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Behavioural Biases and Investment Decision-Making: A Multigroup Analysis of Demographic Differences Using PLS-SEM

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ABSTRACT

The purpose of this study is to investigate the influence of behavioural biases on investment decision-making and the moderating effect of demographic variables using Partial Least Squares Structural Equation Modelling (PLS-SEM) and multigroup analysis (PLS-MGA). Data were collected from 385 MSME entrepreneurs of North-Eastern India using a structured questionnaire. The result indicates that anchoring bias, herding bias, overconfidence bias, illusion of control bias, and regret aversion significantly influence investment decision-making. Herding emerged as the most influencing factor. Age and education level was also found to moderate certain relationships between behavioural biases and investment decisions, whereas gender and income have no significant moderating effect. The study adds to the limited empirical evidence from emerging market contexts and contributes to behavioural finance literature. It also highlights the importance of incorporating behavioural finance insights into investor education programmes and policy frameworks.

Keywords: Behavioural finance, emotional biases, cognitive biases, anchoring bias, herding bias, PLS-MGA

INTRODUCTION

Traditional finance theories assume that investors are rational and make decisions based on complete information to maximise expected utility. However, growing empirical evidence demonstrates that real-world investment behaviour systematically deviates from rationality due to cognitive and emotional influences (Barberis, 2018). These deviations have strengthened the relevance of behavioural finance, which integrates psychological insights to explain market anomalies neglected by classical theory (Kahneman & Tversky, 1979; Barberis & Thaler, 2003). Several behavioural biases are consistently reported as key determinants of irrational investment behaviour. Anchoring bias causes investors to rely excessively on initial information, leading to slow or incorrect adjustment to latest and updated information (Kudryavtsev & Cohen, 2010; Jain et al., 2021). Herding behaviour refers to the propensity of investors to follow the actions of others instead of relying on their own personal analysis and end up making irrational investment decisions (Baker et al., 2019). Investors often ignore information and ideas, instead prioritizing their decisions based on the behaviour of others (Shantha, 2019). Illusion of control leads investors to overestimate their ability to influence market outcomes and as such leads them to assume excessive risk-taking (Fellner, 2009). Overconfidence leads investors to overestimate their financial expertise and forecasting skills, often leading to poor portfolio diversification and excessive trading (Barber & Odean, 2001; Bouteska & Regaieg, 2020). Regret aversion indicates emotional hesitation in decision-making, where investors avoid potentially lucrative investments because of the possibility of unforeseen regret (Statman, 2019).

While behavioural finance research is extensive globally, there remains a shortage of empirical studies focusing on emerging markets, where limited financial literacy, weak institutional development, and high information asymmetry often intensify behavioural distortions (Baker et al., 2019). In the Indian context, significant regional disparities exist in investor participation and awareness, especially in relatively underdeveloped regions such as the northeastern states (Varma & Barua, 2019). Investors in these regions frequently operate under information constraints, increasing susceptibility to cognitive and emotional biases in financial decision-making.

Despite growing interest in behavioural finance, three significant research gaps remain. Firstly, numerous research has analysed behavioural biases considering certain biases, neglecting their cumulative impact on investors behaviour (Baker et al., 2019). Second, demographic characteristics are often used as control factors instead of being analysed as moderators while determining if these variables moderates the effect of behavioural biases on investment decision making, thereby constraining understanding of investor heterogeneity. Third, there is limited evidence of studies utilising multigroup analysis to determine whether the moderating effect of age, gender, education level and income vary across different demographic groups (Hair et al., 2019; Sarstedt et al., 2011).

To bridge these gaps in the literature, this study examines the joint impacts of anchoring, herding, illusion of control, overconfidence, and regret aversion on investment decision-making among MSME entrepreneurs in northeastern India utilizing Partial Least Squares Structural Equation Modelling (PLS-SEM). Additionally, PLS-based Multigroup Analysis (PLS-MGA) is employed to investigate demographic heterogeneity across gender, age, education and income of the respondents.

This study is an attempt to contribute to the existing behavioural finance literature by extending empirical investigation of less explored region, analysing multiple cognitive biases simultaneously, and applying multigroup analysis to reveal demographic variations.

LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

Traditional financial theories, such as the Efficient Market Hypothesis (EMH) and Expected Utility Theory, are grounded on the assumptions that investors act rationally and markets are efficient. However, growing empirical evidence highlights that investors are not often rational decision makers and are usually affected by psychological, emotional, and cognitive biases (Barberis, 2018; Statman, 2019). As such, behavioural finance provides an alternative framework by integrating psychological insights into conventional finance theories, explaining the persistence of systematic anomalies that are associated with making investment decisions (Kahneman & Tversky, 1979; Barberis & Thaler, 2003).

Studies of the past confirm that behavioural biases significantly affect asset pricing, portfolio selection, trading behaviour, and investment intention of the investors (Yao, 2025; Mahmood, 2024; Chishti, 2025; Singh & Dixit, 2025). In emerging markets, where information asymmetry and financial illiteracy are more pronounced, these biases exert a stronger influence (Raut et al., 2018). Investor choices are increasingly shaped by emotional responses rather than objective evaluation, making behavioural finance especially relevant.

Behavioural Biases.

Anchoring bias and investment decision.

Anchoring bias refers to the cognitive tendency of individuals to rely excessively on an initial information, such as historical prices, expected returns, or reference values, when evaluating judgment and investment opportunities, even when that reference is arbitrary or irrelevant (Wang, 2023). As a result, investors often fail to adequately revise their assessments when new information becomes available, leading to asset mis valuation and suboptimal portfolio choices (Schulz, 2023). Anchoring bias is a fundamental cognitive heuristic that explains deviations from rational decision-making and contributes to persistent market inefficiencies (Tlili et al., 2023). Studies in emerging markets further suggested that anchoring bias influences stock selection and holding behaviour, particularly under market uncertainty (Raut et al., 2018). Further studies also found that the influence of anchoring bias differs across different demographic groups. Age influences cognitive processing and risk sensitivity, while gender differences in information processing styles affect susceptibility to anchors (Finke et al., 2017). Education and income level reflect financial sophistication and information exposure, which are likely to moderate reliance on heuristics (Van Rooij et al., 2011). Although gender and financial knowledge are associated with differences in anchoring susceptibility, these factors do not consistently mitigate the bias, highlighting its persistence across investor groups (Owusu & Laryea, 2023). As such, the following hypotheses are developed.

