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Rationality and Behavioral Biases in Investment Decision Making

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ABSTRACT

The objective of this study is to examine the relationship between the rational decision-making process and behavioral biases among investors, as well as to assess the impact of demographic variables on these biases. Employing a quantitative approach with a descriptive and correlational research design, data were collected through a survey conducted from October to December 2021, resulting in 384 valid responses. Confirmatory factor analysis was utilized to validate the factors identified in the exploratory phase, while the Mann-Whitney U test and Kruskal-Wallis H test analyzed associations with demographic characteristics. The findings indicate that Nepalese investors generally adhere to a rational decision-making framework, identifying investment demand, searching for information, and evaluating alternatives. However, they also exhibit notable behavioral biases; female investors are more susceptible to the disposition effect and herding bias, while male investors tend to display greater overconfidence. Age differences showed no significant relationship with the disposition effect or overconfidence, but younger investors (under 25) were more prone to herding bias. This study offers valuable insights for financial advisors, enabling them to understand client psychology better and develop tailored investment strategies. Overall, it enhances the understanding of behavioral biases in the Nepalese context, highlighting the need for further research in this area.

Keywords: behavioral biases, disposition effect, herding, overconfidence, rationality

Introduction

In Nepal, budget gap seems chronic in a public investment also relies on foreign investment (Mishra & Aithal, 2021a & b). Similarly for families rely on the income of a single member, university students often face financial stress that could be managed through proper financial planning. This period is crucial for developing financial habits that will shape their future financial well-being. However, poor implementation and various factors influencing their financial management behavior have played a significant role in how they plan their finances. Despite the acknowledgment of the importance of financial literacy, there remains a gap in comprehending the specific factors that influence financial management behaviors among university students. The prevalence of mental health issues such as depression, anxiety, and stress among undergraduate management students in Kathmandu, Nepal, is concerning, with rates reported at 57.8%, 60.9%, and 43%, respectively (Shrestha, 2019). These mental health challenges are often exacerbated by financial difficulties, including the burden of debt due to high visa fees and ticket costs for students studying abroad (Thapa, 2014). Additionally, the lack of effective governmental support from Nepal and discrimination faced by Nepalese emigrants working abroad lead to lower remittances, further exacerbating financial hardship. Financial literacy among management students in Nepal is also a concern, with MBA students exhibiting below-average scores and reduced unpredictability in financial literacy, ranging from 1.43 to 3.86, with an average of 2.405 and a standard deviation of 0.449 (Rai & Sharma, 2023). This study highlights the complex interplay of factors influencing financial behavior and literacy among MBA students, emphasizing the importance of education, familial influence, and media exposure in shaping financial attitudes and decision-making. To address these issues, it is crucial to identify the specific factors that influence financial management behaviors among university students in Nepal. By understanding these factors, interventions can be developed to improve financial literacy, reduce financial stress, and promote better financial well-being among this population.

Problem Statement

In general, an investment choice will be considered to have been made rationally if an investor's decision-making process follows a logical path, including the steps of detecting demand, looking for information, and evaluating alternatives (Lin, 2011). Investors typically have the ability to perceive their own rationality, according to the actual behavioral observations of individual investors. However, why do the majority of investors still appear to exhibit behavioral biases when they claim that their trading or decision-making process is a logical one? Most empirical data from recent decades generally considers numerous behavioral biases as widespread cognitive fallacies that affect investors' decision-making processes. Previous studies have either classified different investor types or looked into the potential effects of behavioral biases on investing performance. For instance, the overconfidence bias can cause investors to pay excessive brokerage fees and taxes, increase their vulnerability to significant losses as a result of making an excessive number of trades, and take an excessive amount of risk when making investments they are overconfident about (Rathi & Geetha, 2024). Due to a lack of individual decision-making, herding behavior may account for bubbles and bubble bursts in the stock market as a whole (Andersen, 2009). Due to the propensity to link new events to previously recorded events, the representativeness bias may lead investors to buy overvalued equities. The disposition bias suggests selling winners too fast and holding losers too long, which could lower investor returns. However, only a small number of studies have looked at the connection between the causes of behavioral biases and each stage of the decision-making process, particularly for a thorough review of the pertinent literature on behavioral biases in investing. Among the few studies that have looked at the connection between the process of making investment decisions and behavioral biases like overconfidence, herding, and disposition effect are those by Kumar and Goyal (2016) and Lin (2011). In Nepal, there are a large number of studies carried out in understanding investors' behavior and its impact on investment performance. For example; Thapa (2014), Dangol and Manandhar (2020), and Gnawali (2021) found that investment decisions of Nepalese investors are influenced by behavioral biases. Despite a large number of studies on understanding investors' behavior carried out, there have been no empirical studies available in examining the relationship between investment-decision making process and behavioral biases in Nepal. The goal of this study is to determine whether investors' decision-making behaviors are consistent with the theoretical model of rational decision-making. It also identifies the causal links between three behavioral biases that have been postulated and each stage of the decision-making process. Additionally, the impact of different demographic factors on behavioral biases is also examined.

Research Objective

To investigate the connection between cognitive biases, such as overconfidence, the disposition effect, and herding, and the rational decision-making process (demand identification, information searching, and alternative evaluation).

