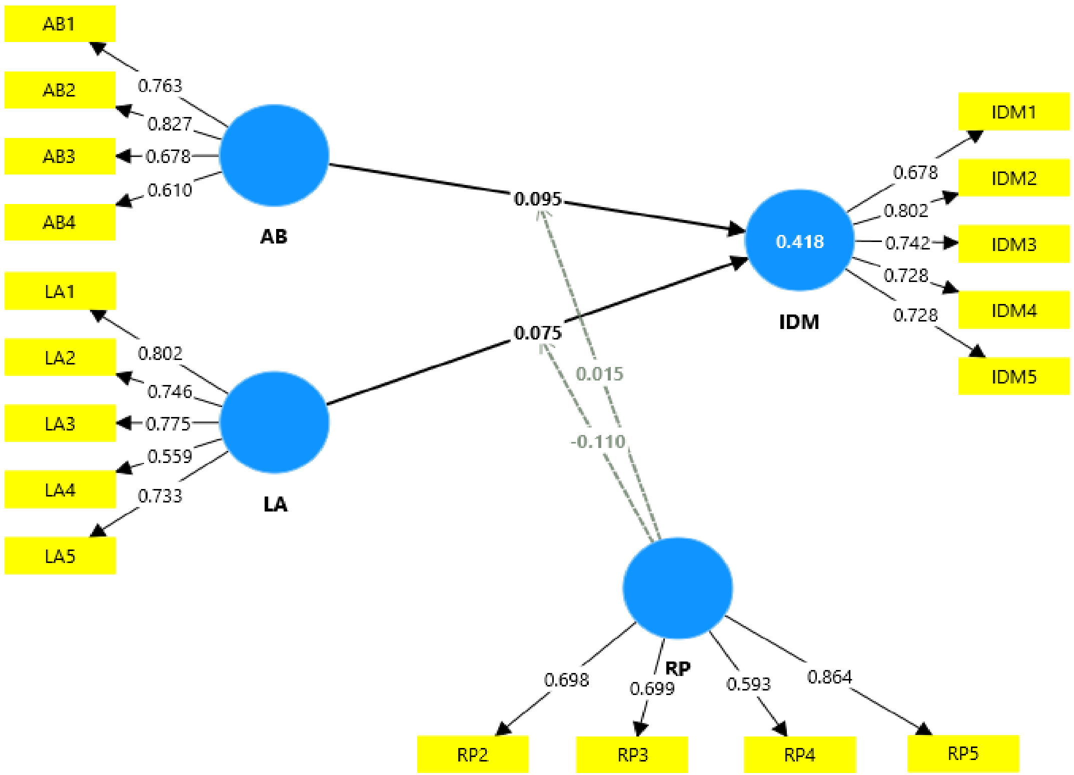

Figure 2: Measurement Model

Table 2 presents the outer loadings, Cronbach's alpha, composite reliability (CR), and average variance extracted (AVE) for the study constructs. According to Hair et al. (2017), loadings above 0.708 are ideal, though values above 0.50 are acceptable if internal consistency and convergent validity are adequate (Hair et al., 2006). In this study, factor loadings range from 0.559 to 0.864, with LA4 (0.559) being the lowest but retained.

Following Hair et al. (2022), internal consistency was checked by excluding items with Cronbach's alpha below 0.50. All constructs meet this threshold, with Cronbach's alpha values above 0.6 (Hair et al., 2014): Availability Bias (0.720), Loss Aversion Bias (0.774), Investment Decision Making (0.791), and Risk Perception (0.691). CR values (rho_a and rho_c) exceed 0.70, confirming strong reliability. AVE values (0.519–0.543) meet the 0.50 cut-off, supporting convergent validity.

Table 2: Construct reliability and validity

Factors and items	Loadings	Cronbach's alpha	CR (rho_a)	CR (rho_c)	AVE
Availability Bias		**0.720**	**0.757**	**0.813**	**0.524**
AB1	0.763				
AB2	0.827				
AB3	0.678				
AB4	0.610				
Loss Aversion Bias		**0.774**	**0.789**	**0.848**	**0.530**
LA1	0.802				
LA2	0.746				
LA3	0.775				
LA4	0.559				
LA5	0.733				
Risk Perception		**0.691**	**0.765**	**0.809**	**0.519**
RP2	0.698				
RP3	0.699				
RP4	0.593				
RP5	0.864				
Investment Decision Making		**0.791**	**0.802**	**0.856**	**0.543**
IDM1	0.678				
IDM2	0.802				
IDM3	0.742				
IDM4	0.728				
IDM5	0.728				

Source: Survey data

Table 3 presents the Fornell-Larcker criterion analysis, which confirms that most constructs exhibit acceptable discriminant validity, as the square root of the AVE for each construct exceeds its correlations with other constructs. However, as shown in Table 3, the correlation between IDM (0.737) and RP (0.720) is relatively high (0.615), indicating a potential concern regarding discriminant validity. To ensure robustness, further validation was conducted using cross-loadings and the Heterotrait-Monotrait (HTMT) ratio.

Table 3: Discriminant validity- Fornell-Larcker Criterion

	AB	IDM	LA	RP
AB	**0.724**			
IDM	0.246	**0.737**		
LA	0.195	0.426	**0.728**	
RP	0.210	0.615	0.543	**0.720**

Source: Survey data

Henseler et al. (2015) recommend HTMT thresholds of 0.90 for conceptually similar constructs and 0.85 for distinct ones; exceeding these indicates potential discriminant validity issues. As shown in Table 4, all HTMT values are below 0.90, confirming strong discriminant validity in this study.

