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Role of Behavioural Bias on Investment Decisions of Equity Investors: A SEM-PLS and NCA Approach

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KEYWORDS

Behavioral biases, Investment Decision-Making (IDM), Equity Retail Investors, Structural Equation Modeling (SEM), Partial Least Squares (PLS), And Necessary Condition Analysis (NCA)

ABSTRACT

Behavioral biases play a critical role in shaping the investment decisions of equity investors, often leading to deviations from rationality as posited by traditional financial theories. This study investigates the influence of four major categories of psychological biases—heuristic bias, prospect bias, herding bias, and the disposition effect—on the investment decision-making (IDM) processes of equity retail investors. Employing Structural Equation Modeling (SEM) combined with Partial Least Squares (PLS) and Necessary Condition Analysis (NCA), the research evaluates both the relative and individual impacts of these biases on IDM. Data was collected from 704 equity investors with at least five years of active portfolio management experience, using a rigorously validated survey instrument. The findings reveal that heuristic biases have the highest impact on IDM, followed by prospect biases, herding bias, and the disposition effect. SEM results show a strong explanatory power with 56.6% variance in IDM accounted for by these biases. Complementary NCA results highlight the sequential necessity of prospect and herding biases before the effects of heuristic bias and disposition effect emerge. This study contributes to behavioral finance by presenting a robust model integrating SEM-PLS and NCA to quantify bias impacts and proposing a framework to mitigate these effects. Practical implications include strategies for enhancing investor decision-making through tailored financial education and tools for bias recognition and management. These insights are valuable for academics, policymakers, and practitioners seeking to reduce the detrimental impact of biases on equity market efficiency..

1. INTRODUCTION

Investment decisions in equity markets are profoundly influenced by a complex interplay of psychological and emotional factors, which challenge the rational assumptions of traditional financial theories (Kahneman & Tversky, 1979). Behavioral finance, an evolving field, seeks to explain these deviations from rationality by integrating insights from psychology and cognitive sciences into economic and financial decision-making frameworks (Barberis & Thaler, 2003). Unlike classical theories like the Efficient Market Hypothesis (Fama, 1970), which assume that investors utilize all available information rationally, behavioral finance demonstrates that emotional responses and cognitive biases significantly shape investment behaviors, often leading to irrational decisions (Tversky & Kahneman, 1992). One of the most pervasive biases is overconfidence, where investors overestimate their knowledge and decision-making abilities, leading to excessive trading and reduced net returns (Odean, 1999). This bias often manifests in equity investors, who, driven by misplaced confidence, neglect critical risks and overvalue their predictive capabilities, resulting in portfolio underperformance (Barberis & Huang, 2001). Similarly, herding behavior, where investors mimic others rather than conducting independent analysis, creates market distortions such as bubbles and crashes, as evidenced in the 2008 financial crisis (Bikhchandani et al., 1992; Shiller, 2000). Behavioral biases, including overconfidence, herding, loss aversion, and availability heuristics, play a significant role in influencing equity investors' decision-making processes. Overconfidence causes investors to overestimate their predictive abilities, leading to excessive trading and an underestimation of associated risks, often resulting in diminished returns (Odean, 1999). Herding behavior, where investors mimic the actions of others instead of conducting independent analyses, exacerbates market volatility and contributes to phenomena such as speculative bubbles and crashes (Bikhchandani et al., 1992).Loss aversion, a key idea in Prospect Theory, shows how investors feel losses more strongly than gains. This often leads them to keep losing stocks for too long, hoping to avoid realizing a loss, while selling winning stocks too quickly to lock in small gains (Shefrin & Statman, 1985). This behavior happens because people judge outcomes based on a reference point, focusing more on avoiding losses than on achieving gains (Kahneman & Tversky, 1979).Additionally, availability bias influences decision-making by prompting investors to rely on recent or easily recalled information, which is often unrepresentative or irrelevant, thereby skewing their judgment and leading to suboptimal investment choices (Tversky & Kahneman, 1974). These biases collectively undermine rational investment practices and highlight the critical impact of psychology on financial decision-making. These behavioral biases cumulatively distort market dynamics, undermining the predictive accuracy of traditional models such as the Capital Asset Pricing Model (CAPM) and creating persistent inefficiencies (Fama, 1991; Barberis et al., 2001). For instance, irrational investor behavior has been linked to the formation of speculative bubbles, as seen during the dot-com boom, and the subsequent financial instability following their burst (Shiller, 2000). Moreover, biases influence not just individual portfolios but also systemic outcomes, reflecting in volatility patterns, trading volumes, and price anomalies across markets (Barberis & Thaler, 2003).