Methodology

Research Philosophy

This study adopts an objective ontological perspective, asserting that social reality exists independently of the researchers' perceptions (Sarantakos, 1998). The epistemological stance is rooted in positivism, which aims to establish generalizable laws regarding the relationship between behavioral biases and rational decision-making processes (Fisher, 2007). This approach ensures a value-free methodology, allowing for unbiased data collection and analysis.

Research Design

A quantitative deductive methodology guides this research, employing a mix of descriptive and correlational research designs. The descriptive approach facilitates the collection of accurate data on respondents' tendencies toward logical decision-making and behavioral biases. Meanwhile, the correlational approach assesses the impact of various behavioral biases on rational decision-making. Structural Equation Modeling (SEM) is utilized to analyze the relationships between each stage of the rational decision-making process and the identified behavioral biases (Mishra, 2023).

Population and Sample

The study targets individual investors who have invested at least once in the Nepal Stock Exchange. A purposive sampling technique is employed, focusing on investors residing in the Kathmandu Valley. This method is chosen due to challenges in identifying the total number of individual investors and the reluctance of some to participate in the survey. Despite the purposive approach, efforts are made to maintain randomness in sample selection.

Sample Size Determination

Using Cochran's (1977) formula for sample size determination, a sample size of 384 is assumed to be sufficient for the study, aligning with recommendations for SEM analysis. This sample size ensures adequate power for statistical testing and generalizability of findings.

Nature and Sources of Data

The research relies on quantitative data collected from primary sources through a structured survey questionnaire distributed between October 2021 and December 2021. The questionnaire is administered via email and in-person visits to brokerage firms.

Questionnaire Design

The structured survey consists of two sections: the first collects demographic information, while the second assesses the relationship between three behavioral biases (overconfidence, disposition effect, and herding) and the rational decision-making process, which includes demand identification, information seeking, and alternative evaluation. The questionnaire features 27 items measured on a 6-point Likert scale, ranging from "strongly disagree" (1) to "strongly agree" (6), to evaluate the intensity of associations between the variables (Taherdoost, 2019; Chang, 1994).

Methods of Data Analysis

Statistical Package for the Social Science (SPSS) 26 and Amos 24 software were used to compile and evaluate the data after it had been collected. To assess the validity and consistency of the questionnaire, a pilot test with 60 participants was undertaken. The outcomes of the pilot test are shown in Table 1. All variables have Cronbach's alpha values above 0.55, which is suitable for further research (Bujang, Omar, & Baharum, 2018).

Table 1

Results of Pilot Test

Variables	Cronbach's Alpha (α)
Demand Identification	0.71
Searching Information	0.59
Evaluating Alternatives	0.55
Disposition Effect	0.64
Herding	0.77
Overconfidence	0.84

Note. N= 60

The study's initial goal was accomplished by doing a cross-section analysis utilizing Structure Equation Modelling (SEM). SEM constructs an ample path and explores how the rational decision-making process of investment and behavioral biases are related. Following measurement and structure model have been developed by referring Lin (2011) in order to explore how the three stages of rational decision-making process and the three behavioral biases are related. The structure equation of Model 1:

$\eta_i = \beta_{ij}\eta_j + \gamma_{ij}\xi_j + \varsigma_i$, i, j = 1, 2, 3, ... (1)

Where,

ξ_j = Exogeneous latent variables, i.e. demand identification

ηi = Endogenous latent variables, i.e. searching information, evaluating alternatives, disposition effect, herding, and overconfidence

γ_{ij} = The regression coefficient of ξ_j on η_i

β_{ij} = The regression coefficient of $_{\eta j}$ on η_i

ς_i = The error variance of structure equation

The measurement equation of Model 1:

$X_i = \lambda_{xij}\xi_j + \delta_i$ ... (2)

$Y_i = \lambda_{yij}\eta_j + \varepsilon_j$ ... (3)

Where,

λ_{xij} = The regression coefficient of Xi on ξ_j

λ_{yij} = The regression coefficient of Yi on ηj

δ_i = Measurement error of exogenous (ξ_j) latent variables

ε_j = Measurement error of endogenous (η_j) latent variables

The fitness indices of the structure model have been evaluated using maximum likelihood estimation utilizing the goodness of fit index (GFI), comparative fit index (CFI), and non-normed fit index (NNFI), where values better than 0.90 are considered to be acceptable.

Additionally, the Mann-Whitney U test and Kruskal Wallis H test have been used in this study to examine the impact of personal traits on behavioral biases, which is the second research purpose.

Respondents' Characteristics

Table 2 summarizes the characteristics of the respondents, comprising 224 males (58.33%) and 160 females (41.67%). The age distribution shows that the largest group is aged 25-35 (33.07%), followed by 36-45 (30.99%), 46-55 (23.18%), and those under 25 (12.76%).In terms of education, 45.83% of respondents hold a master's degree, followed by bachelor's (27.34%), intermediate or +2 (16.67%), and above master's (10.16%). Professionally, 45.57% are engaged in private sectors (excluding banks), while 20.83% work in government and private sector banks, 13.80% in other sectors, 12.24% are self-employed, and 7.55% work in government sectors (excluding banks). Regarding annual income, 24.48% of respondents earn between Rs. 2 lakh-4 lakh and Rs. 4 lakh-6 lakh, followed by Rs. 6 lakh-8 lakh (16.93%), Rs. 8 lakh-11 lakh (14.58%), and over Rs. 11 lakh (19.53%).Investment experience varies, with 31.51% having 1-3 years, 26.30% with 3-5 years, and 14.32% each for 5-7 years and over 7 years. Only 13.54% have less than 1 year of experience. Among respondents, 47.40% are active traders, 44.27% are occasional traders, and 8.33% trade rarely.The majority (83.85%) are optimistic about the Nepalese stock market, and 84.37% believe the economy will improve post-COVID-19.