H1: Anchoring bias influences investment decision-making.

H1a: The effect of anchoring bias on investment decision making differs across gender groups.

H1b: The effect of anchoring bias on investment decision making differs across age groups.

H1c: The effect of anchoring bias on investment decision making differs across income groups.

H1d: The effect of anchoring bias on investment decision making differs across education levels.

Herding bias and investment decision

Herding bias reflects investors' tendency to imitate others' actions rather than relying on their own independent analysis (Vieira & Pereira, 2015). This behaviour is often triggered by uncertainty, social pressure, and fear of missing out (Baker et al., 2019). Empirical evidence suggests that herding amplifies market volatility and contributes to asset price bubbles (Hott, 2009; Fei & Liu, 2025; Pitkakoski, 2025). Demographic attributes shape social interaction and risk perception and hence influence herding tendencies (Kumar & Arora, 2023; Murhadi et al, 2024). Younger and less educated investors are reported to be more susceptible to social influence, while income instability strengthens reliance on peer behaviour (Gonzalez-Igual et al., 2021). Thus, the following hypotheses are developed:

H2: Herding bias influences investment decision-making.

H2a: The effect of herding bias on investment decision making differs across gender groups.

H2b: The effect of herding bias on investment decision making differs across age groups.

H2c: The effect of herding bias on investment decision making differs across income groups.

H2d: The effect of herding bias on investment decision making differs across education levels.

Illusion of control bias and investment decision.

Illusion of control bias refers to the tendency of investors to overestimate their ability to control or influence outcomes that are largely governed by chance (Langer, 1975; Fellner, 2009). This leads to increased trading activity, underestimation of risks, and formulation of aggressive investment strategies (Fenton-O'Creevy et al., 2003). Illusion of control also leads investors to believe that their personal skills or judgment can systematically influence market outcomes, despite the inherent uncertainty of financial markets (Fellner, 2009). Studies found that the illusion of control bias has a significant positive impact on individual investor investment decisions, with financial literacy serving as a moderating factor that weakens this relationship (Ullah et al., 2015). However, empirical findings remain mixed, as some studies report that the illusion of control does not exert a statistically significant direct effect on investment decisions (Fajri & Setiawati, 2023) and may affect indirectly through psychological mechanisms such as emotional maturity, although such indirect effects are often weak or insignificant (Ishak & Sholehah, 2023). Evidence shows that gender and educational level significantly moderate the influence of illusion of control bias on investment decision-making, whereas age does not act as a moderator (Syarkani & Alghifari, 2022). This finding provides rare and valuable empirical support for demographic heterogeneity in behavioral finance, indicating that the illusion of control does not affect all investors uniformly. The literature remains fragmented due to inconsistent findings across investor groups and limited integration of moderators. Hence the following hypotheses are developed:

H3: Illusion of control bias influences investment decision-making.

H3a: The effect of illusion of control biases on investment decisions differs across gender groups.

H3b: The effect of illusion of control biases on investment decisions differs across age groups.

H3c: The effect of illusion of control biases on investment decisions differs across income groups.

H3d: The effect of illusion of control biases on investment decisions differs across education levels.

Overconfidence bias and investment decision

Overconfidence bias refers to investors' tendency to overestimate their knowledge, skills, and predictive ability when making financial decisions (Daniel & Hirshleifer, 2015; Singh et al., 2024). Behavioral finance literature consistently documents overconfidence as one of the most prevalent cognitive biases influencing investment decision-making, contradicting the assumption of rationality in traditional finance theories (Kumar & Prince, 2023). This bias is associated with excessive trading and reduced diversification, which adversely affect investment outcomes (Bouteska & Regaieg, 2020). Research shows that overconfidence can significantly influence investment choices by leading investors to trade excessively and misjudge market risks, thereby affecting investment decision (Nadhila, 2024). Experimental studies show that highly overconfident investors invest excessively, while underconfident investors underinvest, resulting in non-optimal decisions (Pikulina et al., 2017). Further research demonstrates that risk perception mediates the relationship between overconfidence bias and investment decision-making, while financial literacy weakens the adverse effects of overconfidence on investment decisions (Ahmad & Shah, 2022). Gender and age differences are frequently reported in overconfidence research, with younger and male investors displaying higher self-confidence in financial judgment (Finke et al., 2017). Although prior studies document gender and age differences in overconfidence levels, existing empirical research does not provide consistent evidence on education or income as moderating variables. Hence, the study proposed the following hypothesis:

H4: Overconfidence bias influences investment decision-making.

H4a: The effect of overconfidence bias on investment decision making differs across gender groups.

H4b: The effect of overconfidence bias on investment decision making differs across age groups.

H4c: The effect of overconfidence bias on investment decision making differs across income groups.

H4d: The effect of overconfidence bias on investment decision making differs across education levels.

Regret Aversion bias and investment decision

Regret aversion refers to investors' tendency to avoid decisions that may lead to future emotional discomfort arising from unfavorable outcomes or missed opportunities (Bell, 1982; Loomes & Sugden, 1982). This often leads to inertia, preference for familiar assets, and delayed selling of underperforming investments (Statman, 2019). This bias is grounded in regret theory, which is of the opinion that investors evaluate decisions not only based on expected utility but also on anticipated regret from foregone alternatives (Gazel, 2015). Empirical findings suggest that regret aversion significantly influences risk-taking behaviour and is more pronounced in investors with limited financial literacy (Rasool & Ullah, 2020). Due to regret aversion, investors often delay selling losing assets, hold on to underperforming investments, and avoid risky yet potentially profitable opportunities (Gazel, 2015). A meta-analysis synthesizing findings from multiple empirical studies confirms a statistically significant positive relationship between regret aversion bias and investment decision-making behavior (Kumar & Chaurasia, 2024). Regret-averse investors also exhibit limited portfolio diversification, as fear of regret discourages investment in unfamiliar or foreign assets (Komba, 2025). Further research demonstrates that regret aversion bias heightens investors' perceived level of risk, which subsequently leads to cautious and suboptimal investment decisions (Wangzhou et al., 2021). However, financial literacy has been shown to mitigate the adverse effects of regret aversion bias by enabling investors to rely more on analytical judgment rather than emotional responses (Wangzhou et al., 2021; Rahawarin, 2023). Although prior studies have extensively examined the direct effect of regret aversion bias on investment decision-making, limited

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empirical attention has been given to the moderating role of demographic variables such as age, gender, educational level, and income. As such the study proposed the following hypotheses:

H5: Regret aversion bias influences investment decision-making.