Table 4: Heterotrait-Monotrait Ratio (HTMT)

Factors	AB	IDM	LA	RP	RP x LA	RP x AB
AB						
IDM	0.302					
LA	0.253	0.521				
RP	0.269	0.775	0.717			
RP x LA	0.275	0.519	0.566	0.649		
RP x AB	0.256	0.266	0.339	0.365	0.465	

Source: Survey data

Table 5 presents the cross-loadings, confirming that each item loads highest on its intended construct, thereby supporting discriminant validity. The highest loading for each item is bolded for clarity. The table also presents the Variance Inflation Factor (VIF) for each item. According to Diamantopoulos and Siguaw (2006), VIF values below 3.3 indicate no multicollinearity issues. In this study, all VIF values are below 2, showing minimal multicollinearity. The AB, IDM, LA, and RP factors all have low to moderate VIFs, indicating the predictors are not highly correlated and will not cause problems in the regression model.

Table 5: Cross Loading and VIF

Factors	AB	IDM	LA	RP	RP x LA	RP x AB	VIF
AB_1	**0.763**	0.211	0.289	0.212	-0.236	-0.193	1.299
AB_2	**0.827**	0.225	0.144	0.182	-0.215	-0.174	1.439
AB_3	**0.678**	0.13	-0.022	0.07	-0.111	-0.109	1.731
AB_4	**0.610**	0.085	0.043	0.083	-0.124	-0.165	1.625
IDM_1	0.166	**0.678**	0.312	0.425	-0.318	-0.262	1.418
IDM_2	0.169	**0.802**	0.416	0.565	-0.479	-0.29	1.655
IDM_3	0.151	**0.742**	0.231	0.416	-0.297	-0.114	1.600
IDM_4	0.194	**0.728**	0.357	0.474	-0.338	-0.082	1.553
IDM_5	0.24	**0.728**	0.196	0.332	-0.272	-0.124	1.712
LA_1	0.109	0.305	**0.802**	0.369	-0.381	-0.201	1.848
LA_2	0.103	0.321	**0.746**	0.376	-0.392	-0.209	1.561
LA_3	0.119	0.354	**0.775**	0.538	-0.433	-0.235	1.605
LA_4	0.216	0.228	**0.559**	0.249	-0.265	-0.124	1.216
LA_5	0.186	0.325	**0.733**	0.402	-0.334	-0.313	1.449
RP_2	0.153	0.362	0.428	**0.698**	-0.439	-0.204	1.326
RP_3	0.095	0.375	0.355	**0.699**	-0.33	-0.246	1.340
RP_4	0.183	0.33	0.269	**0.593**	-0.307	-0.166	1.178
RP_5	0.176	0.622	0.484	**0.864**	-0.478	-0.259	1.544
RP x LA	-0.253	-0.476	-0.502	-0.546	1	0.465	1.000
RP x AB	-0.222	-0.245	-0.304	-0.306	0.465	1	1.000