Table 2

Respondents' Characteristics

Variable	N	%
Age		
Less than 25	49	12.76
25-35	127	33.07
36-45	119	30.99
46-55	89	23.18

Variable	N	%
Gender		
Female	160	41.67
Male	224	58.33
Educational Qualification		
Intermediate or +2	64	16.67
Bachelors	105	27.34
Masters	176	45.83
Above Masters	39	10.16
Current Profession		
Government and Private Sector Banks	80	20.83
Government Sectors (excluding Banks)	29	7.55
Others	53	13.80
Private Sectors (excluding Banks)	175	45.57
Self-employed	47	12.24
Average Annual Income		
2 - 4 Lakhs	94	24.48
4 - 6 Lakhs	94	24.48
6 - 8 Lakhs	65	16.93
8 - 11 Lakhs	56	14.58
More than 11 Lakhs	75	19.53
Experience Investing in Shares		
Less than 1 year	52	13.54
1 - 3 Years	121	31.51
3 - 5 Years	101	26.30
5 - 7 Years	55	14.32
More than 7 years	55	14.32

Note. N = 384

Exploratory Factor Analysis Results

Table 3 presents the final results of the exploratory factor analysis (EFA). It includes factor loadings, Cronbach's alpha, mean, and standard deviation for each extracted factor. A preliminary EFA indicated the exclusion of three items (y4, d1, and h6) due to communalities below 0.50. The factorability of the correlation matrix for the retained 24 items was confirmed: the Kaiser-Meyer-Olkin (KMO) measure was 0.74, exceeding the recommended threshold of 0.60, and Bartlett's test of sphericity was significant [$\chi^2(276) = 4380.84$, $p < 0.01$]. Additionally, all retained items had communalities above 0.50.The EFA extracted six factors, accounting for 67.11% of the total variance, with eigenvalues greater than one, as suggested by the Kaiser Criterion.

Table 3

Results of Exploratory Factor Analysis (N=384)

Items	Mean	S.D.	Loadings	Cronbach's Alpha (α)
Demand Recognition	**5.39**	**0.12**		**0.73**
x1: "Investing in shares can help me..."			0.75	
x2: "Investment is a better way..."			0.81	
x3: "I invest in shares because..."			0.83	
Evaluating Alternatives	**5.45**	**0.05**		**0.84**
y1: "I think it is important to..."			0.86	
y2: "I collect investment information..."			0.83	
y3: "Past investing experience..."			0.91	
y4: "I think it is better to subscribe..."	Eliminated			
Searching Information	**5.34**	**0.09**		**0.76**
z1: "It is essential to consider..."			0.73	
z2: "I evaluate shares based on..."			0.79	
z3: "My evaluation of the stock..."			0.74	
z4: "I think it is better to evaluate..."			0.77	
Disposition Effect	**4.28**	**0.16**		**0.81**
d1: "I hold my shares until..."	Eliminated			
d2: "I prefer to sell stocks..."			0.68	
d3: "I regret selling a 'winning stock'..."			0.82	
d4: "I regret not selling a 'losing stock'..."			0.84	
d5: "I am reluctant to realize losses..."			0.77	
Herding	**4.26**	**0.28**		**0.85**
h1: "I discuss my investment decision..."			0.70	
h2: "My trading activities are influenced..."			0.75	
h3: "I desire to buy stocks if..."			0.86	
h4: "I desire to sell stocks that..."			0.89	
h5: "My disappointment diminishes..."			0.67	
h6: "I prefer to take a contrarian position..."	Eliminated			
Overconfidence	**4.47**	**0.34**		**0.90**
o1: "I have sufficient knowledge..."			0.82	
o2: "I am confident in my capability..."			0.88	
o3: "I yield full control of my portfolio..."			0.81	
o4: "My past investment feats are due to..."			0.89	
o5: "I believe more in my own evaluation..."			0.77	

Note. Principal component analysis with varimax rotation was used. Factor loadings less than |0.40| are suppressed.

Table 4 shows the correlations among the six extracted variables. Disposition effects have a significant low positive correlation with herding ($r=0.324$, $p<0.01$) and a negligible negative correlation with overconfidence ($r=-0.186$, $p<0.01$). Herding and overconfidence also exhibit a significant negative correlation ($r=-0.127$, $p<0.05$). Overconfidence correlates positively with demand identification ($r=0.139$, $p<0.01$) and evaluating alternatives ($r=0.182$, $p<0.01$). Additionally, demand identification and evaluating alternatives have a significant positive correlation ($r=0.151$, $p<0.01$).