This paper aims to examines the relative influence of the four different psychological biases in equity investors on their investment decision making. The comparative analysis is also done between the results of SEM-PLS and 'necessary condition analysis' (NCA) approach. The four behavioural biases were included in the analysis namely *heuristic bias, prospect bias, herding bias and disposition effect.* The paper examines the influence of the included four biases on investment decision making of equity retail investors with the help of three methods namely PLS-SEM, importance and performance analysis (IPMA) and NCA method. The paper also made effort to explain the reason of the relative influence of the biases and proposed a framework to immune the decision making from the psychological biases for the retail equity investors.

The paper is structured to provide a clear and systematic exploration of behavioral biases in equity investment decisions. The introduction outlines the significance of behavioral finance and its contrast with traditional financial theories. The next section reviews the theoretical underpinnings of key biases, including overconfidence, herding, loss aversion, and availability heuristics, supported by empirical evidence. The following section examines the impact of these biases on equity markets, focusing on their role in creating inefficiencies and market distortions. Subsequently, the methodology section details the approach adopted to analyze these biases and their implications. The findings section discusses the results and practical insights for investors and policymakers. The paper concludes by summarizing the insights gained and proposing actionable strategies to mitigate the effects of biases, alongside directions for future research to integrate behavioral finance further into mainstream investment theories

2. LITERATURE REVIEW

The literature review highlights how heuristics, prospect theory biases, the disposition effect, and herding behavior significantly influence investment decisions. Heuristics, such as availability bias and anchoring, are mental shortcuts that help simplify decisions but often lead to errors and irrational choices (Tversky & Kahneman, 1974). Availability bias causes investors to overemphasize recent information, which skews their judgment when making critical investment decisions (Jain et al., 2023). Anchoring leads individuals to rely heavily on initial reference points, even when irrelevant, often resulting in poor financial choices (Barberis & Thaler, 2003). Overconfidence, another common heuristic, can cause investors to trade excessively, underestimating risks and increasing transaction costs (Odean, 1998). Representativeness bias drives investors to wrongly equate recent trends or specific patterns with long-term outcomes, leading to flawed decision-making (Jain et al., 2021). Prospect theory explains how investors treat potential gains and losses differently, leading to biases like loss aversion and regret aversion, which affect their decision-making (Kahneman & Tversky, 1979). Loss aversion, in particular, causes investors to avoid risks disproportionately, often resulting in overly conservative portfolios that may miss high-reward opportunities (Jain et al., 2023). Regret aversion further compounds this issue as investors fear making decisions they may later regret, leading to procrastination or avoidance of strategic actions (Tversky & Kahneman, 1991).

The disposition effect, driven by loss aversion, causes investors to hold onto losing investments too long and sell profitable ones too soon, which harms portfolio performance (Odean, 1998). This behavior is common in both traditional stock markets and emerging areas like cryptocurrency trading, where emotional decisions are particularly pronounced (Jain et al., 2023). Herding behavior, where investors follow the crowd rather than relying on their analysis, exacerbates market inefficiencies and amplifies speculative bubbles, as seen during financial crises (Shiller, 2000; Jain et al., 2023). Such biases underline the need for greater financial literacy and practical strategies to promote rational decision-making in financial markets (Jain et al., 2023).