Source: Survey data

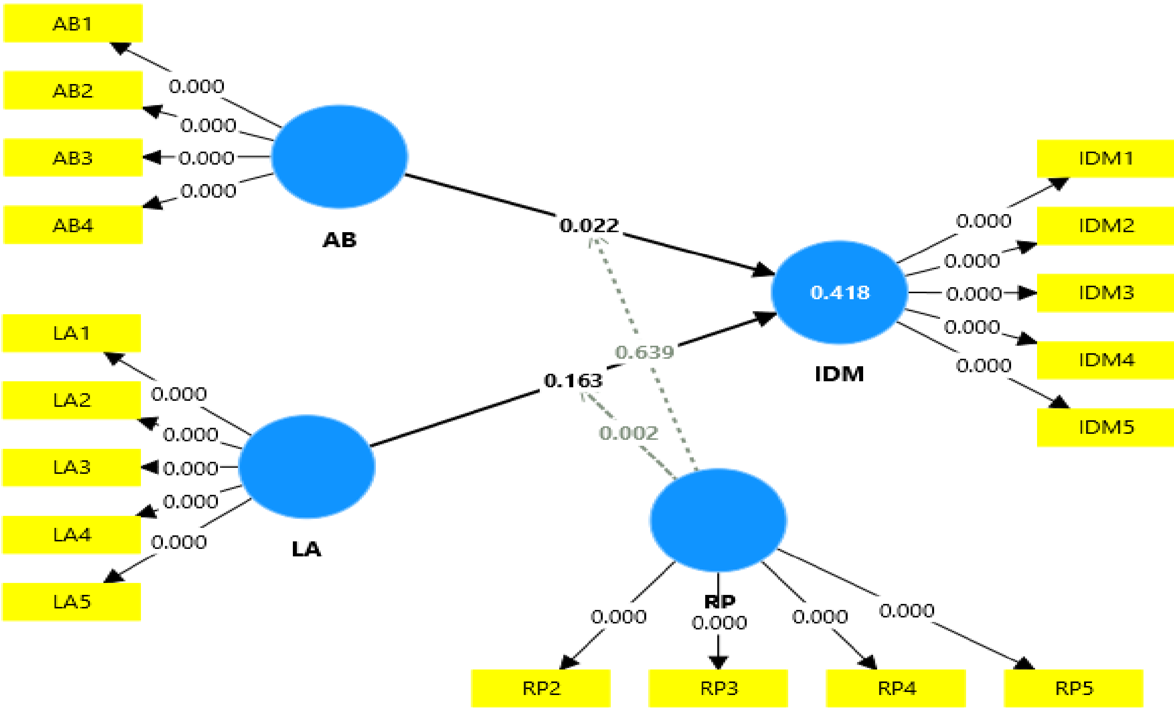

Figure 3: Structural Model

Table 6: Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	5.497	27.486	27.486	5.497	27.486	27.486	2.900	14.502	14.502
2	2.143	10.715	38.201	2.143	10.715	38.201	2.727	13.636	28.137
3	1.752	8.758	46.959	1.752	8.758	46.959	2.488	12.439	40.577
4	1.190	5.950	52.908	1.190	5.950	52.908	2.249	11.244	51.821
5	1.014	5.072	57.980	1.014	5.072	57.980	1.232	6.159	57.980
6	0.897	4.484	62.464						
7	0.862	4.310	66.774						
8	0.780	3.899	70.673						
9	0.748	3.740	74.413						
10	0.696	3.482	77.894						
11	0.692	3.458	81.353						
12	0.559	2.795	84.148						
13	0.530	2.650	86.798						
14	0.468	2.341	89.139						
15	0.439	2.193	91.332						
16	0.434	2.168	93.500						
17	0.369	1.843	95.343						
18	0.359	1.793	97.136						
19	0.312	1.560	98.696						
20	0.261	1.304	100.000						

Source: Survey data

The results presented in Table 6 summarize the outcomes of the principal component analysis conducted to assess the dimensionality of the measurement constructs and potential common-method bias. The initial eigenvalues indicate that five components have eigenvalues greater than 1, collectively explaining 57.98% of the total variance, which exceeds the minimum acceptable threshold of 50%, confirming adequate data representation. The first factor accounts for 27.486% of the variance, well below the 50% cutoff (Podsakoff et al., 2003), suggesting that common method bias is not a serious concern. The extraction sums of squared loadings confirm that these five components retain meaningful explanatory power after extraction. Furthermore, the rotation sums of squared loadings show a more balanced distribution of variance, with each of the five rotated components explaining 14.502%, 13.636%, 12.439%, 11.244%, and 6.159%, respectively. This indicates that the data structure is multidimensional, reflecting diverse underlying constructs rather than dominance by a single factor.

Table 7: Measure of Model Fit

	Saturated model	**Estimated model**
SRMR	0.086	0.084

Source: Survey data

Table 7 presents the SRMR values for both the saturated and estimated models, which are 0.086 and 0.084, respectively. According to Kock (2020), an SRMR value of less than 0.1 is considered acceptable for a model. Since the SRMR values in this study meet this criterion, the research model can be deemed a good fit.

Table 8: Path Coefficient

Paths	**Beta coefficient**	**Sample mean**	**Standard deviation**	**t-stat**	**P values**	**CI 2.5%**	**CI 97.5%**
AB-> IDM	0.095	0.101	0.041	2.296	0.022	0.018	0.181
LA -> IDM	0.075	0.077	0.054	1.394	0.163	-0.028	0.180
RP -> IDM	0.469	0.473	0.053	8.865	0	0.367	0.577
RP x LA -> IDM	-0.11	-0.108	0.035	3.167	0.002	-0.178	-0.041
RP x AB -> IDM	0.015	0.018	0.033	0.470	0.639	-0.046	0.083

Source: Survey data

Table 8 reveals how behavioral biases and risk perception affect investment decision-making. Availability bias has a significant positive effect ($\beta = 0.095$, $p = 0.022$), indicating that investors relying on easily available information tend to make more irrational decisions. This reliance on recent or memorable events leads to biased judgments and affects financial choices. Loss aversion bias, however, does not significantly influence decisions ($\beta = 0.075$, $p = 0.163$), suggesting it may not directly drive irrational behavior in this sample, despite prior studies linking it to suboptimal choices.

Risk perception shows a strong positive effect (β = 0.469, p < 0.001), meaning that higher perceived risk increases the likelihood of irrational investment decisions, possibly due to fear or overreaction.

Regarding moderation, risk perception does not significantly moderate the effect of availability bias on decisions (β = 0.015, p = 0.639), implying availability bias influences decisions regardless of risk perception. Conversely, risk perception significantly and negatively moderates the effect of loss aversion bias (β = -0.11, p = 0.001), indicating that higher risk perception reduces the impact of loss aversion, possibly because risk-aware investors adopt more balanced strategies rather than simply avoiding losses.

Table 9: Coefficient of Determination of Structural Model

Variable	R Square	Sample mean	CI-2.50%	CI-97.50%
IDM	0.418	0.43	0.352	0.51

Source: Survey data

The model's predictive power is assessed by R^2, where values of 0.75, 0.5, and 0.25 reflect strong, moderate, and weak explanatory power, respectively (Hair et al., 2011, 2013). Table 9 shows an R^2 value between 0.25 and 0.5, indicating moderate explanatory power—specifically, 41.8% of the variance in investment decision-making is explained by the combined effects of availability bias, loss aversion bias, and risk perception. The bootstrapped sample mean R^2 is 0.43, suggesting stable predictive capacity. The confidence interval ranges from 0.352 (near weak) to 0.51 (slightly above moderate), indicating some variability depending on the sample. Overall, the model reasonably explains investment decisions but implies that other factors beyond the studied biases and risk perception also play important roles.