H5a: The effect of regret aversion bias on investment decisions differs across gender groups.

H5b: The effect of regret aversion bias on investment decisions differs across age groups.

H5c: The effect of regret aversion bias on investment decisions differs across income groups.

H5d: The effect of regret aversion bias on investment decisions differs across education levels.

Conceptual Model

The conceptual model of the study is presented in Figure 1, illustrating the hypothesized relationships among behavioural biases, investment decision-making, and the moderating role of demographic variables.

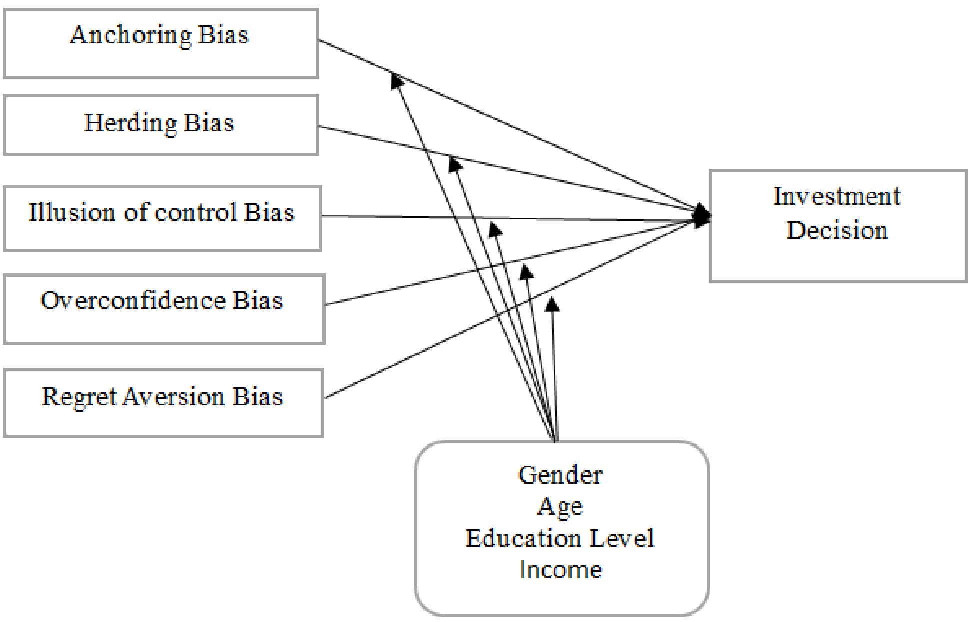

Figure 1: Conceptual model

Source: Author’s own construction.

METHODOLOGY

Research Construct

The questionnaire consisted of 27 self-developed measurement items designed specifically for this study, based on the conceptual definitions of the constructs and prior theoretical foundations in behavioural finance. Regret aversion bias was measured using four items, anchoring bias using three items, illusion of control using four items, herding bias using five items, overconfidence bias using six items, and Investment decision-making using 6 items. All items were assessed using a 5-point Likert scale ranging from 1 = Strongly Disagree to 5 = Strongly Agree. The reliability and validity of these measurement items were validated using SmartPLS 4.0, as shown in table 2 and table 3. Five cognitive biases (representativeness, anchoring, illusion of control, overconfidence and herding) serve as exogenous latent constructs influencing the endogenous construct investment decision-making. Demographic variables (age, gender, education level, and income) are incorporated as moderators to examine group differences through PLS-MGA.

Data and data collection technique

Data for this study were collected from 385 respondents who are entrepreneurs from the North Eastern region of India and who actively invest in various investment avenues. The required sample size was determined using Cochran's (1977) sample size determination formula, which indicated a minimum target of approximately 385 respondents for a large population. The study employed convenience sampling to select respondents who met the criterion of being active investors. The sample size of 385 is justified based on Cochran's (1977) formula for large populations and exceeds the minimum requirements for PLS-SEM as recommended by Hair et al. (2019). The sample also surpasses the 10-times rule required for rigorous SEM analysis.

RESULTS

Respondents Profile.

The study was conducted on a sample of 385 respondents chosen from diverse demographic backgrounds. Out of 385 respondents who reported, 205 of them were male, and 180 were female. Further, 34.29% were between the ages of 35 and 50, 29.09% were between the ages of 20 and 35, 28.05% were between the ages of 50 and 65, and 8.57% were over the age of 65. In terms of education, the largest group of respondents had college degrees (30.39%), followed by those with higher secondary (29.35%), high school (20.52%), and postgraduate or higher degrees (19.74%). In addition, 35.58% of respondents reported earning more than ₹10 lakhs, 33.77% reported earning between ₹5 and ₹10 lakhs, and 30.65% reported earning less than ₹5 lakhs per annum.

Measurement model and discriminant validity assessment

In order to examine the impact of behavioural biases on investment decision-making, Partial Least Squares Structural Equation Modeling (PLS-SEM) was utilised using SmartPLS 4.1.1.6. Before performing structural analysis, the measurement model was assessed through reliability, convergent validity, discriminant and collinearity diagnostics. As stated in Tables 2, 3, and 4, the measurement model shows strong psychometric properties. As all factor loadings exceed the recommended threshold of 0.70, it confirms the reliability of the indicator, and as all VIF value is below 5, it indicates that there is no issue of multicollinearity (Hair et al., 2019). Internal consistency reliability is also established as Cronbach's alpha, and composite reliability values are above 0.70 for all constructs (Hair et al., 2019). Convergent validity is confirmed as Average Variance Extracted (AVE) values exceed the 0.50 threshold (Fornell & Larcker, 1981). Further, the Discriminant validity is assessed using both the Fornell–Larcker criterion and the Heterotrait–Monotrait ratio (HTMT). Since the AVE for each construct is higher than its inter-construct correlations, and all HTMT values are below the threshold of 0.85, it indicates that all the constructs are distinct (Fornell & Larcker, 1981; Henseler et al., 2015). As such, the measurement model meets all reliability and validity requirements and supports progression to the valid structural model analysis.