Table 4

Correlations and Descriptive Statistics for Six Variables

Variable	Mean	S.D.	1	2	3	4	5	6
1. Disposition	17.13	4.034						
2. Herding	21.30	5.824	0.324**					
3. Overconfidence	22.33	4.831	-0.186**	-0.127*				
4. DI	16.17	1.709	0.076	0.067	0.139**			
5. SI	16.36	1.389	-0.029	0.043	0.049	0.062		
6. EA	21.46	2.015	0.046	0.093	0.182**	0.151**	0.006	

Note. N=384. * $p < 0.01$; $p < 0.05$.

Structural Equation Modelling (SEM)

Structural Equation Modeling (SEM) is a multivariate technique that integrates factor analysis and multiple regression, enabling researchers to examine interrelated dependence relationships (Hair et al., 2014). This study employs SEM to achieve the objectives outlined in Chapter I, following these two main steps:

1. **Confirmatory Factor Analysis (CFA):** Verify the measurement model and assess model fit.
2. **Full Structural Model Analysis:** Analyze hypothesized relationships among factors.

Measurement Model Analysis

CFA, a component of SEM, confirms the suitability of factors and variables identified through Exploratory Factor Analysis (EFA). The initial measurement model is illustrated in Figure 1. During CFA, distinguishing between endogenous and exogenous constructs is unnecessary, but it is essential during model testing.

Goodness of Fit Indices

The key task in measurement model analysis is to evaluate the goodness-of-fit between the collected data and the hypothesized model. Hair et al. (2014) provide guidelines for model fit measures (see Table 5). The primary goal of the CFA model is to test the hypothesized relationships between endogenous and exogenous variables. Based on the fit criteria in Table 5, the CFA results indicated that most measures did not meet acceptable thresholds: $\chi^2/df = 3.17$; CFI = 0.878; GFI = 0.863; AGFI = 0.827; RMSEA = 0.075; SRMR = 0.061. This version retains the essential information while being more concise and focused.

Figure 1

The Initial Measurement Model

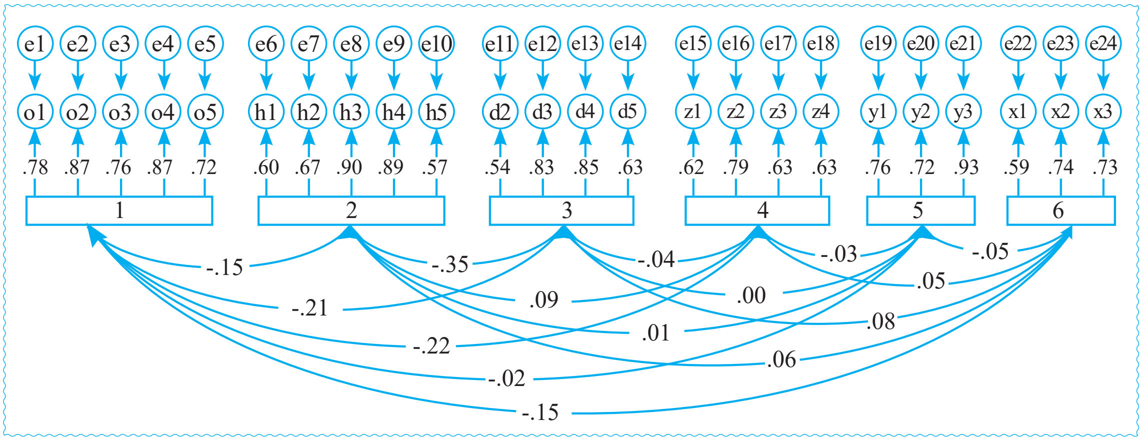


Table 5

Cutoff Criteria for Model Fit

Measure	Threshold
χ2/df	Less than 3
CFI	More than 0.90
GFI	More than 0.90
AGFI	More than 0.80
RMSEA	Less than 0.07
SRMR	Less than 0.08

Note. This table is adapted from Hair et al. (2014), Multivariate Data Analysis

The results indicated room for improvement in achieving a good measurement model fit. To enhance the model, modification indices from AMOS were utilized to identify error terms with high covariance within their factors. Correlating error terms is a recommended approach for improving model fit (Hooper et al., 2007). Specifically, the following error terms were correlated: e1 & e2, e1 & e3, e9 & e10, e11 & e14, and e17 & e18. After implementing these changes, the measurement model was re-evaluated. The final measurement model is illustrated in Figure 2, and a comparison of the final and initial models is presented in Table 6 This version maintains the essential details while being more concise and focused.