Table 10: Hypothesis Testing

Hypothesis	Path	Beta	P Values	Results
H_1	AB-> IDM	0.095	0.022	Supported
H_2	LA -> IDM	0.075	0.163	Not Supported
H_3	RP x AB -> IDM	0.015	0.639	Not Supported
H_4	RP x LA -> IDM	-0.11	0.002	Supported

Source: Authors

Table 10 presents the results of hypothesis testing using beta coefficients and p-values to examine the relationships with investment decision-making (IDM). For H1, availability bias shows a positive and significant effect on investment decisions (β = 0.095, p = 0.022), indicating that investors influenced by availability bias are more likely to make irrational investment choices. Thus, H1 is supported.

In contrast, H2, which proposed a significant impact of loss aversion bias on investment decisions, is not supported. Although the beta coefficient is positive (β = 0.075), the relationship is not statistically significant (p = 0.163). This suggests that, in this study, loss aversion bias does not meaningfully affect irrational investment behavior.

Regarding moderation hypotheses, the results indicate a very weak positive moderation effect (β = 0.015) with a non-significant p-value (p = 0.639), suggesting that risk perception does not significantly influence the effect of availability bias on investment decisions. Therefore, H3 is rejected.

However, H4 is supported, as risk perception significantly and negatively moderates the relationship between loss aversion bias and investment decision-making (β = -0.11, p < 0.05). This means that as investors' risk perception increases, the influence of loss aversion bias on their decisions decreases, highlighting the important role of risk awareness in mitigating biased investment behaviors.

Table 11: Multi-Group Analysis (MGA) - Gender

Paths	Male	Female	Original difference	Permutation mean difference	2.50%	97.50%	p value
AB -> IDM	0.097	0.131	-0.035	-0.008	-0.17	0.15	0.646
LA -> IDM	0.136	-0.075	0.21	-0.002	-0.217	0.227	0.068
RP -> IDM	0.372	0.68	-0.307	-0.005	-0.222	0.218	0.004
RP x AB -> IDM	0.036	0.041	-0.006	-0.001	-0.134	0.133	0.942
RP x LA -> IDM	-0.18	0.043	-0.223	-0.002	-0.158	0.14	0

Source: Survey data

Table 11 reveals no significant gender difference in availability bias (p = 0.646), indicating that both men and women are similarly influenced by readily available information. However, women exhibit slightly higher irrationality (0.131) than men (0.097). For loss aversion, a marginal gender difference exists (p = 0.068), with men exhibiting greater irrationality (0.136) compared to women, who have a negative coefficient (-0.075), suggesting loss aversion might encourage more rational decisions among women. A significant gender gap is observed in risk perception (p = 0.004), where women (0.68) are more affected than men (0.372), resulting in greater irrational investment behavior. The interaction between risk perception and loss aversion is highly significant (p = 0.000), reducing irrationality in men (-

0.18) but slightly increasing it in women (+0.043), implying women may find it harder to balance these biases. Meanwhile, the combined effect of risk perception and availability bias shows no significant impact on irrationality for either gender (p = 0.942).

Table 12: MGA Age

Paths	below 36	Above 36	difference	Permutation mean difference	2.50%	97.50%	p value
AB -> IDM	0.049	0.128	-0.079	-0.01	-0.18	0.158	0.389
LA -> IDM	0.061	0.146	-0.085	-0.006	-0.234	0.215	0.486
RP -> IDM	0.439	0.544	-0.105	-0.004	-0.228	0.226	0.368
RP x AB -> IDM	0.019	0.044	-0.025	-0.006	-0.147	0.132	0.737
RP x LA -> IDM	-0.133	-0.095	-0.038	-0.002	-0.151	0.145	0.616

Source: Survey data

Table 12 indicates no significant age-based differences in the impact of cognitive biases and risk perception on irrational investment decisions. Availability bias (AB) affects both age groups similarly (p = 0.389), as does loss aversion (LA) (p = 0.486). Risk perception (RP) also shows no significant difference (p = 0.368), though older investors (0.544) are slightly more influenced than younger ones (0.439). Moreover, interactions between RP and both AB (p = 0.737) and LA (p = 0.616) are insignificant, indicating that risk perception does not alter the effects of these biases across age groups.

Table 13: MGA Investment Experience

Paths	Less than 5 years	Above 5 years	Original difference	Permutation mean difference	2.50%	97.50%	p value
AB -> IDM	0.057	0.245	-0.188	-0.005	-0.176	0.169	0.031
LA -> IDM	0.056	0.061	-0.005	-0.004	-0.229	0.226	0.97
RP -> IDM	0.5	0.394	0.106	0	-0.205	0.214	0.326
RP x AB -> IDM	0.043	0.009	0.034	0	-0.142	0.141	0.607
RP x LA -> IDM	-0.1	-0.146	0.046	0	-0.145	0.147	0.547

Source: Survey data

Table 13 shows that availability bias (AB) significantly impacts investors with over 5 years of experience (0.245) more than those with less experience (0.057), with a significant difference of -0.188 (p = 0.031). This suggests that experienced investors are more likely to be influenced by readily available information when making irrational decisions. In contrast, loss aversion (LA) affects both groups similarly (0.056 vs. 0.061), with an insignificant difference ($p = 0.970$). Risk perception (RP) has a more substantial effect on less experienced investors (0.500 vs. 0.394), but the difference (0.106) is not statistically significant ($p = 0.326$). The interaction effects of RP × AB ($p = 0.607$) and RP × LA ($p = 0.547$) are also insignificant, indicating that experience does not significantly moderate these relationships.