Table 2: Assessment of the Measurement Model

Factors/Construct	Measurement Items	Factor Loadings	Collinearity (VIF)	Cronbach's alpha(α)	Composite reliability (rho a)	Average variance extracted (AVE)
Anchoring	ANCH1	0.877	2.133	0.863	0.863	0.785
	ANCH2	0.888	2.234			
	ANCH4	0.892	2.263			
Herding	HERD1	0.885	3.038	0.929	0.93	0.778
	HERD2	0.890	3.050			

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	HERD3	0.881	3.019			
	HERD5	0.873	2.723			
	HERD6	0.881	2.905			
Illusion of Control	IOC1	0.852	2.328	0.883	0.897	0.738
	IOC2	0.857	2.262			
	IOC3	0.850	2.276			
	IOC4	0.878	2.227			
Overconfidence	OC1	0.845	2.491	0.906	0.914	0.726
	OC2	0.850	2.379			
	OC4	0.821	2.143			
	OC5	0.870	2.603			
	OC6	0.873	2.569			
Representativeness	RA1	0.861	2.198	0.885	0.892	0.742
	RA2	0.876	2.334			
	RA3	0.840	2.210			
	RA4	0.870	2.380			
Investment Decision	ID1	0.826	2.220	0.917	0.918	0.707
	ID2	0.860	2.731			
	ID4	0.873	2.862			
	ID5	0.842	2.471			
	ID6	0.819	2.214			
	ID7	0.823	2.297			

Source: Computed by author using SmartPLS4

Table 3: Discriminant validity assessment (Fornell and Larcker criterion)

	ANCH	**HERD**	**ID**	**IOC**	**OC**	**RA**
ANCH	0.886					
HERD	0.181	0.882				
ID	0.419	0.463	0.841			

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IOC	0.249	0.086	0.294	0.859		
OC	0.146	0.092	0.249	0.265	0.852	
RA	0.226	0.105	0.332	0.219	0.251	0.862
Notes: ANCH=Anchoring; HERD=Herding; ID=Investment Decision; IOC=Illusion of Control, OC= Overconfidence; RA=Regret Aversion						

Source: Computed by author using SmartPLS4

Table 4: Discriminant validity assessment (Heterotrait-Monotrait Ratio-HTMT)

	ANCH	**HERD**	**ID**	**IOC**	**OC**	**RA**
ANCH						
HERD	0.202					
ID	0.470	0.499				
IOC	0.280	0.091	0.322			
OC	0.163	0.100	0.270	0.291		
RA	0.258	0.117	0.364	0.244	0.279	
Notes: ANCH=Anchoring; HERD=Herding; ID=Investment Decision; IOC=Illusion of Control, OC= Overconfidence; RA=Regret Aversion						

Source: Computed by author using SmartPLS4

Model Fit, Explanatory Power, and Predictive Relevance

As shown in Table 5, the SRMR (Standardized Root Mean Square Residual) for the saturated and estimated model is 0.040, and is well below the maximum threshold of 0.08. The NFI (Normed Fit Index) of 0.903 is also close to the suggested value of 0.90. This indicates that the model fits well (Hair et al., 2019; Henseler et al., 2013).

Table 5: Model fit result

	Saturated model	**Estimated model**
SRMR	0.040	0.040
d_ULS	0.614	0.614
d_G	0.288	0.288
Chi-square	670.686	670.686
NFI	0.903	0.903

Source: Computed by author using SmartPLS4

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Table 6 shows the explanatory power of the structural model. The R^2 value of 0.407 indicates that approximately 40.7 % of the variance in the endogenous latent construct is explained by the exogenous latent constructs. This level of explanatory power is considered moderate in behavioural finance research (Hair et al., 2011; Vinzi et al., 2010; Henseler et al., 2009).

Table 6: R-Square-Overview

	R-square	**R-square adjusted**
ID	0.407	0.399
Note: ID = Investment Decision		

Source: Computed by author using SmartPLS4

Table 7 shows the PLS prediction summary. The Q^2 predict value is 0.387, which is more than zero and hence it can be stated that the model possesses strong predictive relevance (Hair et al., 2019). The results stated in tables 5, 6, and 7 confirm that the model demonstrates adequate fit, moderate explanatory power, and strong predictive relevance, thereby supporting the suitability of the PLS-SEM approach for examining the impact of behavioural biases in investment decision-making.

Table 7: Latent Variable Prediction Summary-PLS-SEM

	Q^2predict	**RMSE**	**MAE**
ID	0.387	0.786	0.636
Note: RMSE=Root mean Square Error; MAE=Mean Absolute Error; ID=Investment decision			

Source: Computed by author using SmartPLS4

Path analysis and hypothesis testing

Path analysis is conducted to determine the strength and significance of the relationships between independent latent constructs and a dependent latent construct (Kline, 2023; Hair et al., 2019; Henseler et al., 2009). In this study, path analysis is performed using the bootstrapping procedure in PLS-SEM to assess the statistical significance of the hypothesised relationships between behavioural biases and investment decision-making. The analysis of the path coefficient in Table 8 shows that all five independent variables, herding, anchoring, regret aversion, Illusion of control, and overconfidence, have a significant relationship with investment decisions, supporting H1, H2, H3, H4, and H5.

Table 8: Path Analysis (Direct Path)

Hypothesis	**Path**	**β**	**Standard deviation (STDEV)**	**T statistics (|O/STDEV|)**	**P values**	**Decisions**
H1	ANCH -> ID	0.264	0.044	6.049	0.000	Supported
H2	HERD -> ID	0.376	0.039	9.760	0.000	Supported
H3	IOC -> ID	0.131	0.044	2.969	0.003	Supported
H4	OC -> ID	0.096	0.044	2.193	0.028	Supported

H5	RA -> ID	0.181	0.040	4.458	0.000	Supported
Notes: ANCH=Anchoring; HERD=Herding; ID=Investment Decision; IOC=Illusion of Control, OC= Overconfidence; RA=Regret Aversion						

Source: Computed by author using SmartPLS4

Multigroup Analysis

In this study, PLS-MGA (Partial least squares-multigroup analysis) is applied to assess whether the influence of behavioural biases on investment decision-making varies across different heterogeneous demographic groups. This technique enables group-wise comparison of path coefficients without requiring interaction effects and is particularly suitable when the objective is to detect heterogeneity across demographic segments (Henseler et al., 2009; Hair et al., 2019). Moreover, PLS-MGA does not impose strict assumptions regarding data normality and performs well with unequal group sizes, making it appropriate for behavioural finance research involving survey data (Sarstedt et al., 2011).

