http://jaa.kbsaa.org

ISSN (Online): 2583-5203

जर्नल ऑफ एकेडमिक एडवांसमेंट

JOURNAL OF ACADEMIC ADVANCEMENT

[Bi-Annual Peer Reviewed Refereed Journal]

Volume No. 4 | Issue No. 02 | December, 2025

कोलकाता बिधाननगर सोसायटी फॉर एकेडमिक एडवांसमेंट
पश्चिम बंगाल, भारत

Kolkata Bidhannagar
SOCIETY FOR ACADEMIC ADVANCEMENT
West Bengal, India

जर्नल ऑफ एकेडमिक एडवांसमेंट

JOURNAL OF ACADEMIC ADVANCEMENT

(Bi-Annual Peer Reviewed Refereed Journal)
ISSN (Online): 2583-5203 | Volume 4 | No. 02 | December, 2025
Publication Impact Factor (I2OR): **4.360** (2025)

EDITORIAL

We feel honoured and privileged to present the Bi-Annual Peer Reviewed Refereed Journal, ISSN (Online): 2583-5203, Volume 4, No. 02, December, 2025 among our esteemed readers and academic fraternity.

This Journal is the outcome of the contributions of insightful research-oriented papers/articles by various eminent academicians, and research scholars in a highly organized and lucid manner with a clear and detailed analysis related to the emerging areas in the fields of Social Sciences and Allied Areas.

The views expressed in the research-oriented papers/articles solely belong to the paper contributor(s). Neither the Publisher nor the Editor(s) in any way can be held responsible for any comments, views and opinions expressed by **paper contributors.** While editing, we put in a reasonable effort to ensure that no infringement of any intellectual property right is tolerated.

We also express our sincere thanks and gratitude to all the contributors to research papers/articles who have taken pain in preparing manuscripts, incorporating reviewer(s) valuable suggestions and cooperating with uxs in every possible way.

We also express our heartfelt gratitude to all the esteemed members of the Editorial Board, Esteemed Reviewer(s) who despite their busy schedules have given their valuable time, suggestions and comments to enrich the quality of the contributory resears paper(s) in bringing to light this June issue.

Last, but not least, we revere the patronage and moral support extended by our parents and family members whose constant encouragement and cooperation made it possible for us to complete on time.

We would highly appreciate and look forward to your valuable suggestions, comments and feedback at **editorbr2022@gmail.com**

December, 2025
West Bengal, India

PEMA LAMA
Editor-in-Chief

CONTENTS

http://jaa.kbsaa.org

जर्नल ऑफ एकेडमिक एडवांसमेंट
JOURNAL OF ACADEMIC ADVANCEMENT
(Bi-Annual Peer Reviewed Refereed Journal)
ISSN (Online): 2583-5203 | Volume: 4 | No.: 2 | December, 2025
https://doi.org/10.58574/jaa.2025.v4.i2.09
Publication Impact Factor (I2OR): **4.360** (2025)

RESEARCH ARTICLE

How Heuristics Shape Investment Decisions: Survey Evidence from Indian Retail Investors

Deep Dutta
Research Scholar (Ph.D-SRF), Dept. of Commerce, University of Calcutta, Kolkata, India

CMA Dr. Samyabrata Das
Associate Professor, Dept. of Commerce, New Alipore College, Kolkata, India

Corresponding Author: Deep Dutta (deepduttacoc@gmail.com)

Received: November 11, 2025 | **Revised:** November 30, 2025 | **Accepted:** December 02, 2025

Index Terms: Behavioural Finance | Heuristic Biases | India | Investment Decisions | Retail Investors

ABSTRACT

This study examines the influence of heuristic biases (HB) like representativeness bias (RB), availability bias (AB) and anchoring and adjustment bias (A&AB) on investment decisions (ID) among Indian retail investors. Drawing upon behavioural finance theory, the research employs 'Partial Least Squares Structural Equation Modelling (PLS-SEM)' with data from 367 active young investors aged 18–44. Results reveal that all three heuristics significantly and positively influence investment decisions. Multi-group analysis (MGA) results indicate no significant moderating impact of age (Millennials vs. Gen Z) or gender (Male vs. Female) on these relationships.

The outcomes illustrate the persistence of cognitive shortcuts regarding financial decisions irrespective of demographic differences. By providing integrated empirical evidence on several heuristic effects in the context of retail investments in India, this work extends to the pool of knowledge on behavioural finance (BF).

1 INTRODUCTION

Old finance theories such as the 'Efficient Market Hypothesis', 'Modern Portfolio Theory' and 'Expected Utility Theory' assume that traders are always rational and make perfect decisions. These theories believe that investors are logical, process information objectively and aim to maximise their returns. However, empirical evidence has repeatedly contradicted this assumption by revealing that traders frequently depart from reasoning because of emotional and cognitive limitations (Barber & Odean, 2001; Shah et al., 2018). The area of BF, which incorporates cognitive aspects into the analysis of financial choices, emerged in consequence of these discrepancies to explain why investors make inconsistent or suboptimal investment choices (H. Baker & Filbeck, 2013).

Kahneman and Tversky's (1979, 1974) seminal works on 'bounded rationality' and 'prospect theory' introduced the concept of heuristics. Heuristics are psychological tricks that make complex decisions easier to make under uncertainty but may result in systematic biases. Investors frequently rely on these heuristics when processing financial information, especially in uncertain and volatile market environments (Tversky & Kahneman, 1973). These mental shortcuts (RB, AB and A&AB) cause traders to jump to conclusions. This leads to predictable mistakes in how they invest and manage risk. Studies on emerging markets, including India, show that new investors here are even more influenced by behavioural biases. Experts like Ahmad & Shah (2020) and Jain et al. (2023) point to lower financial literacy and different cultural attitudes towards risk as key reasons.

2 RESEARCH GAP

There is still not enough clarity about how the major behavioural biases interact to influence Indian investors. Most studies have looked at these biases separately or in different countries. Furthermore, the impact of age and gender is understudied. It's unclear whether these biases affect Millennial and Generation Z investors differently, or how gender impacts their decisions. Comprehending this is critical because these groups comprise the main segment of India's new digital investment community.