5. Discussion

This study explores how behavioral biases, specifically availability bias, loss aversion, and risk perception, influence investment decisions. The findings confirm that availability bias significantly affects investor behavior, with individuals often relying on readily accessible information, such as recent news or personal experience, instead of conducting thorough analyses. This supports previous studies (Rasheed et al., 2018; Dangol & Manandhar, 2020; Silwal & Bajracharya, 2021; Dhungana et al., 2022), emphasizing the need for improved financial literacy to counteract cognitive shortcuts. In contrast, the results challenge findings by Khan (2017) and Elhussein & Abdelgadir (2020), potentially due to their smaller sample sizes (163 and 207) compared to the 390 respondents in this study.

Contrary to Prospect Theory (Kahneman & Tversky, 1979), the study finds no significant link between loss aversion and investment decisions. This may indicate that Nepali investors, facing economic volatility, have developed adaptive strategies or diversified their investments. These results align with those of Karmacharya et al. (2022) and Dhakal & Lamsal (2023), but contradict the findings of Khan (2017), Kartini & Nahda (2021), and Kumar & Chaurasiya (2024), who found that loss aversion has a strong influence on investment behavior.

Risk perception plays a crucial role in shaping irrational investment choices, as heightened risk sensitivity leads investors to deviate from rational decision-making, a finding consistent with Khan (2016). However, risk perception does not moderate the effect of availability bias ($\beta = 0.015$, $p = 0.639$), indicating that even in high-risk contexts, investors continue to rely on familiar information. This contradicts Khan (2017), possibly due to cultural or financial literacy differences between Nepal and Pakistan. Interestingly, risk perception significantly weakens the influence of loss aversion ($\beta = -0.11$, $p < 0.05$), supporting Thaler et al. (1997) and Khan (2017), who argued that greater risk awareness and long-term thinking reduce emotional biases. This finding, however, diverges from Ardini et al. (2023), who found no such moderating effect.

The Multi-Group Analysis (MGA) reveals significant gender-based differences in how cognitive biases and risk perception influence investment decisions. Both men and women are equally affected by availability bias, consistent with Tversky & Kahneman (1974). However, women display a higher risk perception, often resulting in more irrational decisions, aligning with Bajtelsmit & Bernasek (1997) but contradicting Rau (2014), who found that women are more loss-averse. Men show a stronger tendency toward loss aversion ($\beta = 0.136$), whereas for women ($\beta = -0.075$), it appears to encourage caution. This supports Barber & Odean's (2001) findings on conservative female investment behavior. The interaction of risk perception and loss aversion (RP × LA) exhibits contrasting effects, reducing irrationality in men (-0.18) but increasing it in women (0.043), suggesting gendered emotional responses to financial risk (Eckel & Grossman, 2008).

The findings indicate that age does not significantly influence the effect of cognitive biases and risk perception on irrational investment decisions. Availability bias (AB) remains consistent across age groups, aligning with Kovalchik and Camerer (2009), who found that reliance on familiar information persists regardless of age. Similarly, loss aversion (LA) shows no significant variation, supporting Mata et al. (2011) and contradicting studies such as Samanez-Larkin and Knutson (2015), which suggest that older adults are more loss-averse due to greater financial responsibilities. Risk perception (RP) is slightly higher among older investors, but the difference is not statistically significant. This challenge claims by Rolison et al. (2013) and supports Alhakami and Slovic (1994), who argue that risk perception is shaped more by individual judgment than by age. The lack of significant interaction effects between RP and other biases further suggests that age does not alter how these psychological factors contribute to irrational behavior, supporting the conclusions of Peters et al. (2007) and De Bruin et al. (2020).

Regarding investment experience, availability bias has a greater influence on seasoned investors than on newer ones, likely due to their greater reliance on heuristics. Loss aversion affects both groups similarly, contradicting Gupta & Ahmed (2016), while risk perception has a slightly greater, albeit non-significant, effect on less experienced investors. Interaction effects involving risk perception do not vary meaningfully by experience, suggesting a uniform pattern across investor types.

6. Theoretical and managerial Implications

This study extends the behavioral finance literature by confirming the significant role of availability bias in irrational investment decisions, while showing that loss aversion does not directly predict such behavior in the Nepali context. Notably, the results reveal that risk perception moderates the relationship between loss aversion and decision-making, providing new evidence that heightened awareness of risk can mitigate the influence of emotional biases. These findings refine Prospect Theory by highlighting the conditions under which loss aversion may be less dominant. The multi-group analysis further enriches the theory by demonstrating that demographic factors, such as gender and investment experience, influence the strength of cognitive biases, highlighting the importance of context-sensitive models.

From a practical standpoint, the findings offer clear guidance for both market participants and regulators. Investors should be made aware of the risks associated with relying too heavily on readily available information and encouraged to base their decisions on broader and more reliable data. Financial advisors can play a key role in designing training programs that emphasize long-term planning and help clients reduce emotional reactions to potential losses. Policymakers, including Nepal Rastra Bank and the Securities Board of Nepal, may use these insights to design literacy campaigns and regulatory measures aimed at minimizing bias-driven decision-making. Collectively, these actions can strengthen market stability and promote more rational investment behavior.

7. Conclusion

This study examined the effects of availability bias (AB) and loss aversion (LA) on investment decisions (IDM) in Nepal, with risk perception (RP) as a moderator. AB significantly influenced irrational decisions, while LA showed no direct effect. RP had a direct impact on IDM and moderated the LA-IDM link, but not the AB-IDM relationship. These findings underscore the importance of financial education in reducing reliance on cognitive shortcuts and mitigating fear-driven decision-making. Future research should explore other biases and the role of digital platforms in shaping investor behavior.

References

Ahmad, M., Shah, S. Z. A., & Abbass, Y. (2020). The role of heuristic-driven biases in entrepreneurial strategic decision making: Evidence from an emerging economy. *Management Decision, 59*(3), 669–691. https://doi.org/10.1108/MD 09-2019-1231.