Table 6

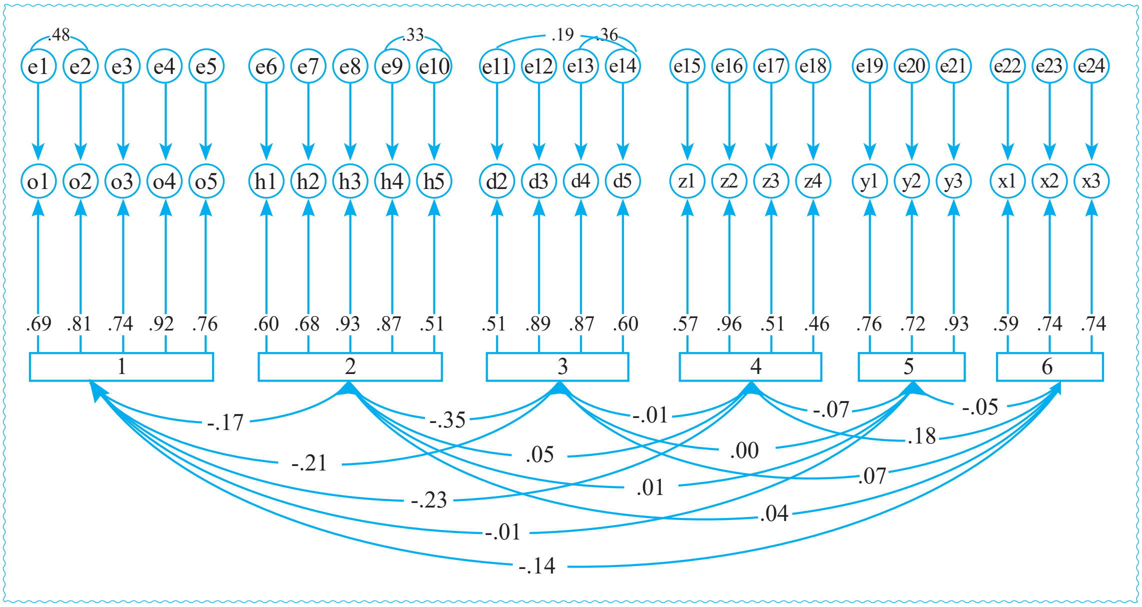
Model Fit Indices – Comparison between Initial and Final measurement Model

Measure	Recommended Value	Initial Measurement Model	Final Measurement Model
χ2/df	<3	3.17	2.472
CFI	>0.90	0.878	0.919
GFI	>0.90	0.863	0.926
AGFI	>0.80	0.827	0.832
RMSEA	<0.07	0.075	0.062
SRMR	<0.08	0.061	0.059

Note. The values of different measures for initial and final measurement model have been copied from the output table of AMOS 24 software.

Figure 2

The Final Measurement Model



All measures of the final measurement model, shown in Table 6, met the acceptable criteria. The next step is to assess validity and reliability to evaluate the psychometric properties of the measurement model.

Construct Validity and Reliability

Examining the validity and reliability of the measures is crucial, as it impacts the research outcomes (Hair et al., 2014). Validity refers to how well the data covers the area of investigation (Ghauri & Gronhaug, 2005) and whether the results accurately measure what they intend to measure. According to Hair et al. (2014), validity and reliability can be assessed using Composite Reliability (CR), Average Variance Extracted (AVE), Maximum Shared Squared Variance (MSV), and Average Shared Squared Variance (ASV). The criteria for reliability include a CR > 0.6, preferably > 0.7. For convergent validity, AVE should be > 0.5, and CR must exceed AVE. Discriminant validity is supported if MSV < AVE and ASV < AVE. Using AMOS 24 plugins developed by Gaskin et al. (2019), the values for CR, AVE, and MSV were calculated and are presented in Table 7. This version retains the necessary information while being more direct and succinct.

Table 7

Convergent, Discriminant and Construct Reliability

	CR	AVE	MSV	MaxR(H)	OPT	HRD	DIS	EVA	SER	DEM
OPT	0.89	0.62	0.05	0.92	0.784					
HRD	0.85	0.54	0.12	0.915	-0.18	0.73				
DIS	0.8	0.52	0.12	0.861	-0.2	0.35	0.72			
EVA	0.74	0.48	0.05	0.826	0.222	0.07	0.03	0.656		
SER	0.85	0.65	0	0.899	0.005	0.01	0	-0.07	0.81	
DEM	0.73	0.49	0.04	0.747	0.142	0.04	0.07	0.194	0.06	0.69

As shown in Table 7, the Average Variance Extracted (AVE) is above 0.5 for most constructs, except EVA (0.48) and DEM (0.49), which are marginally low. However, the Composite Reliability (CR) for both exceeds 0.70, so they are included in further analysis. Fornell and Larcker (1981) argue that AVE is more conservative than CR, and convergent validity is adequate if over 50% of the variance is due to error. Malhotra and Dash (2011) also suggest that reliability can be established through CR alone.

All CR values are above 0.7, indicating adequate convergent validity. To establish convergent validity, Hair et al. (2014) state that CR should exceed AVE, which is the case here.