3 RESEARCH QUESTIONS

In light of these gaps, the following essential research issues are the focus of this study:

1. To what extent do representativeness, availability and A&AB influence the ID of Indian retail investors?
2. Do these relationships vary across generational (Millennial vs. Gen Z) and gender groups?

To answer these questions, the study employs a quantitative approach using "Partial Least Squares-Multi group Analysis (PLS-MGA)" to assess both direct heuristic effects and demographic moderations. By examining these relationships in an integrated behavioural framework, the research advances our comprehension of cognitive mechanisms that shape retail ID in emerging markets. Furthermore, it extends BF literature by furnishing empirical data on how heuristic biases operate across diverse investor segments in the dynamic financial scenario in India.

4 OBJECTIVES OF THE STUDY

The objectives of the study are to -

- Gauge how much representativeness, availability, and anchoring biases sway Indian investors' choices;
- Check if Millennials and Gen Z are affected differently;
- See if men and women experience these biases in distinct ways; and
- Combine these findings into a single, practical model for understanding investor behaviour.

5 LITERATURE REVIEW

HB→ID

In uncertain and complex financial environments, traders frequently use "rules of thumb" or cognitive shortcuts to make decisions easier. This thing is known as a heuristic (Tversky & Kahneman, 1974; Waweru et al., 2008). While heuristics can make decision processes faster and more efficient but they frequently lead to systematic judgmental errors and irrational financial choices (Gigerenzer & Gaissmaier, 2011; Ritter, 2003). In BF, heuristics elucidate the reasons behind investors' divergence from the logical presumptions of traditional financial models like the Efficient Market Hypothesis and Expected Utility Theory (De Bondt & Thaler, 1995). Tversky & Kahneman (1974) identified three primary heuristics, which include RB, AB and A&AB that influence human judgment under uncertainty. Empirical studies have shown that these biases shape investment strategies, asset preferences and trading frequency, thereby influencing market outcomes (Chen et al., 2007; Mushinada, 2020; Shah et al., 2018).

RB→ID

RB refers to the 'tendency to evaluate probabilities or outcomes based on how closely they resemble existing stereotypes or familiar patterns' (Tversky & Kahneman, 1974). Investors affected by this bias often overgeneralize from limited observations by assuming that past trends will continue in forthcoming future (Busenitz & Barney, 1997; Shefrin, 2008). Regarding market conditions, this leads to overreaction as investors chase "hot" stocks or avoid those that have had inadequate outcomes (De Bondt & Thaler, 1995; Waweru et al., 2008).

Studies have shown that traders frequently rely on representativeness when facing uncertainty, using recent performance or personal experiences to judge investment potential (Irshad et al., 2016; Rasheed et al., 2018). This bias distorts rational evaluation, resulting in mispricing and excessive trading. For instance, Chinese and Pakistani retail investors demonstrated a strong tendency to invest in recently successful stocks despite weak fundamentals (Abdin et al., 2017; Chen et al., 2007). Similar behaviour is also evident among Indian investors who equate short-term performance with long-term value (Jain et al., 2021).

Since representativeness leads to intuitive but often erroneous judgments, it can have considerable effects on how Indian retail traders make decisions.

H_1: RB will significantly influence ID

AB→ID

AB occurs "when individuals rely excessively on information that is readily available or easily recalled rather than on comprehensive and objective analysis" (Tversky & Kahneman, 1974). Traders who are impacted by these biases typically focus their decisions on recent news, personal experiences, or widely discussed market events and neglect less salient but relevant information (Montier, 2007; Ngoc, 2013). Empirical research has shown that availability bias drives investors to focus on contemporary issues, local stocks and media-highlighted opportunities (Shukla et al., 2020; Waweru et al., 2008). Sachan & Chugan (2020) found that rural investors in Gujarat relied heavily on easily accessible information, making them more prone to availability bias than urban investors. Similarly, den Steen (2004) and Javed et al. (2017) reported that investors' emotional responses to recent or memorable events lead to irrational decisions, often resulting in poor portfolio diversification.

Due to these, the following hypothesis is framed:

H_2: AB will significantly influence ID

A&AB→ID

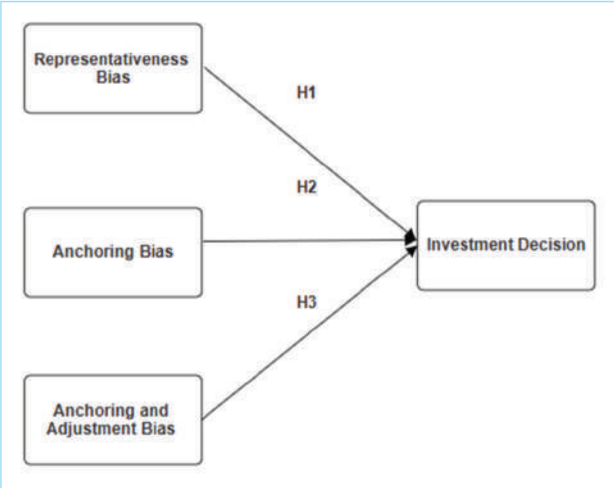
A&AB reflects "the human tendency to rely excessively on an initial reference point (known as an anchor) when making subsequent judgments" (Tversky & Kahneman, 1974). In investment contexts, anchors often include past stock prices, market benchmarks or personal purchase prices (Andersen, 2010; Singh, 2019). Once an anchor is set, investors adjust insufficiently from it, resulting in systematic decision errors (Kartini & Nahda, 2021).

This bias leads investors to cling to outdated reference values rather than reassessing based on new market data (Cen et al., 2013; Murithi, 2014). For example, individuals may hold on to losing stocks hoping they will return to their initial purchase price or avoid profitable exits by anchoring to prior highs (Phuoc Luong & Thi Thu Ha, 2011). Research by S. Z. A. Shah et al. (2018) and Ishfaq & Anjum (2015) confirmed that A&AB significantly affects both institutional and retail investors by distorting their perception of value and risk.