To examine whether the measurement model operates equivalently across heterogenous demographic groups based on age, gender, income and education level, the Measurement Invariance of Composite Model (MICOM) procedure proposed by Henseler et al. (2016) was perform using permutation test and the result showed that full measurement invariance was established in case of gender groups, age groups, and income group for all the construct and a partial measurement invariance was established in case of education level allowing a valid bootstrap multigroup analysis. According to Henseler et al. (2009), in (PLS-MGA), the p-value must be less than 0.05 or higher than 0.95 to show that there is a significant difference in the specific path coefficient between groups. A p-value below 0.05 indicates that the effect of Group 1 is greater than Group 2, and a p-value above 0.95 means that the effect of Group 2 is greater than Group 1.

Table 9 presents the results of the multigroup analysis examining whether gender moderates the relationships between behavioural biases and investment decision-making. The findings indicate that none of the group differences between male and female respondents are statistically significant, as all reported p-values exceed the 0.05 threshold (Hair et al., 2019; Sarstedt et al., 2011). As a result, Hypotheses H1a, H2a, H3a, H4a, and H5a are rejected, indicating that gender does not moderate the influence of behavioural biases on investment decisions across different gender groups.

Table 9: Consolidated MGA Result (Gender as a Moderator)

Hypothesis	**Path**	**(Male vs Female) p value**	**Decision**
H1a	ANCH -> ID	0.631	Rejected
H2a	HERD -> ID	0.74	Rejected
H3a	IOC -> ID	0.558	Rejected
H4a	OC -> ID	0.497	Rejected
H5a	RA -> ID	0.816	Rejected

Source: Computed by author using SmartPLS4

The bootstrap MGA result presented in Table 10 reveals that, among the five behavioural biases examined, only the illusion of control showed a significant variation across age groups. Especially, the impact of illusion of control bias on investment decision was found to be significantly stronger in Age_G1 as compared to Age_G2, as the p value is 0.007, which is less than 0.05, indicating that younger investors may exhibit higher susceptibility to illusion of control bias while making investment decisions. A p-value below 0.05 means that Group 1 has a

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stronger effect than Group 2, while a p-value above 0.95 indicates that Group 2 has a stronger effect than Group 1 (Hensler et al., 2009). However, the comparisons between Age_G1 and Age_G3 (p=0.062) and between Age_G2 and Age_G3 (p=0.779) were not significant. For anchoring, herding, overconfidence, and regret aversion, no significant differences were observed across age groups (p>0.05); as such, H1b, H2b, H4b, and H5b are rejected, indicating that the impact of these biases on investment decision-making do not differ significantly across age groups.

Table 10: Consolidated MGA Result (Age as a Moderator)

Hypothesis	**Path**	**(Age_G1 vs Age_G2) p value**	**(Age_G1 vs Age_G3) p value**	**(Age_G2 vs Age_G3) p value**	**Decisions**
H1b	ANCH -> ID	0.548	0.155	0.337	Rejected
H2b	HERD -> ID	0.683	0.149	0.09	Rejected
H3b	IOC -> ID	0.007 (Sig.)	0.062	0.779	Significant for Age_G1 vs Age_G2 (Age_G1> Age_G2)
H4b	OC -> ID	0.483	0.62	0.31	Rejected
H5b	RA -> ID	0.995	0.562	0.573	Rejected
Note: Sig. indicates significant differences between groups; Age_G1=20 years to 35 years; Age_G2=35 to 50 years; Age_G3=50 to 65 Years.					

Source: Computed by author using SmartPLS4

Table 11 presents the results of the multigroup analysis based on education level. The findings indicate that education level moderates the relationships between anchoring bias, illusion of control, overconfidence bias, and regret aversion bias with investment decisions, as the effects differ across education groups. However, the effect of herding bias remains same across all education groups, indicating no moderation effect. Hence, H1c, H3c, H4c, and H5c are supported, whereas H2c is rejected, indicating that educational attainment does not moderate the effect of herding bias in investment decision making.

Table 11: Consolidated MGA Result (Education Level as Moderator)

Hypothesis	**Path**	**β (Edu_G1)**	**p value (Edu_G1)**	**β (Edu_G2)**	**p value (Edu_G2)**	**β (Edu_G3)**	**p value (Edu_G3)**	**β (Edu_G4)**	**p value (Edu_G4)**	**Decisions**
H1c	ANCH -> ID	0.353	0 (Sig)	0.329	0 (Sig)	0.123	0.1	0.298	0.009 (Sig)	Supported (Significant for Edu_G1, Edu_G2 & Edu_G4
H2c	HERD -> ID	0.365	0 (Sig)	0.29	0 (Sig)	0.525	0 (Sig)	0.314	0 (Sig)	Rejected (Significant across all groups)

H3c	IOC -> ID	0.111	0.24	0.17	0.017 (Sig)	0.083	0.269	0.114	0.346	Supported (Significant only for Edu_G2)
H4c	OC -> ID	0.04	0.707	0.138	0.043 (Sig)	0.14	0.052	0.076	0.538	Supported (Significant only for Edu_G2)
H5c	RA -> ID	0.17	0.105	0.28	0 (Sig)	0.026	0.746	0.185	0.062	Supported (Significant only for Edu_G2)
Note: Sig. indicates significant; Edu_G1= Up to high school; Edu_G2=Higher Secondary; Edu_G3=Undergraduate; Edu_G4=Postgraduate and Higher.										

Source: Computed by author using SmartPLS4

The multigroup analysis results in Table 12 indicate that no statistically significant differences among the three income groups across all paths, as the p values fall within the acceptable region of $0.05 \leq p \leq 0.95$ (Henseler et al., 2009). However, despite high p-value observed in the case of relationship between overconfidence bias and investment decision making, in the income group Inc_G2 vs Inc_G3 (0.998), the negligible coefficient difference between the groups (0.001) indicates no practically meaningful variations among groups. Hence, H6d, H7d, H8d, H9d, H10d is rejected, indicating that the impact of anchoring, herding, illusion of control, overconfidence, and regret aversion on investment decisions does not differ across different income groups.