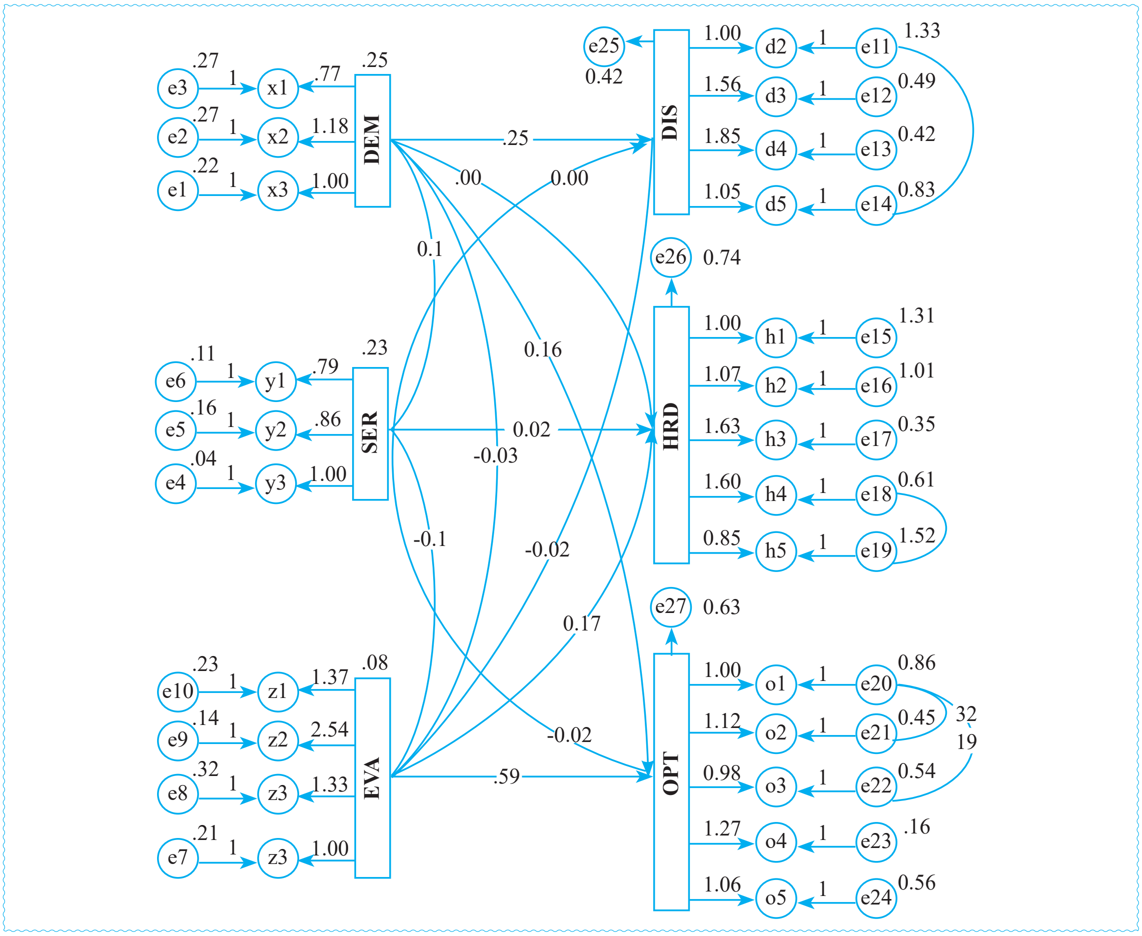
For discriminant validity, AVE must be greater than Maximum Shared Variance (MSV), and the square root of AVE should exceed inter-construct correlations. Table 7 shows that AVE is greater than MSV, and the square root of AVE (in bold on the diagonal) exceeds inter-construct correlations.

The proposed model demonstrates construct validity, with adequate composite reliability, convergent validity, and discriminant validity. The final measurement model, after assessing goodness-of-fit indices, validity, and reliability, is shown in Figure 2.

Structural Model Analysis

Figure 3

The Final Structural Model



The main research question examines the relationship between the rational decision-making process (demand identification, information search, and alternative evaluation) and behavioral biases (overconfidence, disposition effect, and herding). With reliability, convergent validity, and discriminant validity established, the next step is to test the relationships between exogenous and endogenous latent variables during the structural model stage (Hair et al., 2014).

Following the Structural Equation Modeling approach, the model was improved based on modification indices, resulting in a very good model fit. The final structural model is presented in Figure 2. This version is more concise and specific, focusing on the key points and eliminating unnecessary details.

Goodness of Fit Indices of the Research Model

Kline (2016) recommends several indices for assessing the goodness of fit of a research model, including chi-square (χ^2), Comparative Fit Index (CFI), Normed Fit Index (NFI), and Root Mean Square Error of Approximation (RMSEA).

Chi-Square Test

The chi-square test is the first measure of model fit. The relative chi-square (χ^2/df) is calculated by dividing χ^2 by the degrees of freedom. A smaller χ^2 indicates a better fit. According to Hu and Bentler (1999), a χ^2/df value of 5 or less is acceptable. In this study, the χ^2/df ratio is 2.69 ($\chi^2 = 632.182$, df = 235, p = 0.000), indicating an acceptable model fit.

Comparative Fit Index (CFI)

The CFI measures model fit, with values close to 1 indicating a very good fit. A CFI of 0.90 or higher is generally acceptable. This study reports a CFI of 0.906, exceeding the recommended threshold, which is encouraging.

Normed Fit Index (NFI)

The NFI, or Bentler-Bonett normed fit index, ranges from 0 to 1, with values above 0.95 considered good and values between 0.90 and 0.95 acceptable. The NFI for this model is 0.859, which is marginally acceptable.

Root Mean Square Error of Approximation (RMSEA)

RMSEA assesses the model's fit, with values ≤ 0.05 indicating good fit and ≤ 0.08 indicating adequate fit (Browne & Cudeck, 1992). The RMSEA for this model is 0.066, falling into the fair fit category.