2.1 HEURISTICS BIAS AND IDM

Heuristic biases, arising from mental shortcuts used to simplify complex decision-making, significantly influence investment behavior and often lead to systematic errors that affect portfolio performance. Overconfidence is a prominent heuristic bias where investors overestimate their knowledge and control over outcomes, leading to frequent trading, increased transaction costs, and reduced returns (Ahmad & Shah, 2020). This bias drives investors to underestimate risks and create imbalanced portfolios that are more vulnerable to market downturns (Baker et al., 2019). Furthermore, overconfidence leads individuals to disregard critical data in favor of their assumptions, resulting in flawed investment decisions (Kasoga, 2021). Overconfident investors are also prone to ignoring professional advice, relying instead on self-assessment, which often exacerbates losses and diminishes long-term portfolio performance by increasing exposure to volatile assets (Jain et al., 2023; Suresh, 2021). Anchoring bias is another key heuristic that influences investment decisions by causing investors to fixate on an initial piece of information, such as a stock’s past price, and use it as a reference point, even when new data is available (Tversky & Kahneman, 1974). This fixation often leads to poor timing in buying or selling, as decisions are driven by arbitrary price targets rather than current market conditions (Kasoga, 2021). Anchoring also contributes to under-diversification, as investors stick to familiar investments and fail to adapt to market dynamics (Ahmad & Shah, 2020). This inability to adjust portfolios optimally often results in missed opportunities and reduced returns, as outdated valuations and expectations persist (Gavrilakis & Floros, 2022; Bashir et al., 2013). Availability bias occurs when investors rely heavily on recent or easily accessible information while ignoring a comprehensive analysis of historical or fundamental data, leading to impulsive decision-making (Khan et al., 2021). This bias often results in skewed asset allocation, as investors disproportionately favor stocks or sectors that are heavily publicized, rather than constructing diversified portfolios (Baker et al., 2019). Such reliance on readily available information can drive panic buying or selling during market volatility, as decisions are based more on media narratives than rigorous analysis (Ahmad & Shah, 2020). Over time, availability bias impairs portfolio performance, as choices driven by superficial factors often fail to align with long-term investment goals (Kasoga, 2021). Representativeness bias, another heuristic commonly observed in investment decision-making, involves basing decisions on perceived patterns or recent events, leading investors to assume that these trends will persist indefinitely (Tversky & Kahneman, 1974). This bias often results in overinvestment in trending assets, under the mistaken belief that past performance guarantees future success (Bashir et al., 2013). Representativeness can also lead to poor stock selection, as investors prioritize companies associated with positive recent events while neglecting broader financial fundamentals (Khan et al., 2021). Over time, this bias reduces diversification and increases portfolio risk, making investments more vulnerable to market corrections and downturns (Ahmad & Shah, 2020; Ahmed et al., 2022). The gambler’s fallacy, another manifestation of heuristic bias, reflects an erroneous belief that past events influence future probabilities, often leading investors to expect reversals in market trends without any supporting evidence (Tversky & Kahneman, 1974). This fallacy prompts investors to buy declining assets under the assumption that they are due for a rebound, which may lock in further losses if the trend persists (Baker et al., 2019). Conversely, it can cause premature selling of outperforming assets out of fear of an impending reversal, thereby limiting potential gains (Ahmad & Shah, 2020). Such behavior, driven by perceived patterns rather than sound analysis, contributes to suboptimal portfolio performance over the long term (Suresh, 2021; Kasoga, 2021). Collectively, heuristic biases like overconfidence, anchoring, availability, representativeness, and the gambler’s fallacy distort rational decision-making and hinder optimal investment outcomes. By over-relying on cognitive shortcuts, investors expose themselves to systematic errors that reduce returns, increase risk, and impair long-term financial performance. Addressing these biases through education, behavioral training, and reliance on data-driven strategies is critical for improving investment decision-making and mitigating the adverse effects of heuristic-driven errors.

Hypothesis (H1a): *“Heuristic biases in equity retail investors significantly influences their investment decision making”*

2.2. PROSPECT BIAS AND IDM

Prospect bias, rooted in Prospect Theory developed by Kahneman and Tversky (1979), reflects the influence of cognitive and emotional distortions on investors’ decision-making processes. This bias, encompassing loss aversion, regret aversion, and mental accounting, leads investors to deviate from rational and optimal behavior, thereby affecting portfolio performance and wealth accumulation. Loss aversion, a central aspect of prospect bias, causes investors to fear losses more intensely than they value equivalent gains, often leading to overly conservative investment decisions that limit potential returns (Kengatharan & Kengatharan, 2014). This bias manifests in the tendency to hold onto losing investments for too long, as investors seek to avoid realizing losses, thereby locking up capital in underperforming assets (Shah et al., 2018). The reluctance to sell at a loss hinders the reallocation of funds to better-performing opportunities, leading to missed potential gains (Ahmed et al., 2022). Additionally, the emotional stress and fear associated with losses cloud judgment, resulting in suboptimal investment choices (Suresh, 2021). Over time, the overly cautious behavior driven by loss aversion stifles portfolio growth and reduces wealth accumulation (Jain et al., 2023). Regret aversion bias, another dimension of prospect bias, stems from the desire to avoid decisions that could lead to regret, often resulting in inertia or overly conservative choices (Kahneman & Tversky, 1979). Investors with this bias frequently miss profitable opportunities due to the fear of making incorrect decisions, leading to a risk-averse approach that limits portfolio growth (Baker et al., 2019). This bias also discourages selling poorly performing assets, as investors hesitate to acknowledge past mistakes, causing prolonged underperformance in their portfolios (Khan et al., 2021). Furthermore, regret aversion reduces diversification, as investors cling to familiar assets to avoid potential regret associated with venturing into new or risky investments (Ahmad & Shah, 2020). Over time, this conservative behavior restricts returns, as the failure to take calculated risks curtails portfolio gains (Gavrilakis & Floros, 2022). Mental accounting, another form of prospect bias, involves the cognitive segmentation of money into different accounts based on subjective criteria, rather than considering overall portfolio performance (Thaler, 1999). This segmentation often results in irrational behavior, such as taking higher risks with "house money" (profits) while being overly cautious with principal investments (Suresh, 2021). The failure to view a portfolio holistically leads to suboptimal asset allocation, as investors focus on individual accounts rather than the broader portfolio's performance (Jain et al., 2023). Mental accounting encourages a short-term focus on gains or losses within specific accounts, often at the expense of long-term wealth accumulation (Shah et al., 2018). This fragmented approach to decision-making introduces inefficiencies, such as inconsistent risk management and missed opportunities for diversification, which ultimately undermine portfolio performance (Ahmed et al., 2022).