Table 12: Consolidated MGA Result (Income Level as Moderator)

Hypothesis	**Path**	**(Inc_G1 vs Inc_G2) p value**	**(Inc_G1 vs Inc_G3) p value**	**(Inc_G2 vs Inc_G3) p value**	**Decisions**
H1d	ANCH -> ID	0.446	0.699	0.66	Rejected
H2d	HERD -> ID	0.895	0.836	0.947	Rejected
H3d	IOC -> ID	0.922	0.798	0.716	Rejected
H4d	OC -> ID	0.775	0.755	0.998	Rejected
H5d	RA -> ID	0.3	0.223	0.874	Rejected
Note: Sig. indicates significant differences between groups Inc_G1= Less than 5 Lakhs; Inc_G2=5 to 10 Lakhs; Inc_G1=Above 10 Lakhs.					

Source: Computed by author using SmartPLS4

FINDINGS AND DISCUSSION

The findings reveal that behavioural biases significantly influence investment decision-making, confirming that investors do not act fully rationally but are guided by cognitive and emotional distortions. The result of path coefficient confirms, herding bias to be the strongest determinant that influences investment decisions (β = 0.376), indicating that investors rely heavily on peer influence and market trends when making financial choices. This finding is consistent with prior research suggesting that social influence and information cascades dominate investor behaviour, especially in uncertain market conditions (Baker et al., 2019). With a coefficient of β = 0.264, anchoring bias stands as the second most influential factor, indicating that investors tend to rely heavily on initial and prior information such as historical prices or expectations while evaluating investment choices. Regret aversion also shows a strong and significant influence (β = 0.181), reflecting investors' tendency to avoid decisions that may lead to emotional discomfort or future regret. This behaviour often results in holding losing stocks too long or avoiding potentially profitable investments. Although comparatively weaker, illusion of control (β = 0.131) and overconfidence (β = 0.096) remain statistically significant, indicating that investors overestimate both their ability and control over market outcomes. These findings are consistent with evidence that investors often trade excessively and underestimate risk due to inflated self-confidence (Bouteska & Regaieg, 2020). The model explains approximately 41% of the variance in investment decision-making, indicating moderate but meaningful explanatory power. This is comparable to prior behavioural finance studies where psychological variables typically account for substantial, but not exhaustive, variance in decision-making (Hair et al., 2019). The model also demonstrates strong predictive relevance ($Q^2 > 0$), suggesting that the findings are not only explanatory but also practically useful in forecasting investor behaviour.

The study also examined whether demographic differences moderates the effects of behavioural biases on investors' decision-making processes and the result reveals that gender and income do not moderate the relationship between behavioural biases and investment decisions, which is in line with past studies indicating that these variables are becoming less predictive once financial literacy is accounted for (Kumar & Goyal, 2016). Age moderated only the illusion of control bias, supporting earlier work that shows younger investors are comparatevely more prone to overestimate their investment ability (Glaser & Weber, 2007; Din et al., 2021). Education emerged as the strongest moderating variable, validating evidence that financial knowledge improves rationality while partial knowledge can increase overconfidence (Rasool & Ullah, 2020). Unlike other behavioural biases, herding remained invariant across demographic segments, indicating that gender, age, education attainment, and income does not have a moderating effect, which is in line with the findings that state investment behaviour is strongly shaped by social influence rather than personal attributes (Banerjee, 1992; Devenow & Welch, 1996; Lachhwani & Oza, 2024).

The findings of this study reinforce the central propositions of behavioural finance and prospect theory, demonstrating that investors do not always behave rationally but are systematically influenced by psychological and cognitive biases during decision-making (Kahneman & Tversky, 1979)

Implications, Limitations and Future Research Directions

Implications

The findings of this study have important implications for investors, financial professionals, and policymakers. The significant influence of behavioural biases on investment decisions highlights the need for investor education programmes that go beyond traditional financial literacy and incorporate behavioural awareness. Educating investors about biases such as herding, anchoring, and regret aversion can help them recognise irrational tendencies and adopt more reflective decision-making strategies. The financial advisors and portfolio managers can use these insights to design behavioural profiling tools that identify clients' susceptibility to specific biases and offer personalised advisory services. Understanding the investors' psychological tendencies will allow financial professionals to provide better investment recommendations and help clients get rid of these cognitive and emotion-driven errors. The policymakers can also develop regulatory frameworks and investor protection mechanisms, which will reduce the impact of market misinformation and excessive speculation.

Limitations and future research directions.

Despite its contributions, the current study has certain limitations that have to be acknowledged. First, the study is based on primary data; as such, respondents might underreport irrational tendencies or overestimate their rationality, affecting the accuracy of the results. Second, since the data were collected from only one group of society, particularly from entrepreneurs who own Micro Small and Medium enterprises, geographically confined to only the North Eastern states of India, this may limit the generalisability of the findings to other regions with different economic, cultural, or market structures. Thirdly, only five exogenous constructs are being used to measure the level of influence on the endogenous construct. There may be a potential impact of unobserved variables such as personality traits, risk tolerance, social influences, etc. Furthermore, the study also relies on purposive sampling, which may cause selection bias and restrict the representativeness of the sample.

Future research may incorporate objective financial data such as transaction records and portfolio performance to complement self-reported measures. Studies may also consider other groups of samples beyond entrepreneurs and extend the geographical scope to improve generalisability. Studies can also include more variables, such as loss aversion, personality traits, risk tolerance, cognitive dissonance, conservatism, etc., in the same study to see the combined effect of various biases on investment decisions of the investors. Future work can also adopt probability sampling techniques and employ longitudinal or experimental designs to enhance causal inference and capture changes in investor behaviour over time.

CONCLUSION

The current study determined the influence of behavioural biases on investment decision-making of entrepreneurs in north North-Eastern States of India. The result revealed that investment decisions are not solely driven by rational evaluation but are significantly shaped by cognitive and emotional biases. Among the examined behvioural biases, herding bias, anchoring bias, and regret aversion bias emerged as the most influential factors, and hence highlight the role of social and emotional influence on financial decision-making. The findings of multigroup analysis also revealed that gender and income do not significantly moderate the impact of behavioural biases; whereas age and educational qualification of the investors were found to moderate certain relationships. Specifically, age affects the influence of the illusion of control, whereas education influences anchoring, illusion of control, overconfidence, and regret aversion. These results indicate that behavioural tendencies are not uniform across individuals and that demographic characteristics shape how biases manifest in investment decisions.