Due to these, the following hypothesis is considered

H_3: A&AB will significantly influence ID.

Figure 1
CONCEPTUAL FRAMEWORK



6 AGE (MILLENNIAL AND GEN Z) AND GENDER AS MODERATORS BETWEEN HEURISTIC BIASES AND ID

The research also utilises 'Multi-group analysis (MGA)' to investigate the relationship between 'age (Millennials and Gen Z) and gender (Male and Female)' between HB and ID. The strength and direction of these biases may vary across demographic segments, affecting how users interpret financial data and deal with uncertainty (Bushra et al., 2024; Parveen & Siddiqui, 2017).

Age

Cognitive psychology highlights those age-specific changes in mental processes like attention, memory and information processing affect financial decision-making (Salthouse, 2012). Older investors may rely more heavily on heuristics due to declining cognitive flexibility, while younger investors often benefit from faster information processing but may exhibit impulsive tendencies (Kumar & Goyal, 2016). Generational Cohort Theory further explains that individuals shaped by similar socio-historical activities foster a sense of united goals and attitudes that influence their financial behaviour (Ryder, 1985).

Millennials and Generation Z are the two dominant age cohorts in today's financial landscape that display distinct investment orientations. Millennials who grew up during economic instability and witnessed the evolution of digital finance tend to prioritise financial security, risk management and extensive research before investing (Anderson et al., 2015; Kurz et al., 2019). Contrary to Gen Z having matured in a digitally saturated era, they exhibit higher adaptability to technology and a preference for rapid as well as tech-enabled investment solutions (Rosdiana, 2020). Their decision-making is shaped by immediacy and access to online financial tools, leading to a more experimental yet calculated approach (Kalra Sahi & Pratap Arora, 2012). Thus, age may moderate the extent to which heuristic biases influence ID, with Millennials and Gen Z responding differently to the same cognitive triggers.

Gender

Gender-based variations in investment behaviour have been extensively documented in behavioural finance. Women are generally characterised by higher risk aversion and cautious financial attitudes. Whereas men often demonstrate greater confidence and sometimes border on overconfidence in their investment abilities (Bajtelsmit & Bernasek, 1997; Barber & Odean, 2001). Empirical evidence reveals that male traders are inclined to overestimate their knowledge and exchange more regularly, which frequently lowers their returns (Bhandari & Deaves, 2006; Prasad & Mohta, 2012). In contrast, female investors prefer stability and exhibit stronger loss aversion, resulting in conservative portfolio choices (Arora & Kumari, 2015).

The interaction between gender and heuristic biases is nuanced. Studies show that males are more prone to representativeness and anchoring biases, often relying on stereotypes or initial information to make judgments (H. K. Baker et al., 2019; Kumar & Goyal, 2016). Women prefer to align their decisions with collective opinions or expert advice (H. K. Baker et al., 2019; Nair et al., 2017). Lots of other researchers also found group differences based on gender in the behavioural finance domain (Gupta & Goyal, 2024; Li, 2021; Pushpa et al., 2023).

Accordingly, the following hypotheses are framed:

H_4: The association between representativeness bias and ID varies across age (Millennials and Gen Z) and gender (Male and Female) among investors.

H_5: The association between availability bias and ID varies across age (Millennials and Gen Z) and gender (Male and Female) among investors.

H_6: The association between A&AB and ID varies across age (Millennials and Gen Z) and gender (Male and Female) among investors.

7 METHODOLOGY

Data Collection and Sampling

The research approach utilised in this study is quantitative using a single method. The "cross-sectional" descriptive research strategy was used for this research. The data was gathered using an online survey. Young investors who are in the 18-44 age range made up the research's respondents. Convenience and snowball sampling techniques were employed in this research to gather 367 responses who had prior experience in investing between June and September 2025. 'At least ten times the largest number of structural paths directed at a particular latent construct in the model' (Hair et.al, 2011) is the PLS-SEM's minimal number of samples requirement. The sample size needs to be in excess of 30 because, as shown in Fig. 1, there are three routes (from RB, AB and A&AB) that lead to ID. Consequently, our study's sample of 367 responses satisfies the PLS-SEM minimum size requirement. This study does not exhibit non-response bias according to a comparison between 'response and non-response data' (Armstrong and Overton 1977).

Measurement of Constructs

'Five-point Likert scales' with 1 denoting 'strongly disagree' and 5 denoting "strongly agree" are employed in our research to measure the items. 6 items for Representativeness Bias metrics have been collected from earlier research and modified appropriately to demonstrate content validity (Waweru et al., 2008; Sarwar et al., 2014; H. K. Baker et al., 2019). The Availability Bias scales were derived from H. K. Baker et al. (2019); Phuoc Luong & Thi Thu Ha (2011); Waweru et al. (2008), and Ritika & Kishor (2020) and had four items for the construct. The structure has five elements on the Anchoring and Adjustment Bias scales, which are modified versions of Nada & Moa'mer (2013). Five items make up the investment decision scale, which was modified from Jain et al. (2023), Wang & Nuangjamnong (2022), and Karthikeyan (2024).

Data Analysis

We analyse our data using the PLS-SEM approach. PLS-SEM has been in use for a long time (Hair et.al, 2011) and does not need data normality or an enormous sample size (Hair et.al, 2019). As per Hair et al (2011), the analysis includes two processes. The initial phase is to evaluate an outer model where reliability and validity' are needed to be appropriate. The subsequent phase is to evaluate an inner model in order to produce "loadings and structural model links" for the latent constructs and the observed variables. The statistical significance of the stated associations in the model was then appraised using a bootstrap. For data analysis in this specific investigation, we used "Smart PLS version 3.3.3" (Ringle et.al, 2015). Another causal-predictive method for SEM is PLS-SEM. In statistical model estimation, it places a strong emphasis on prediction (Hair et al., 2021).