Hypothesis (H1b): *"Prospect biases in equity retail investors significantly influences their investment decision making"*

2.3 DISPOSITIONS EFFECT AND IDM

Disposition Effect: The disposition effect describes the tendency of investors to sell winning stocks too early to lock in gains, while holding onto losing stocks for too long, hoping they will bounce back (Shefrin & Statman, 1985). This behavior can significantly hinder portfolio growth, as it limits potential profits from successful investments while tying up capital in underperforming assets (Gavrilakis & Floros, 2022). By avoiding losses at all costs, investors may end up with a skewed portfolio that is weighted with losing investments, reducing overall returns (Kengatharan, 2014). The disposition effect also contributes to emotional decision-making, as the fear of regret drives investors to avoid realizing losses (Khan et al., 2021). Ultimately, this bias undermines rational investment strategies, as holding onto losers contradicts fundamental investment principles of cutting losses and maximizing winners (Ahmad & Shah, 2020).

Hypothesis: (H1c) *"Disposition effect in equity retail investors significantly influences their investment decision making"*

2.4 HERDING BIAS AND IDM

Herding bias drives investors to mirror the actions of others, often resulting in the collective buying or selling of assets, which can create artificial price inflation or market bubbles (Gavrilakis & Floros, 2022). This behavior undermines individual analysis, as investors disregard their research to align with perceived group behavior (Khan et al., 2021). Herding can intensify market volatility, as large groups of investors react simultaneously to market events, amplifying price swings (Ahmed et al., 2022). Additionally, this bias can lead to significant losses when market trends reverse, as investors are left with overvalued assets purchased at peak prices (Kengatharan, 2014). Herding behavior often emerges during periods of uncertainty, with investors seeking reassurance from the actions of others rather than market fundamentals (Shah et al., 2018). The following hypothesis is proposed on the basis of above discussion:

Hypothesis (H1d): *"Herding biases in equity retail investors significantly influences their investment decision making"*

The following model is proposed to be examined with the help of PLS-SEM, IPMA and NCA approach