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REFERENCES

1. Ahmad, M., & Shah, S. Z. A. (2022). Overconfidence heuristic-driven bias in investment decision-making and performance: mediating effects of risk perception and moderating effects of financial literacy. Journal of Economic and Administrative Sciences, 38(1), 60-90.
2. Baker, H. K., Kumar, S., Goyal, N., & Gaur, V. (2019). How financial literacy and demographic variables relate to behavioural biases. Managerial Finance, 45(1), 124–147. https://doi.org/10.1108/MF-01-2018-0003
3. Banerjee, A. V. (1992). A simple model of herd behavior. The quarterly journal of economics, 107(3), 797-817.
4. Barber, B. M., & Odean, T. (2001). Boys will be boys: Gender, overconfidence, and common stock investment. Quarterly Journal of Economics, 116(1), 261–292. https://doi.org/10.1162/003355301556400
5. Barberis, N. (2018). Psychology-based models of asset prices and trading volume. In Handbook of behavioral economics: applications and foundations 1 (Vol. 1, pp. 79-175). North-Holland.
6. Barberis, N., & Thaler, R. H. (2003). A survey of behavioral finance. In G. Constantinides, M. Harris, & R. Stulz (Eds.), Handbook of the economics of finance (Vol. 1, pp. 1053–1128). Elsevier. https://doi.org/10.1016/S1574-0102(03)01027-6
7. Bell, D. E. (1982). Regret in decision making under uncertainty. Operations research, 30(5), 961-981.
8. Bouteska, A., & Regaieg, B. (2020). Loss aversion, overconfidence of investors and their impact on market performance evidence from the US stock markets. Journal of Economics, Finance and Administrative Science, 25(50), 451-478.

9. Chishti, M. F., Ali, F., Khan, M. R., Khan, I., Luong, N. T., & Ghouri, A. M. (2025). Understanding behavioural biases in investment decisions: empirical insights from an emerging market. Cogent Economics & Finance, 13(1), 2567499.
10. Daniel, K., & Hirshleifer, D. (2015). Overconfident investors, predictable returns, and excessive trading. Journal of Economic Perspectives, 29(4), 61-88.
11. Din, S. M. U., Mehmood, S. K., Shahzad, A., Ahmad, I., Davidyants, A., & Abu-Rumman, A. (2021). The impact of behavioral biases on herding behavior of investors in Islamic financial products. Frontiers in Psychology, 11, 600570. https://doi.org/10.3389/fpsyg.2020.600570
12. Fajri, A., & Setiawati, E. (2023). The Influence of Over Confidence, Illusion of Control, Availability, Anchoring Bias and Financial Literacy on Investment Decision Making in the Community of Demak District As Beginning Investors. The International Journal of Business Management and Technology, 7(4), 187-198.
13. Fei, T., & Liu, X. (2021). Herding and market volatility. International Review of Financial Analysis, 78, 101880.
14. Fellner, G. (2009). Illusion of control as a source of poor diversification: Experimental evidence. The Journal of Behavioral Finance, 10(1), 55-67.
15. Fenton-O'Creevy, M., Nicholson, N., Soane, E., & Willman, P. (2003). Trading on illusions: Unrealistic perceptions of control and trading performance. Journal of occupational and organizational psychology, 76(1), 53-68.
16. Finke, M. S., Howe, J. S., & Huston, S. J. (2017). Old age and the decline in financial literacy. Management Science, 63(1), 213-230.
17. Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. Journal of Marketing Research, 18(1), 39–50.
18. Gazel, S. (2015). The regret aversion as an investor bias. International Journal of Business and Management Studies, 4(02), 419-424.
19. Glaser, M., & Weber, M. (2007). Overconfidence and trading volume. The Geneva Risk and Insurance Review, 32(1), 1-36.
20. Gonzalez-Igual, M., Santamaria, T. C., & Vieites, A. R. (2021). Impact of education, age and gender on investor's sentiment: A survey of practitioners. Heliyon, 7(3).
21. Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2019). A primer on partial least squares structural equation modeling (PLS-SEM) (2nd ed.). Sage Publications.
22. Hair, J. F., Ringle, C. M., & Sarstedt, M. (2011). PLS-SEM: Indeed a silver bullet. Journal of Marketing theory and Practice, 19(2), 139-152.
23. Henseler, J., & Sarstedt, M. (2013). Goodness-of-fit indices for partial least squares path modeling. Computational statistics, 28(2), 565-580.
24. 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.
25. Henseler, J., Ringle, C. M., & Sarstedt, M. (2016). Testing measurement invariance of composites using partial least squares. International marketing review, 33(3), 405-431.
26. 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
27. Hott, C. (2009). Herding behavior in asset markets. Journal of Financial Stability, 5(1), 35-56.
28. Ishak, P., & Sholehah, N. L. H. (2023). Implications of Financial Literacy, Illusion of Control and Overconfidence through Emotional Maturity towards People's Investment Decisions during a Pandemic. Journal Of Accounting Management Business And International Research, 2(1), 34-47.
29. Jain, G., Nayakankuppam, D., & Gaeth, G. J. (2021). Perceptual anchoring and adjustment. Journal of Behavioral Decision Making, 34(4), 581-592. https://doi.org/10.1002/bdm.2231.
30. Kahneman Devenow, A., & Welch, I. (1996). Rational herding in financial economics. European economic review, 40(3-5), 603-615.
31. Kahneman, D. (2018). Thinking, fast and slow. Penguin Books.
32. Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. Econometrica, 47(2), 263–291. https://doi.org/10.2307/1914185