8 FINDINGS AND OBSERVATIONS

Demographic Profile of the Respondents

The respondents' 367 complete questionnaires were gathered. Table 1 displays the demographic information of the participants. 50.68% were men and nearly 53.6%were between the ages of 29 and 44 (millennials). Approximately 50.41% of those who responded to the survey said they had earned a post-graduate degree. The majority of participants (46.87%) said that their typical monthly income is above Rs. 50000.

Table 1
DEMOGRAPHIC ATTRIBUTES

Variables	n	(%)
Gender:		
Male	186	50.68
Female	181	49.32
Age (years):		
18-28	171	46.59
29-44	196	53.41
Education level:		
Under Graduate	59	16.08
Graduate	123	33.51
Post Graduate	185	50.41
Monthly Income (Rs.):		
Up to 30000	72	19.62
30001-50000	123	33.51
Above 50000	172	46.87

Source: Authors' self-calculation

Assessment of Measurement Model

Measurement items 'reliability, discriminant validity (DV) and convergent validity were checked to examine the outer model. All of the examined items satisfied the significance level of .7 according to the indicator loading outcomes, which are shown in Table 2 below (Huland, 1999). 'Cronbach's alpha (α), composite reliability (CR) and average variances extracted (AVE)' were computed to assess the items' 'internal consistency and reliability' (Hair et al., 1998). When an item's alpha scores reach .7 or above, it is considered reliable. The suggested threshold for CR is .7 or more (Hair et al., 2013). Hair et al. (1998) advised that AVE must be greater than .5 in order to be deemed appropriate. All four constructs have CRs that surpass the suggested level of .7 and all constructs have AVEs > the .5 criterion. This implies that the constructs account for a minimum half of the item variation. The outcomes shown in Table 2 demonstrate that α scores of each of the four factors, ranging from .857 to .909, had surpassed the minimum requirement of .7. The test of DV was used to evaluate the intercorrelations between the constructs. When performing the DV test, we adhered to the standards put forth by Fornell and Larcker (1981).

A construct score must be > its associated coefficient in order to attain DV (Huland, 1999). Because the construct scores exceed the associated coefficient, the outcomes presented in Table 3 demonstrate DV. We used the 'heterotrait-monotrait (HTMT) technique' advised by Henseler et al. (2015) to perform DV in light of the limitations found with the Fornell and Larcker procedure. As per Hair et al. (2021), HTMT is a more credible method of assessing DV. When the underlying scores are below .9 (Henseler et al., 2015) or .85 (Clark & Watson, 1995; Kline, 2011), DV is prevalent. All of the construct's scores fall below the suggested criterion of .85, indicating that DV has been attained (see Table 4).

Table 2
OUTCOME OF MEASUREMENT MODEL

Factors	Items	Factor Loading	CR	rho_A	AVE	Cronbach's α
Anchoring and Adjustment Bias	A&AB1 A&AB2 A&AB3 A&AB4	.882 .87 .852 .833	.919	.886	.739	.882
Availability Bias	AB1 AB2 AB3 AB4 AB5 AB6	.743 .862 .838 .836 .848 .843	.93	.91	.688	.909
Investment Decision	ID1 ID2 ID3 ID4 ID5	.718 .871 .848 .852 .801	.911	.885	.672	.877
Representativeness Bias	RB1 RB2 RB3 RB4 RB5	.751 .835 .802 .823 .774	.897	.861	.636	.857

Source: Authors' self-calculation

Table 3
FORNELL AND LARCKER CRITERION

	A&AB	AB	ID	RB
A&AB	.859			
AB	.646	.829		
ID	.719	.703	.82	
RB	.598	.625	.691	.798

Source: Authors' self-calculation

Table 4
HETEROTRAIT-MONOTRAIT (HTMT) RATIO

	A&AB	AB	ID	RB
A&AB				
AB	.717			
ID	.813	.783		
RB	.68	.702	.789	

Source: Authors' self-calculation

Assessment of the Measurement Invariance

The MICOM approach was used in the current research to evaluate measurement invariance. Configural invariance has been evaluated in the initial step. Configural invariance had been determined when the analysis and evaluation of the 'measurement models' (including validity and reliability) for all groups were completed. 'Compositional invariance' was examined in the subsequent stage. This study assessed compositional invariance utilising 5000 samples from bootstrapping in SmartPLS 3 and permutation analysis.

All 'compositional invariance correlation (c) scores' were near 1 and remain within the '95% confidence limit' as Table 5 illustrates. As a result, compositional invariance was established for both groups. The 'equality of means and variances' of constructs across groups was tested in the third step of the MICOM method. Significant variations in the mean value of the compositions among groups were found in the results of the permutation test, which included 5000 permutations. Full measurement invariance was not supported by Step 3 of the MICOM method. Consequently, a partial measure of invariance between the two groups was constructed. This makes it possible to compare the structural model's standardised coefficients across several groups.

Table 5
MEASUREMENT INVARIANCE (MICOM) RESULT

Age (Millennials vs Gen Z)											
Compositional Invariance (correlation = 1)					Equal Mean Assessment			Equal Variance Assessment			
Variable	Configural Invariance	C=1	Confidence Interval	Partial Measurement Invariance Established	Differences	Confidence Interval	Equal	Differences	Confidence Interval	Equal	Full Measurement Invariance Established
A&AB	Yes	1	[0.999;1.000]	Yes	0.07	[-0.204 ;0.191]	Yes	-0.111	[-0.291 ;0.306]	Yes	Yes
AB	Yes	1	[0.999;1.000]	Yes	0.034	[-0.189 ;0.202]	Yes	-0.092	[-0.267 ;0.268]	Yes	Yes
ID	Yes	1	[0.999;1.000]	Yes	0.118	[-0.199 ;0.198]	No	-0.371	[-0.302 ;0.334]	Yes	No
RB	Yes	0.999	[0.999;1.000]	Yes	0.081	[-0.204 ;0.196]	Yes	-0.088	[-0.318 ;0.346]	Yes	Yes
Gender (Male vs Female)											
A&AB	Yes	1	[0.999;1.000]	Yes	0.062	[-0.196 ;0.215]	Yes	-0.21	[-0.304 ;0.285]	Yes	Yes
AB	Yes	1	[0.999;1.000]	Yes	0.059	[-0.216 ;0.214]	Yes	-0.067	[-0.282 ;0.269]	Yes	Yes
ID	Yes	1	[0.999;1.000]	Yes	0.034	[-0.195 ;0.196]	Yes	-0.189	[-0.309 ;0.309]	Yes	Yes
RB	Yes	0.999	[0.998;1.000]	Yes	0.092	[-0.208; 0.205]	Yes	-0.179	[-0.318; 0.337]	Yes	Yes