Summary of Fit Indices

Overall, the proposed research model demonstrates satisfactory fit across several indices: $\chi^2 = 632.182$, p = 0.000, df = 235, $\chi^2/df = 2.69$, CFI = 0.906, NFI = 0.859, RMSEA = 0.066.

Table 8

Summarizes Results

Model Fit Indices	GFI	AGFI	CFI	NFI	RMR	RMSEA	χ^2/df
Recommended Value	>0.9	>0.8	>0.9	>0.9	<0.10	<0.08	<3
Obtained Value	0.90	0.851	0.906	0.859	0.09	0.066	2.69

Table 8 shows that most parameter values are adequate, supporting the model's validity for further analysis. This version is more concise and focused, highlighting the key points and results related to the goodness of fit indices.

Results of Structure Equation Modelling

Figure 3 presents the results of structure equation modeling by the path between the latent variables. On the basis of the final structural model, the result of the path coefficients for the hypothesized relationships with the proposed research model are presented in Table 9.

Table 9

The Summary of Results for the Direct Hypothesized Relationships

			Estimate	P	Study Result
DIS		DEM	0.073	0.001	Supported
HRD	←	DEM	0.052	0.64	Not Supported
OPT	←	DEM	0.157	0.03	Supported
DIS	←	SER	0.002	0.98	Not Supported
HRD	←	SER	0.023	0.82	Not Supported
OPT	←	SER	0.021	0.001	Supported
DIS	←	EVA	0.024	0.87	Not Supported
HRD	←	EVA	0.167	0.38	Not Supported
OPT	←	EVA	0.594	0.001	Supported

Hypothesis Testing

- 4 out of 9 hypotheses were supported in the model
- H1a, H1b, H1c and H2a were strongly supported

Demand Identification and Information Search

- Demand identification has a significant positive relationship with information search ($\beta = 0.23, p<0.05$)

Information Search and Evaluation of Alternatives

- Information search has a significant positive relationship with evaluation of alternatives ($\beta = 0.17, p<0.05$)
- This implies a sequential association between decision making stages

Decision Making and Behavioral Biases

- Demand identification has significant positive relationships with disposition effect ($\beta = 0.07, p<0.05$) and overconfidence bias ($\beta = 0.15, p<0.05$)
- Information search ($\beta = 0.02, p<0.05$) and evaluation of alternatives ($\beta = 0.59, p<0.05$) have significant positive relationships with overconfidence bias
- Decision making stages do not significantly impact herding bias

Results of Mann-Whitney U Test

The Mann-Whitney U test is a non-parametric alternative to the independent samples t-test. It compares two sample means from the same population to determine if they are equal. This test is typically used for ordinal data or when the assumptions of the t-test are not met (Corder & Foreman, 2014).

Table 10

Mann-Whitney Test for Gender Difference in Behavioral Biases

	Disposition Effect	Herding Bias	Overconfidence Bias
Mann-Whitney U	14676.5	14534.5	9276
Asymp. Sig. (2-tailed)	0.002	0.002	0.001

In this study, the Mann-Whitney test analyzes mean rank differences between gender and behavioral biases.

Statistical Significance – The results indicate statistically significant mean differences at the 5% level.

Key Findings:

- Female investors are more prone to the disposition effect and herding bias.
- Male investors are more prone to overconfidence bias.

These findings support hypotheses H4a, H4b, and H4c.

Table 11

Mean rank for Gender Difference in Behavioral Biases

	Gender	Mean Rank
Disposition Effect	Male	178.02
	Female	212.77
Herding Bias	Male	177.39
	Female	213.66
Overconfidence Bias	Male	231.09
		138.48

Note. N=384

Results of Kruskal–Wallis H Test

Kruskal-Wallis H Test

The Kruskal-Wallis H test is a non-parametric alternative to the one-way ANOVA, used to determine significant differences between two or more independent groups on a continuous or ordinal dependent variable (Corder & Foreman, 2014).

Age Differences and Behavioral Biases

- **Disposition Effect and Overconfidence Bias:** Age differences are not statistically significant at the 5% level, rejecting hypotheses H7a and H7b.
- **Herding Bias:** Age differences are statistically significant at the 5% level, supporting hypothesis H7c.

Mean Rank Analysis

Respondents under 25 years old are more prone to herding bias compared to other age groups.

Educational Qualification Differences in Behavioral Biases

The Kruskal-Wallis H test results for educational qualifications and behavioral biases are presented in Tables 12 and 13

Findings

Educational qualification differences show no statistically significant impact on the disposition effect, herding bias, or overconfidence bias at the 5% level, leading to the rejection of hypotheses H5a, H5b, and H5c.

Conclusion

There are no significant mean differences in behavioral biases based on the educational qualifications of individual investors.