Alhakami, A. S., & Slovic, P. (1994). A psychological study of the inverse relationship between perceived risk and perceived benefit. *Risk Analysis*, *14*(6), 1085–1096. https://doi.org/10.1111/j.1539-6924.1994.tb00080.x.

Ardini, F. S., SE, F. A., & MSi, N. (2023). The influence of overconfidence, regret aversion, loss aversion, and herding behavior on investment decisions in the capital market, with the moderating role of risk perception in Generation Z students. *International Journal of Social Science and Economic Research*, *8*(5), 936–950. https://doi.org/10.46609/ijsser.2023.v08i05.001.

Bajtelsmit, V. L., & Bernasek, A. (1997). Why Do Women Invest Differently than Men? *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.2238.

Baker, H. K., & Nofsinger, J. R. (2002). Psychological biases of investors. *Financial Services Review, 11*(2), 97–116.

Barber, B. M., & Odean, T. (1999). The courage of misguided convictions. *Financial Analysts Journal, 55*(6), 41–55.

Barber, B. M., & Odean, T. (2001). Boys Will Be Boys: Gender, Overconfidence, and Common Stock Investment. *The Quarterly Journal of Economics*, *116*(1), 261–292. https://doi.org/10.1162/003355301556400.

Bowers, A. H., Greve, H. R., Mitsuhashi, H., & Baum, J. A. (2014). Competitive parity, status disparity, and mutual forbearance: Securities analysts' competition for investor attention. *Academy of Management Journal, 57*(1), 38–62.

De Bruin, W. B., Parker, A. M., & Fischhoff, B. (2020). Decision-Making competence: more than intelligence? *Current Directions in Psychological Science*, *29*(2), 186–192. https://doi.org/10.1177/0963721420901592.

Budiman, J., & Patricia. (2021). Pengaruh overconfidence bias, herding bias, representativeness bias, loss aversion, dan risk perception terhadap investment decision di Kota Batam. *CoMBInES, 1*(1), 1979–1987.

Conway JM, Lance CE (2010). What reviewers should expect from authors regarding common method bias in organizational research. *J. Bus. Psychol. 25*(3), 325–334. https:// doi. org/ 10. 1007/s10869- 010-9181-6.

Cuandra, F., & Rinaldo, J. (2021). Why do investors choose a mutual fund? *Jurnal Inovasi Ekonomi*, *6*(03), 133–138. https://doi.org/10.22219/jiko.v6i03.18221.

Davis, M. D. (2001). The psychology of investing. In *Springer eBooks* (pp. 103–120). https://doi.org/10.1007/978-1-4757-4334-0_7.

Dhakal, S. & Lamsal, R. (2023). Impact of cognitive biases on investment decisions of investors in Nepal. *The Lumbini Journal of Business and Economics, 11*(1), 35–48. https://doi.org/10.3126/ljbe.v11i1.54315.

Eckel, C. C., & Grossman, P. J. (2008). Chapter 113 Men, Women and Risk Aversion: Experimental evidence. In *Handbook of Experimental Economics Results* (1061–1073). https://doi.org/10.1016/s1574-0722(07)00113–8.

Fama, E. F. (1970). Efficient Capital Markets: A review of theory and Empirical work. *The Journal of Finance*, *25*(2), 383. https://doi.org/10.2307/2325486.

Folkes, V. S. (1988). The availability heuristic and perceived risk. *Journal of Consumer Research*, *15*(1), 13-23. https://doi.org/10.1086/209141.

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, *18*(1), 39–50. https://doi.org/10.1177/002224378101800104.

Gupta, Y., & Ahmed, S. (2016). The impact of psychological factors on investment decision making of investors: an Empirical analysis. *SSRN Electronic Journal*. https://papers.ssrn.com/sol3/Delivery.cfm/SSRN_ID2880059_code641510.pdf?abstractid=2880059&mirid=1&type=2.

Hair, J. F., Babin, B. J., & Krey, N. (2017). Covariance-based structural equation modeling in the Journal of Advertising: Review and recommendations. *Journal of Advertising*, *46*(3), 163-177. https://doi.org/10.1080/00913367.2017.1329496.

Hair, J. F., Black, W. C., Babin, B. J., Anderson, R. E., & Tatham, R. L. (2006). *Multivariate data analysis* (6th Ed.). Pearson.

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2022). *A primer on partial least squares structural equation modeling (PLS-SEM) (3e)*. Thousand Oaks, CA: Sage.

Hair, J. F., Jr, Sarstedt, M., Hopkins, L., & Kuppelwieser, V. G. (2014). Partial least squares structural equation modeling (PLS-SEM). *European Business Review*, 26(2), 106–121. https://doi.org/10.1108/ebr-10-2013-0128.

Hair, J. F., Ringle, C. M., & Sarstedt, M. (2011). PLS-SEM: Indeed, a Silver Bullet. *The Journal of Marketing Theory and Practice, 19*(2), 139–152. https://doi.org/10.2753/mtp1069-6679190202.

Hair, J. F., Ringle, C. M., & Sarstedt, M. (2013). Partial least squares structural equation modeling: Rigorous applications, better results, and higher acceptance. *Long Range Planning, 46*(1-2), 1-12.

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review, 31*(1), 2–24. https://doi.org/10.1108/ebr-11-2018-0203.

Hedegaard, E., & Hodrick, R. (2014). *Measuring the Risk-Return Tradeoff with Time-Varying Conditional Covariances*. https://doi.org/10.3386/w20245.