Source: Authors' self-calculation

Assessment of Structural Model

'PLS-SEM' has been applied to examine the relevance of the inner model associations. Hair et al. (2013) recommended that the assessment be conducted using a "bootstrap of 5000 sub-samples" to investigate the significance of the proposed associations. Next tests were conducted to determine the scores of the 'variance inflation factor (VIF)' for the detection of "collinearity concerns". Third, for the predictive power, the R^2 value was examined. Fourth, the effect size of exogenous factors was calculated by looking at the f^2 value. Lastly, the predictive ability of the models was examined employing the Q^2 value. Table 6 displays the outcomes of the inner model (VIF, f^2, R^2 and Q^2).

One often used metric to determine the collinearity is the VIF. Collinearity difficulties may arise even at lesser VIF scores of 3, according to Becker et al. (2015). As a result, three or lower VIF ratings are desirable. All of the observed VIFs, however, were below 3, suggesting that there were no collinearity problems. As such, Table 4 was used for calculating the VIF. Consequently, the Q^2 value is a measure of the "predictive relevance of the model" whereas the R^2 values are a measurement of prediction accuracy. Q^2 values >0 for reflected endogenous constructs in SEM models indicate the predictive importance of the route model for a particular construct (Hair et al., 2013). Blindfolding shows that all Q^2 results are significantly higher than the estimated values. R^2 value for ID is 0.663 and $Q^2$is

0.440. According to Hair et al. (2019), the Investment decision construct has moderate predictive relevance for the model due to its Q^2 value of 0.440. According to Cohen's (1988) criteria, the model was considered significant because the R^2 value was higher than the suggested cut-off of 0.26.

The criterion had been established by Cohen (1988), who argued that in order to evaluate the degree of association between the model's latent factors, scores of 0.35, 0.15 and 0.02 were designated for substantial, medium and low correlations, respectively. The f^2 values indicate that A&AB towards ID had a medium-high effect (0.194) whereas AB and RB towards ID had moderate effects of 0.120 and 0.146, respectively.

Table 6
VALUES OF INNER MODEL

Q2	Endogenous Variables	Value
	ID	0.440
Coefficient of determination (R2)	Endogenous Variables	R2
	ID	0.663
Effect size (f2)	Exogenous Variables	ID
	A&AB	0.194
	AB	0.120
	RB	0.146
Collinearity Inner VIF	Exogenous Variables	ID
	A&AB	1.92
	AB	2.024
	RB	1.835

Source: Authors' self-calculation

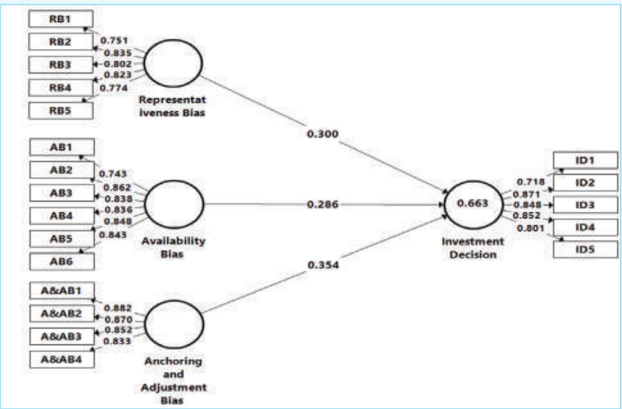
The outcomes of the hypothesis test are shown in Table 7 and Figure 2. Investment decision is significantly and favourably impacted by each of the three Heuristic constructs: Representativeness Bias (H_1) (β = 0.300, t-score = 4.155, sig= .000), Availability Bias (H_2) (β = 0.286, t-score = 4.306, sig= .000) and A&AB (H_3) (β = 0.354, t-score = 5.883, sig= .000). Consequently, every hypothesis is validated.

Table 7
HYPOTHESIS TESTING

	Path Coefficients	SD	t-value	Sig. Values	Decision
Anchoring and Adjustment Bias -> Investment Decision	0.354	0.06	5.883	.000	Supported
Availability Bias -> Investment Decision	0.286	0.066	4.306	.000	Supported
Representativeness Bias -> Investment Decision	0.3	0.072	4.155	.000	Supported

Source: Authors' self-calculation

Figure 2
STRUCTURAL MODEL OUTCOME



Assessment of Group Differences

After full or partial measurement invariance is established, PLS-MGA uses the Welch-Satterthwaite Test to determine the differences between Millennials and Gen Z investors as well as between male and female investors (Hair et al., 2017). The differences in the path coefficients between the two data sets for each group are shown in Table 8. Between the data sets of male and female investors, as well as between Millennials and Gen Z, no path was found that would significantly differ.

Table 8
OUTCOMES OF PATH DIFFERENCES FOR MGA

	Age (Millennials vs Gen Z)				Gender (Male vs Female)			
	Path Coefficients-diff (Millennials-Gen Z)	t-Values	P-Values	Decision	Path Coefficients-diff (Male-Female)	t-Values	P-Values	Decision
A&AB ->ID	0.077	0.644	0.52	NS	0.022	0.187	0.852	NS
AB ->ID	-0.09	0.713	0.477	NS	-0.057	0.433	0.666	NS
RB ->ID	-0.044	0.319	0.75	NS	0.038	0.268	0.789	NS

Source: Authors' self-calculation

9 CONCLUSION

The study demonstrates that HB substantially shape retail investors' decision-making in India, reaffirming the limitations of rational choice assumptions proposed by traditional finance theories. Among the examined biases, A&AB emerged as particularly influential. This bias occurs when traders rely heavily on initial historical indicators, such as previous rates or benchmarks, to guide their financial decisions. RB, where investors judge probabilities based on perceived similarities to past patterns, and AB, where decisions are influenced by information that is most easily recalled or readily accessible, also significantly influenced investment behaviour. This suggests a continued reliance on intuitive judgments and readily available information.