33. Kline, R. B. (2023). Principles and practice of structural equation modeling. Guilford publications.
34. Komba, G. V. (2025). Individual Investors and Domestic Stock Preferences: The Effects of Availability Bias, Ambiguity Aversion, and Regret Aversion at the Dar es Salaam Stock Exchange, Tanzania. African Journal of Empirical Research, 6(1), 812-822.
35. Kudryavtsev, A., & Cohen, G. (2010). Anchoring and pre-existing knowledge in economic and financial settings. American Journal of Social and Management Sciences, 1(2), 164-180.
36. Kumar, J., & Prince, N. (2023). Overconfidence bias in investment decisions: a systematic mapping of literature and future research topics. FIIB Business Review, 23197145231174344.
37. Kumar, S., & Arora, M. (2023). Herd Behavior Unveiled: How Demographics Shape Investment Patterns in North India. Journal of Research in Business and Management, 11(8), 114-121.
38. Kumar, S., & Chaurasia, A. (2024). The relationship between emotional biases and investment decisions: A meta-analysis. IIMT Journal of Management, 1(2), 171-185.
39. Kumar, S., & Goyal, N. (2016). Evidence on rationality and behavioural biases in investment decision making. Qualitative Research in Financial Markets, 8(4), 270-287.
40. Lachhwani, H., & Oza, V. (2024). Understanding Herd Behaviour And Risk Among Investors In Gujarat. Educational Administration: Theory and Practice, 30(5), 1441 – 1446. https://doi.org/10.53555/kuey.v30i1.6316
41. Loomes, G., & Sugden, R. (1982). Regret theory: An alternative theory of rational choice under uncertainty. The economic journal, 92(368), 805-824.
42. Mahmood, F., Arshad, R., Khan, S., Afzal, A., & Bashir, M. (2024). Impact of behavioral biases on investment decisions and the moderation effect of financial literacy; an evidence of Pakistan. Acta Psychologica, 247, 104303.
43. Murhadi, W. R., Frederica, D., & Marciano, D. (2024). The effect of financial literacy and demographic variable on behavioral biases. Asian Economic and Financial Review, 14(4), 312-325.
44. Nadhila, A., Sembel, R. S. R., & Malau, M. (2024). The influence of overconfidence and risk perception on investment decisions: the moderating effect of financial literacy on individual millennial generation investors. Eduvest-Journal of Universal Studies, 4(6), 5280-5299.
45. Owusu, S. P., & Laryea, E. (2023). The impact of anchoring bias on investment decision-making: evidence from Ghana. Review of Behavioral Finance, 15(5), 729-749.
46. Pikulina, E., Renneboog, L., & Tobler, P. N. (2017). Overconfidence and investment: An experimental approach. Journal of Corporate Finance, 43, 175-192.
47. Pitkäkoski, I. (2025). Herding behavior and market bubbles: A behavioral finance perspective.
48. Rasool, N., & Ullah, S. (2020). Financial literacy and behavioural biases of individual investors: empirical evidence of Pakistan stock exchange. Journal of Economics, Finance and Administrative Science, 25(50), 261-278.
49. Raut, R. K., & Kumar, R. (2018). Investment decision-making process between different groups of investors: A study of Indian stock market. Asia-Pacific Journal of Management Research and Innovation, 14(1-2), 39-49.
50. Sarstedt, M., Henseler, J., & Ringle, C. M. (2011). Multigroup analysis in partial least squares (PLS) path modeling: Alternative methods and empirical results. In Measurement and research methods in international marketing (pp. 195-218). Emerald Group Publishing Limited.
51. Sarstedt, M., Ringle, C. M., Smith, D., Reams, R., & Hair Jr, J. F. (2014). Partial least squares structural equation modeling (PLS-SEM): A useful tool for family business researchers. Journal of family business strategy, 5(1), 105-115.
52. Schulz, B. (2023). Behavioral finance and how its behavioral biases affect German investors. Acta VŠFS-ekonomické studie a analýzy, 17(1), 39-59.
53. Shantha, K. V. A. (2019). Individual investors' learning behavior and its impact on their herd bias: an integrated analysis in the context of stock trading. Sustainability, 11(5), 1448.
54. Singh, D., Malik, G., & Jha, A. (2024). Overconfidence bias among retail investors: A systematic review and future research directions. Investment Management & Financial Innovations, 21(1), 302.
55. Singh, P., & Dixit, A. K. Impact of Behavioural Biases on Investment Decisions of Retail Investors: Evidence from Indian Capital Markets. International Journal for Multidisciplinary Research, 7(6), 1-13.
56. Statman, M. (2019). Behavioral finance: The second generation. CFA Institute Research Foundation.

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57. Syarkani, Y., & Alghifari, E. S. (2022). The influence of cognitive biases on investor decision-making: the moderating role of demographic factors. Jurnal Siasat Bisnis, 183-196.
58. Tabachnick, B. G., & Fidell, L. S. (2013). Using multivariate statistics (6th ed.). Pearson Education.
59. Thorndike, R. M. (1995). Book Review: Psychometric Theory (3rd ed.) by Jum Nunnally and Ira Bernstein New York: McGraw-Hill, 1994, xxiv + 752 pp. Applied Psychological Measurement. https://doi.org/10.1177/014662169501900308
60. Tlili, F., Chaffai, M., & Medhioub, I. (2023). Investor behavior and psychological effects: herding and anchoring biases in the MENA region. China Finance Review International, 13(4), 667-681.
61. Ullah, S. (2015). An empirical study of illusion of control and self-serving attribution bias, impact on investor's decision making: moderating role of financial literacy. Research Journal of Finance and Accounting, 6(19), 109-118.
62. Van Rooij, M., Lusardi, A., & Alessie, R. (2011). Financial literacy and stock market participation. Journal of Financial economics, 101(2), 449-472.
63. Varma, J. R., & Barua, S. K. (2019). Indian financial markets. Vikalpa, 44(4), 155–165.
64. Vieira, E. S., & Pereira, M. S. V. (2015). Herding behaviour and sentiment: Evidence in a small European market: Comportamiento gregario y sentimiento: la evidencia sobre un pequeño mercado europeo. Revista de Contabilidad-Spanish Accounting Review, 18(1), 78-86.
65. Vinzi, V. E. (2010). Handbook of partial least squares. https://doi.org/10.1007/978-3-540-32827-8.
66. Wang, B. (2023). The impact of anchoring bias on financial decision-making: exploring cognitive biases in decision-making processes. Studies in Psychological Science, 1(2), 41-50.
67. Wangzhou, K., Khan, M., Hussain, S., Ishfaq, M., & Farooqi, R. (2021). Effect of regret aversion and information cascade on investment decisions in the real estate sector: The mediating role of risk perception and the moderating effect of financial literacy. Frontiers in Psychology, 12, 736753.
68. Yao, S. (2025, July). The Impact of Psychological Biases on Asset Pricing in Behavioral Finance. In 2025 International Conference on Financial Risk and Investment Management (ICFRIM 2025) (pp. 849-858). Atlantis Press.