Table 12

Kruskal-Wallis H Test for Educational Qualification Differences in Behavioral Biases

	Disposition Effect	Herding Bias	Overconfidence Bias
Kruskal-Wallis H	3.746	5.009	1.249
df	3	3	3
Asymp. Sig.	0.29	0.171	0.741

Table 13

Mean rank for Educational Qualification Differences in Behavioral Biases

	Educational Qualification	Mean Rank
Disposition Effect	Intermediate or +2	201.05
	Bachelors	206.81
	Masters	183.04
	Above Masters	182.63

	Educational Qualification	Mean Rank
Herding Bias	Intermediate or +2	211.3
	Bachelors	201.6
	Masters	185.41
	Above Masters	169.13
Overconfidence Bias	Intermediate or +2	201.29
	Bachelors	183.48
	Masters	193.21
	Above Masters	199.15

Note. N=384

Income Differences in Behavioral Biases

The Kruskal-Wallis H test results for income differences and behavioral biases are summarized as

Kruskal-Wallis H Test Results

- **Disposition Effect:** H = 12.463, p = 0.014
- **Herding Bias:** H = 7.61, p = 0.107
- **Overconfidence Bias:** H = 2.727, p = 0.604

Mean Rank by Income Level

- **Disposition Effect:** More than 11 lakhs: 230.21
- **Herding Bias:** 2-4 lakhs: 212.24
- **Overconfidence Bias**: 6-8 lakhs: 203.36

Findings

- **Herding Bias and Overconfidence Bias:** No statistically significant differences at the 5% level, leading to the rejection of hypotheses H6a and H6c.
- **Disposition Effect:** Statistically significant at the 5% level, supporting hypothesis H6b. Respondents with an average annual income over 11 lakhs are more prone to the disposition effect.

Experience Differences in Behavioral Biases

The Kruskal-Wallis H test results for experience differences and behavioral biases found as:

- **Disposition Effect and Herding Bias:** No statistically significant differences at the 5% level, leading to the rejection of hypotheses H8b and H8c.
- **Overconfidence Bias:** Statistically significant at the 5% level, supporting hypothesis H8a. Respondents with less than 1 year of investing experience are more prone to overconfidence bias.

Participation in Market and Behavioral Biases

The Kruskal-Wallis H test results for participation differences and behavioral biases found Disposition Effect and Herding Bias: No statistically significant differences at the 5% level, leading to the rejection of hypotheses H9b and H9c.

Overconfidence Bias

Statistically significant at the 5% level, supporting hypothesis H9a. Respondents who actively participate in the stock market are more prone to overconfidence bias.

Connection Between Behavioral Biases and Rational Decision-Making

This study uniquely explores the relationship between rational decision-making and behavioral biases among individual investors in the emerging Nepalese stock market. Findings indicate that investors generally follow a rational decision-making process: they identify investment demand, search for information, and evaluate alternatives. This aligns with previous research by Lin (2011) and Kumar and Goyal (2016). All three stages of rational decision-making significantly contribute to overconfidence. Once investors identify their motivation, they may develop a risk-taking attitude, leading to overconfidence based on their understanding of risk and return. However, bounded rationality can cause them to rely on limited information and past experiences, further reinforcing their overconfidence. Literature suggests that investors often overreact to private information rather than public data (Daniel et al., 1998). Only the demand identification stage significantly contributes to the disposition effect. During this stage, overconfidence can lead to excessive trading (Odean, 1999) and poor decision-making. Research has shown a positive association between overconfidence and the disposition effect (Pi-Chuan & Hsiao, 2006; Raheja & Dhiman, 2019). Interestingly, the stages of decision-making do not significantly impact herding bias, suggesting that herding behavior may be influenced by external factors, such as market conditions, rather than personal decision-making processes.

Demographic Factors Affecting Behavioral Biases

The study also examines how demographic variables influence behavioral biases. Gender differences are significant: female investors are more prone to the disposition effect, while male investors exhibit greater overconfidence. These findings are consistent with prior studies (Lin, 2011; Barber & Odean, 2001) but contradict others (Da Costa et al., 2008).Age does not significantly affect disposition and overconfidence biases, supporting Lin (2011), although it contradicts findings from. However, younger investors (under 25) are more likely to exhibit herding behavior, aligning with Lin (2011). Educational qualifications show no significant relationship with behavioral biases, and income levels above 11 lakhs correlate with a higher disposition effect, contradicting Ahn (2022). Experience also plays a nuanced role: it does not significantly affect herding or disposition effects, contradicting Ahn (2022). However, investors with less than one year of experience tend to be more overconfident, which contrasts with Mishra & Metilda (2015). Trading frequency significantly influences overconfidence, with active traders displaying higher levels of overconfidence than occasional or rare traders, supporting Toma (2015).

Conclusion

The first model demonstrates that investors typically follow a rational decision-making process when investing. This process involves three critical stages: identifying investment demand, searching for relevant information, and evaluating alternatives or establishing criteria for investment. These findings suggest that individual investors engage in a systematic approach to decision-making, which aligns with established theories in behavioral finance. The second model investigates the impact of personal characteristics—such as gender, age, and investment experience—on behavioral biases. The results indicate that these personal characteristics significantly influence behavioral biases, highlighting the complexity of investor behavior. For instance, gender differences were observed in the propensity to exhibit biases like the disposition effect and overconfidence, while age and experience also played roles in shaping these biases.

Despite the myriad antecedents that can lead to behavioral biases, this study provides empirical evidence linking rational decision-making processes with the irrational behaviors exhibited by investors. It confirms that individual investors often navigate a landscape where rational and irrational thought processes coexist, which can lead to suboptimal investment decisions. The findings underscore the importance of understanding these biases, as they can significantly impact investment outcomes and overall market efficiency.

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