By analysing these biases collectively and integrating demographic factors, this work closes a significant gap in academic research on BF that has often examined heuristics in isolation. The insignificance of age and gender as moderators suggests that cognitive shortcuts are universally present among digital-era investors regardless of generational or gender differences.

However, the study is constrained by its reliance on voluntary information and non-probability sampling, which may limit generalisability. Further investigations could use experimental techniques or longitudinal approaches to verify causal relationships and explore additional psychological or contextual moderators influencing heuristic-driven investment decisions.

10 RECOMMENDATIONS

The results of this study demonstrate the necessity of concentrated efforts meant to enhance the quality of investment choices made by Indian retail investors. Investor education programs need to more clearly incorporate behavioural finance principles as all three heuristic biases, which are RB, AB and A&AB were found to significantly affect investment decisions regardless of age or gender. Digital investment platforms and regulatory agencies like SEBI and AMFI should create interactive learning modules, organised awareness programs and real-world examples to assist investors in identifying and reducing the effects of cognitive biases. In order to help investors make better-informed and logical decisions without limiting their autonomy, trading applications can also include behavioural nudges such as cautions when users depend too much on current information, historical stock peaks or short-term patterns.

The findings also highlight the need to promote varied and research-based investment strategies. Financial institutions and fintech platforms can assist young retail investors in shifting away from instinctive decisions by providing simplified analytics, evidence-based risk indicators and long-term performance reports. Financial advisors play an important role as well. They should be trained to recognise behavioural characteristics in customers and offer advice that reduces biased or impulsive decision-making. By establishing rules that induce middlemen to display bias-related risk indicators at critical decision phases and by making sure that financial advertisements include behavioural alert notes in addition to statutory disclaimers, policymakers can further promote behavioural transparency.

Regulators and financial service providers should make it easier to obtain reliable, long-term, data-driven market analysis. They should make sure that investment data is distributed responsibly on social media networks since availability bias frequently results from exposure to unreliable or sensational market information. Lastly, by utilising probability-based sampling techniques and establishing causality through longitudinal or experimental research designs and investigating additional psychological, contextual or technological moderators that may influence heuristic-driven investment decisions, future research can expand on this study. Additionally, examining behavioural data directly from exchanges would strengthen the validity of self-reported replies and increase knowledge of how decisions are made in India's quickly changing retail investment sector.

REFERENCES

[1] Abdin, S. Z. ul, Farooq, O., Sultana, N., & Farooq, M. (2017). The impact of heuristics on investment decision and performance: Exploring multiple mediation mechanisms. *Research in International Business and Finance*, 42, 674-688. https://doi.org/10.1016/j.ribaf.2017.07.010

[2] Ahmad, M., & Shah, S. Z. A. (2020). 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. https://doi.org/10.1108/JEAS-07-2020-0116

[3] Andersen, J. V. (2010). Detecting Anchoring in Financial Markets. *Journal of Behavioural Finance*, 11(2), 129-133. https://doi.org/10.1080/15427560.2010.483186

[4] Anderson, A., Dreber, A., & Vestman, R. (2015). Risk Taking, Behavioural Biases and Genes: Results from 149 active investors. *Journal of Behavioural and Experimental Finance*, 6, 93-100. https://doi.org/10.1016/j.jbef.2015.04.002

[5] Armstrong, J. S., & Overton, T. S. (1977). Estimating nonresponse bias in mail surveys. *Journal of Marketing Research*, 16(August), 396-402.

[6] Arora, M., & Kumari, S. (2015). Risk Taking in financial decisions as a function of age, gender: Mediating role of loss aversion and regret. *International Journal of Applied Psychology*, 5(4), 83–89. https://doi.org/10.5923/j.ijap.20150504.01

[7] Bajtelsmit, V. L., & Bernasek, A. (1997). *Why Do Women Invest Differently from Men?* (SSRN Scholarly Paper No. 2238). Social Science Research Network. https://doi.org/10.2139/ssrn.2238

[8] Baker, H., & Filbeck, G. (2013). Paradigm shifts in finance: lessons from the financial crisis. *European Financial Review*, 18.

[9] Baker, H. K., Kumar, S., Goyal, N., & Gaur, V. (2019). How financial literacy and demographic variables relate to behavioural biases. *Managerial Finance*, 45(1), 124–146. https://doi.org/10.1108/MF-01-2018-0003

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

[11] Becker, Jan-Michael & Ringle, Christian & Sarstedt, Marko & Völckner, Franziska. (2015). How Collinearity Affects Mixture Regression Results. *Marketing Letters*. 10.1007/s11002-014-9299-9.

[12] Bhandari, G., & Deaves, R. (2006). The Demographics of Overconfidence. *The Journal of Behavioural Finance*. https://doi.org/10.1207/s15427579jpfm0701_2

[13] Bihari, A., Dash, M., Kar, S. K., Muduli, K., Kumar, A., & Luthra, S. (2022). Exploring behavioural bias affecting investment decision-making: A network cluster-based conceptual analysis for future research. *International Journal of Industrial Engineering and Operations Management*, *4*(1–2), 19-43. https://doi.org/10.1108/IJIEOM-08-2022-0033

[14] Busenitz, L. W., & Barney, J. B. (1997). Differences between entrepreneurs and managers in large organisations: Biases and heuristics in strategic decision-making. *Journal of Business Venturing*, 12(1), 9-30. https://doi.org/10.1016/S0883-9026(96)00003-1

[15] Bushra, B., Srivastav, S., & Kapoor, S. (2024). Impact of gender, age, and education on investors' behaviour: An Empirical Study of Delhi-NCR. *International Journal of System Assurance Engineering and Management*. https://doi.org/10.1007/s13198-024-02534-1