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science, 43*(1), 115–135. https://doi.org/10.1007/s11747-014-0403-8.

Henseler, J., Ringle, C. M., & Sinkovics, R. R. (2009). The use of partial least squares path modeling in international marketing. *Advances in International Marketing, 20*, 277–319. https://doi.org/10.1108/S1474-7979(2009)0000020014.

Hilton, D. J. (2001). The psychology of financial decision making: Applications to trading, dealing, and investment analysis. *The Journal of Psychology and Financial Markets, 2*(1), 37 53.

Jain, J., Walia, N., & Gupta, S. (2019). Evaluation of behavioral biases affecting investment decision-making of individual equity investors by fuzzy analytic hierarchy process. *Review of Behavioral Finance*, *12*(3), 297–314. https://doi.org/10.1108/rbf-03-2019-0044.

Javed, H., Bagh, T., & Razzaq, S. (2017). Herding Effects, Overconfidence, Availability Bias, and Representativeness as Behavioral Determinants of Perceived Investment Performance: An Empirical Evidence from Pakistan Stock Exchange (PSX). *Journal of Global Economics*, *06*(01), 1-13. https://doi.org/10.4172/2375-389.1000275.

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

Kahneman, D., Knetsch, J.L. & Thaler, R.H. (1991). Anomalies: the endowment effect, loss aversion, and status quo bias. *Journal of Economic Perspective, 5*(1), 193-206.

Karmacharya, B., Chapagain, R., Dhungana, B. R., & Singh, K. (2022). Effect of perceived behavioral factors on investors' investment decisions in stocks: Evidence from Nepal Stock Market. *Journal of Business and Management Research*, *4*(01), 17–33. https://doi.org/10.3126/jbmr.v4i01.46680.

Khan, M. U. (2017). Impact of availability bias and loss aversion bias on investment decision making, moderating role of risk perception. *Management & Administration (IMPACT: JMDGMA)*, *1*(1), 17–28.

Khan, S. (2016). Impact of financial literacy, financial knowledge, moderating role of risk perception on investment decision. *SSRN Electronic Journal.* https://doi.org/10.2139/ssrn.2727890.

Kharel, K. R., Upadhyaya, Y. M., Acharya, B., Budhathoki, D. K., & Gyawali, A. (2024). Financial literacy among management students: Insights from universities in Nepal. *Knowledge and Performance Management*, *8*(1), 63–73. https://doi.org/10.21511/kpm.08(1).2024.05.

Kovalchik, S., & Camerer, C. F. (2009). Aging and decision-making: A neuroeconomic perspective. In D. R. Riddle (Ed.), *Handbook of the neuroscience of aging* (pp. 377–384). Academic Press. https://doi.org/10.1016/B978-0-12-374898-0.00039-6.

Kock, N. (2015). Common method bias in PLS-SEM: A full collinearity assessment approach. *International Journal of e-Collaboration (IJeC), 11*(4), 1–10. https://doi.org/10.4018/ijec.2015100101

Kraus S, Rehman SU, García FJS (2020). Corporate social responsibility and environmental performance: the mediating role of environmental strategy and green innovation. *Technol Forecast Soc Chang*, 160, 120262. https://doi.org/10.1016/j.techfore.2020.120262

Kudryavtsev, A., Cohen, G., & HonSnir, S. (2013). "Rational" or “Intuitive”: Are behavioral biases correlated across stock market investors? *Contemporary Economics*, *7*(2), 31–53.

Kumar, A. A., & Babu, M. (2018). Effect of loss aversion bias on investment decision: A study. *Journal of Emerging Technologies and Innovative Research*, *5*(11), 71–76.

Kumar, S., & Chaurasia, A. (2024). The relationship between emotional biases and investment decisions: A meta-analysis. *IIMT Journal of Management*, *1*(2), 171–185. https://doi.org/10.1108/iimtjm-03-2024-0034.

Luong, L., & Ha, D.T. (2011). *Behavioral factors influencing individual investors' decision-making and performance: A survey at the Ho Chi Minh Stock Exchange.*

Lyu, H. (2023). Research on applications of availability heuristics. *Advances in Economics Management and Political Sciences*, *21*(1), 165–169. https://doi.org/10.54254/2754-1169/21/20230249.

Mahina, J. N., Muturi, W. M., & Memba, F. S. (2017). The Influence of Loss Aversion Bias on Investments at the Rwanda Stock Exchange. *International Journal of Accounting, Finance and Risk Management*, *2*(5), 131–137.

Mata, R., Josef, A. K., Samanez-Larkin, G. R., & Hertwig, R. (2011). Aging and decision-making: A lifespan perspective. *Frontiers in Neuroscience, 5*(26), 1-22. https://doi.org/10.3389/fnins.2011.00026.

Merton, R. C. (1987). A simple model of capital market equilibrium with incomplete information. *The Journal of Finance*, *42*(3), 483–510.

Nagaeva, E. A. (2024). Making an Investment Decision (Using the Example of Mechanical Engineering Organizations). *Ekonomika I Upravlenie Problemy Resheniya*, *10/3*(151), 138–142. https://doi.org/10.36871/ek.up.p.r.2024.10.03.015.

Peters, E., Hess, T. M., Västfjäll, D., & Auman, C. (2007). Adult age differences in dual information Processes: Implications for the role of affective and deliberative processes in older adults’ decision making. *Perspectives on Psychological Science*, *2*(1), 1–23. https://doi.org/10.1111/j.1745-6916.2007.00025.x.

Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology, 88*(5), 879–903. https://doi.org/10.1037/0021-9010.88.5.879

Rasheed, M. H., Rafique, A., Zahid, T., & Akhtar, M. W. (2018). Factors Influencing Investors' Decision-Making in Pakistan. *Review of Behavioral Finance, 10*(1), 70–87. https://doi.org/10.1108/rbf-05-2016-0028.

Rau, H. A. (2014). The disposition effect and loss aversion: Do gender differences matter? *Economics Letters*, *123*(1), 33–36. https://doi.org/10.1016/j.econlet.2014.01.020.

Ritter, J. R. (2003). Behavioral finance. *Pacific-Basin Finance Journal*, *11*(4), 429–437. https://doi.org/10.1016/S0927-538X(03)00048–9.

Rolison, J. J., Hanoch, Y., Wood, S., & Liu, P. (2013). Risk-Taking differences across the adult life span: a question of age and domain. *The Journals of Gerontology Series B*, *69*(6), 870–880. https://doi.org/10.1093/geronb/gbt081.

Sabatimy, N. V., & Nur, N. D. I. (2023). Pemberdayaan pemahaman masyarakat dalam mengoptimalkan peluang keuangan. *Cakrawala Jurnal Pengabdian Masyarakat Global*, *2*(3), 63–71. https://doi.org/10.30640/cakrawala.v2i3.1336.

Samanez-Larkin, G. R., & Knutson, B. (2015). Decision-making in the ageing brain: Changes in affective and motivational circuits. *Nature Reviews Neuroscience*, *16*(5), 278–289. https://doi.org/10.1038/nrn3917.

Sadeeq, N. U., & Butt, N. K. A. (2024). Impact of heuristic-driven availability bias on investment decision making in Indian stock market: An empirical study. *EPRA International Journal of Economic and Business Review*, 6–11. https://doi.org/10.36713/epra16692.

Salman, M., Khan, B., Khan, S. Z., & Khan, R. U. (2020). The impact of heuristic availability bias on investment decision-making: Moderated mediation model. *Business Strategy & Development*, *4*(3), 246–257. https://doi.org/10.1002/bsd2.148.

Scott, S. G., & Bruce, R. A. (1995). Decision-making style: The development and assessment of a new measure. *Educational and Psychological Measurement*, *55*(5), 818–831.

Shafqat, S. I., & Malik, I. R. (2021). Role of regret aversion and loss aversion emotional biases in determining individual investors' trading frequency: Moderating effects of risk perception. *Humanities & Social Sciences Reviews*, *9*(3), 1373–1386. https://doi.org/10.18510/hssr.2021.93137.

Sharma, B., & Pyati, S. (2022). Evaluating R&D Premium in the Indian Health and Pharmaceuticals Industries. Jurnal Manajemen Dan Kewirausahaan, *24*(2), 118-128.

Sharma, B., Srikanth P, & Jeevananda, S. (2023). Financial Distress and Value Premium using Altman Revised Z-score Model. *Vision: The Journal of Business Perspective*. https://doi.org/10.1177/09722629231198604

Sharma, B., Srikanth, P., & Suresha, B. (2022). *Scientific Papers of the University of Pardubice. Series D. Faculty of Economics and Administration, 30*(2). https://doi.org/10.46585/sp30021490

Shefrin, H., & Statman, M. (1985). The disposition to sell winners too early and ride losers too long: theory and evidence. *The Journal of Finance*, *40*(3), 777–790. https://doi.org/10.1111/j.1540-6261.1985.tb05002.x.

Shindu, K., & Kumar, S. R. (2014). Influence of risk perception of investors on investment decisions: An empirical analysis. *Journal of Finance and Bank Management, 2*(2), 15–25.

Sitkin, S. B., & Weingart, L. R. (1995). Determinants of risky decision-making behavior: A test of the mediating role of risk perceptions and propensity. *Academy of Management Journal, 38*(6), 1573–1592. https://doi.org/10.2307/256844

Slovic, P. (1987). Perception of risk. *Science*, *236*(4799), 280–285. https://doi.org/10.1126/science.3563507.

Subedi, P. P., Sharma, D. R., & Sharma, B. (2025). Herding behavior, risk perception, and investment performance: A serial mediation analysis. *Scientific Papers of the University of Pardubice, Series D, Faculty of Economics and Administration*, *33*(1), 2242. https://doi.org/10.46585/sp33012242

Sugianto, S., Hasriani, H., & Noor, R. M. (2024). Innovations in risk measurement and management for strategic financing decisions. *Advances in Management & Financial Reporting*, *2*(2), 59–71. https://doi.org/10.60079/amfr.v2i2.263.

Thaler, R. H., Tversky, A., Kahneman, D., & Schwartz, A. (1997). The effect of myopia and loss aversion on risk taking: An experimental test. *The Quarterly Journal of Economics*, *112*(2), 647–661. https://doi.org/10.1162/003355397555226.

Tversky, A., & Kahneman, D. (1974). Judgment under uncertainty: Heuristics and biases. *Science, New Series*, *185*(4157), 1124–1131. https://doi.org/10.4324/9781912282562.

Wang, Z. (2023). Research on the application of availability bias on decision making. *Lecture Notes in Education Psychology and Public Media*, *22*(1), 60–64. https://doi.org/10.54254/2753-7048/22/20230218.

Weber, E. U., & Hsee, C. (1998). Cross-cultural differences exist in risk perception, but similarities in attitudes towards perceived risk are observed across cultures. *Management Science*, *44*(9), 1205–1217. http://www.jstor.org/stable/2634710.