[16] Cark, L. A., & Watson, D. (1995). Constructing validity: Basic issues in objective scale development. *Psychological Assessment*, 7(3), 309-319. https://doi.org/10.1037/1040-3590.7.3.309

[17] Cen, L., Hilary, G., & Wei, K. C. J. (2013). The Role of Anchoring Bias in the Equity Market: Evidence from Analysts' Earnings Forecasts and Stock Returns. *Journal of Financial and Quantitative Analysis*, 48(1), 47–76. https://doi.org10.1017/S0022109012000609

[18] Chen, G., Kim, K. A., Nofsinger, J. R., & Rui,

O. M. (2007). Trading performance, disposition effect, overconfidence, representativeness bias, and experience of emerging market investors. *Journal of Behavioural Decision Making*, 20(4), 425-451. https://doi.org/0.1002/bdm.561

[19] De Bondt, W. F. M., & Thaler, R. H. (1995). Chapter 13 Financial decision-making in markets and firms: A Behavioural Perspective. In *Handbooks in Operations Research and Management Science* (Vol. 9, pp. 385-410). Elsevier. https://doi.org/10.1016/S0927-0507(05)80057-X

[20] Gigerenzer, G., & Gaissmaier, W. (2011). Heuristic Decision Making. *Annual Review of Psychology*, 62(1), 451–482. https://doi.org/10.1146/annurev-psych-120709-145346

[21] Gupta, P., & Goyal, P. (2024). Herding the influencers for investment decisions: Millennials bust the gender stereotype. *Journal of Financial Services Marketing*, 29(2), 229-241. https://doi.org/10.1057/s41264-022-00195-4

[22] Fornell, C., & Larcker, D. F. (1981). Evaluating Structural Equation Models with Unobservable Variables and Measurement Error. *Journal of Marketing Research*, 18(1), 39. https://doi.org/10.2307/3151312

[23] Hair, J. F., Anderson, R. E., Tatham, R. L., & Black, W. C. (1998). Multivariate Data Analysis with Reading. Prentice Hall.

[24] Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2021). A Primer on Partial Least Squares Structural Equation Modelling (PLS-SEM). Sage Publications

[25] Hair, J., Hult, G. T. M., Ringle, C., & Sarstedt, M. (2013). A Primer on Partial Least Squares Structural Equation Modelling (PLSSEM). Sage Publications

[26] Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, Marko. (2017). *A Primer on Partial Least Squares Structural Equation Modelling (PLS-SEM)*. Sage.

[27] Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. In *European Business Review* (Vol. 31, Issue 1, pp. 2–24). Emerald Group Publishing Ltd. https://doi.org/10.1108/EBR-11-2018-0203

[28] 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. https://doi.org/10.2753/MTP1069-6679190202

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

[30] Hulland, J. (1999). Use of partial least squares (Pls) in strategic management research: a review of four recent studies. Strategic Management Journal, 20(2), 195–204. https://doi.org/10.1002/(sici)1097-0266(199902)20:23.0.co;2-7

[31] Irshad, S., Badshah, W., & Hakam, U. (2016). Effect of representativeness bias on investment decision making. *Management and Administrative Sciences Review*, 5(1), 26–30.

[32] Ishfaq, M., & Anjum, N. (2015). Effect of Anchoring Bias on Risky Investment Decision. Evidence from the Pakistan Equity Market. *International Journal of Engineering and Management Research*, *5*(4), Article 4.

[33] Jain, J., Walia, N., Kaur, M., & Singh, S. (2021). Behavioural biases affecting investors' decision-making process: A Scale Development Approach. *Management Research Review*, 45(8), 1079–1098. https://doi.org/10.1108/MRR-02-2021-0139

[34] Jain, J., Walia, N., Singla, H., Singh, S., Sood, K., & Grima, S. (2023a). Heuristic Biases as Mental Shortcuts to Investment Decision-Making: A Mediation Analysis of Risk Perception. *Risks*, 11(4), Article 4. https://doi.org/10.3390/risks11040072

[35] Jain, J., Walia, N., Singla, H., Singh, S., Sood, K., & Grima, S. (2023b). Heuristic Biases as Mental Shortcuts to Investment Decision-Making: A Mediation Analysis of Risk Perception. *Risks*, 11(4), Article 4. https://doi.org/10.3390/risks11040072

[36] Javed, H., Bagh, T., & Razzaq, S. (2017). Herding effects, overconfidence, availability bias and representativeness as behavioural determinants of perceived investment performance: An empirical evidence from Pakistan stock exchange (PSX). *Journal of Global Economics*, 6(1), 1–13. https://doi.org/10.4172/2375-4389.1000275

[37] Kahneman, D., & Tversky, A. (1979). Prospect Theory: An Analysis of Decision Under Risk. In *Handbook of the Fundamentals of Financial Decision Making* (2nd edn, Vol. 47, pp. 263–292). Econometrica.

[38] Kalra Sahi, S., & Pratap Arora, A. (2012). Individual investor biases: A segmentation analysis. *Qualitative Research in Financial Markets*, *4*(1), 6–25. https://doi.org/10.1108/17554171211213522

[39] Karthikeyan, S. (2024). *A Study on the Impact of Psychological Factors on Investment Decisions of Gen Y IT Employees, Tamil Nadu* [Sastra University]. https://shodhganga.inflibnet.ac.in/handle/10603/586950

[40] Kartini, K., & Nahda, K. (2021). Behavioural Biases on Investment Decision: A Case Study in Indonesia. *The Journal of Asian Finance, Economics and Business*, 8(3), 1231–1240. https://doi.org/10.13106/jafeb.2021.vol8.no3.1231

[41] Kasoga, P. S. (2021). Heuristic Biases and Investment Decisions: Multiple Mediation Mechanisms of Risk Tolerance and Financial Literacy, a Survey at the Tanzania Stock Market. *Journal of Money and Business*,

1(2), 102–116. https://doi.org/10.1108/JMB-10-2021-0037

[42] Kumar, S., & Goyal, N. (2016). Evidence on Rationality and Behavioural Biases in Investment Decision-Making. *Qualitative Research in Financial Markets*, 8(4), 270–287. https://doi.org/10.1108/QRFM-05-2016-0016

[43] Kurz, C. J., Li, G., & Vine, D. J. (2019). Are millennials different? In A. Haughwout & B. Mandel (Eds), *Handbook of US Consumer Economics* (pp. 193-232). Academic Press. https://doi.org/10.1016/B978-0-12-813524-2.00008-1

[44] Li, Z. (2021). The Gender Psychology of Mental Accounting Financial Decision Making. *2021, 5th International Conference on Business and Information Management*, 62-68. https://doi.org/10.1145/3483794.3483804

[45] Mushinada, V. N. C. (2020). Are individual investors irrational or adaptive to market dynamics? *Journal of Behavioural and Experimental Finance*, 25, 100243. https://doi.org/10.1016/j.jbef.2019.100243

[46] Nair, M. A., Balasubramanian, & Yermal, L. (2017). Factors influencing herding behaviour among Indian stock investors. *2017 International Conference on Data Management, Analytics and Innovation (ICDMAI)*, 326-329. https://doi.org/10.1109/ICDMAI.2017.8073535

[47] Ngoc, L. T. B. (2013). Behaviour Pattern of Individual Investors in the Stock Market. *International Journal of Business and Management*, 9(1), p1. https://doi.org/10.539/ijbm.v9n1p1

[48] Parveen, S., & Siddiqui, M. A. (2017). Decision making and behavioural heuristics of investors in the non-financial sector: A case of the Pakistan Stock Exchange. *Journal of Managerial Science*, 11(3), 109–126.

[49] Prasad, H., & Mohta, B. (2012). Loss Aversion and Overconfidence: Does Gender Matter? *Annamalai International Journal of Business Studies & Research*, 4(1), 48.

[50] Raj, G. (2025). Biases and investment decision: An analysis of demographics using PLS-MGA. *International Journal of Accounting and Information Management*. https://doi.org/10.1108/IJAIM-08-2024-0282

[51] Rasheed, M. H., Rafique, A., Zahid, T., & Akhtar, M. W. (2018). Factors influencing investors' decision-making in Pakistan: Moderating the role of locus of control. *Review of Behavioural Finance*, 10(1), 70–87. https://doi.org/10.1108/RBF-05-2016-0028

[52] Ringle, C. M., Wende, S., & Becker, J. M. (2015). *A primer on partial least squares structural equations modelling (PLS-SEM)*. SAGE.

[53] Ritika, & Kishor, N. (2020). Development and validation of behavioural biases scale: A SEM approach. *Review of Behavioural Finance*, 14(2), 237–259. https://doi.org/10.1108/RBF-05-2020-0087

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

[55] Rosdiana, R. (2020). Investment Behaviour in Generation Z And Millennial Generation. *Dinasti International Journal of Economics, Finance & Accounting*, 1(5), 766-780. https://doi.org/10.38035/dijefa.v1i5.595

[56] Ryder, N. B. (1985). The Cohort as a Concept in the Study of Social Change. In W. M. Mason & S. E. Fienberg (Eds), *Cohort Analysis in Social Research: Beyond the Identification Problem* (pp. 9-44). Springer. https://doi.org/10.1007/978-1-4613-8536-3_2

[57] Sachan, A., & Chugan, P. K. (2020). *Availability Bias of Urban and Rural Investors: Relationship Study of the Gujarat State of India* (SSRN Scholarly Paper No. 3664546). Social Science Research Network. https://papers.ssrn.com/abstract=3664546

[58] Salthouse, T. (2012). Consequences of Age-Related Cognitive Declines. *Annual Review of Psychology*, 63 (Volume 63, 2012), 201-226. https://doi.org/10.1146/annurev-psych-120710-100328

[59] Sarwar, A., Mansoor, Z., & Butt, N. (2014). Investor's Behaviour in Pakistan Mercantile Exchange (PMEX). *Science International*, 26, 1371-1377.

[60] Shah, S. Z. A., Ahmad, M., & Mahmood, F. (2018). Heuristic biases in investment decision-making and perceived market efficiency: A survey at the Pakistan stock exchange. *Qualitative Research in Financial Markets*, 10(1), 85–110. https://doi.org/10.1108/QRFM-04-2017-0033

[61] Shukla, A., Rushdi, D. N. J., & Katiyar, D. R. C. (2020). *Impact of Behavioural Biases on Investment Decisions - A Systematic Review* (SSRN Scholarly Paper No. 3600023). https://papers.ssrn.com/abstract=3600023

[62] Sumantri, M. B. A., Susanti, N., & Yanida, P. (2024). *Effect of Representativeness Bias, Availability Bias and Anchoring Bias on Investment Decisions* (SSRN Scholarly Paper No. 4857731). Social Science Research Network. https://apers.ssrn.com/abstract=4857731

[63] Tversky, A., & Kahneman, D. (1973). Availability: A Heuristic for judging frequency and probability. *Cognitive Psychology*, 5(2), 207-232. https://doi.org/10.1016/0010-0285(73)90033-9

[64] Tversky, A., & Kahneman, D. (1974). Judgment under Uncertainty: Heuristics and Biases. *Science*, *185*(4157), 1124–1131. https://doi.org/10.1126/science.185.4157.1124

[65] Van den Steen, E. (2004). Rational Overoptimism (and

Other Biases). *American Economic Review*, 94(4), 1141-1151. https://doi.org/10.1257/0002828042002697

[66] Wang, P., & Nuangjamnong, C. (2022). Determinant Factors of Overconfidence, Herding Behaviour, and Investor Elements on Investment Decision Making in China. *Universal Journal of Financial Economics*, 1(1), 23-42. https://doi.org/10.37256/ujfe.1120221810

[67] Waweru, N. M., Munyoki, E., & Uliana, E. (2008). The effects of behavioural factors in investment decision-making: A survey of institutional investors operating at the Nairobi Stock Exchange. *International Journal of Business and Emerging Markets*, 1(1), 24-41. https://doi.org/10.1504/IJBEM.2008.019243