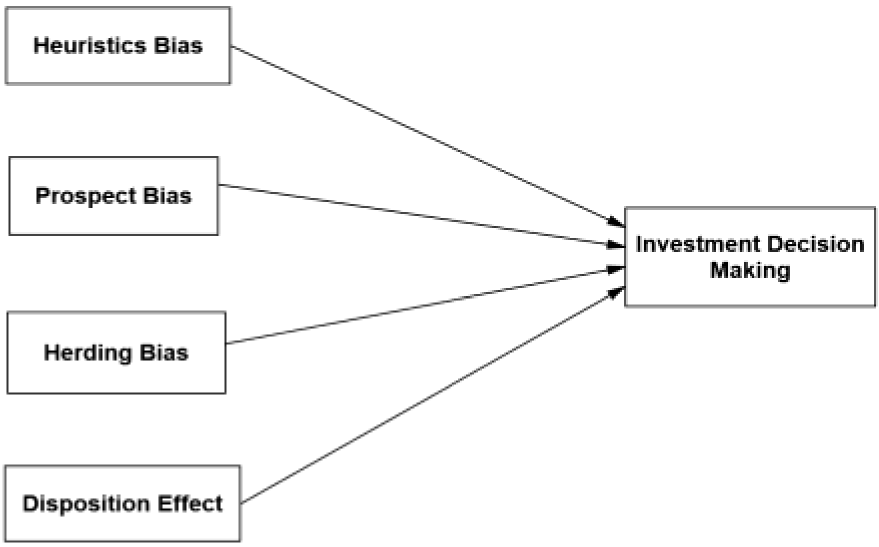


Figure 1: Proposed theoretical model

3. RESEARCH METHODOLOGY

3.1 Research objective

This research paper made an effort to examines the relative influence of the four different psychological biases in equity investors on their investment decision making and a comparative analysis between the results of SEM PLS and NCA approach. The four behavioural biases were included in the analysis namely *heuristic bias, prospect bias, herding bias and disposition effect.* The paper examines the influence of the included four biases on investment decision making along with their relative influence on IDM, using IPMA and NCA method. The paper also made effort to explain the reason of the relative influence of the biases and proposed a framework to immune the decision making from the psychological biases for the retail equity investors.

3.2 DATA TYPE AND SAMPLING DESIGN

The responses were collected from the 704 equity retail investors using survey method. The equity investors were selected in the survey on the basis of three criteria, first, the equity investors must have five-year investment experience in equity market, actively manage their equity portfolio (avoiding passive investors) and finally invested their own earned income rather than investing income earned by others family members or friends etc. The responses were collected from the selected equity investors with the help of google form, which was developed from the adapted research instrument (questionnaire) framed for the study. The generated link of the google-form was sent to different investment related platforms, groups, communities available on social media, websites, WhatsApp and telegram groups etc. The developed research instrument was designed to begin with few criteria questions, satisfying which, the equity investors can provide their response in the remaining part of the instrument. In case the criteria questions were not satisfied, the respondents were not able to proceed with the instrument.

We adopted the non-probability sampling method '*judgmental sampling'* to collect the responses from the equity retail investors. The reason for adopting non-probability sampling method is lack of proper sampling frame for the equity investors. The primary responses collected from the equity investors using research instrument took the period of six months, from April 24 till Sep 24. During the period of six months, the 704 responses were collected, and also assumed as representative sample for the final data analysis and hypothesis testing. The responses were collected using five-point interval scale (*where 1 represents 'strongly disagree', 2 'disagree', 3 can't say, 4 agree and 5 represents 'strongly agree')* used in the questionnaire.

3.3 SCALE DEVELOPMENT AND QUESTIONNAIRE DESIGN

The research instrument was adapted from the existing literature and developed in three stages. The statements measuring the different psychological biases were identified from the literature review. The first stage ends with a draft questionnaire, prepared on the basis of extensive literature review. The second stage includes the discussion about the draft questionnaire with the three industry and four academic experts to ensure the content validity of the research instrument. The industry experts were selected on the basis of their long experience of more than 25 years with the equity market and academic experts were selected on the basis of their publications. In second stage, the research instrument was modified as per the suggestions provided by the selected experts. In the third stage, the pilot study was conducted with 89 equity investors to examine the face validity of the research instruments. The pilot study helps in further improving the instrument by removing a few statements, modifying the language of the statements etc. Finally, after the modifications made in the instrument after pilot survey the instrument was used for collecting the data for the study.

The study adopts a validated 39-item questionnaire from Jain et al. (2021) to assess ten key behavioral biases affecting investment decision-making, including Availability Bias, Representativeness, Overconfidence, Herding, Anchoring, and others. The scale uses a 5-point Likert format (1 = "Strongly Disagree" to 5 = "Strongly Agree") and is empirically validated through rigorous processes like expert review, pilot testing, and confirmatory factor analysis.

3.4 STATISTICAL METHODS

The collected responses were analyzed with different statistical methods to achieve the research objectives and hypothesis testing. The analysis includes the estimation of frequency distribution for sample demographics, estimating mean score and standard deviation of the included constructs, examining the reliability and construct validity of the instrument using '*confirmatory factor analysis* (CFA). The item multi-collinearity examined with '*variance inflation factor'* (VIF). The '*common method bias'* of the instrument was examined using '*Harman single factor method'.* The proposed framework was examined using SEM-PLS approach using SmartPLS software, 'importance and performance analysis' (IPMA) and 'necessary condition analysis' (NCA) approach. The section 4 discusses the results of the statistical analysis applied on the collected responses.

4. DATA ANALYSIS AND INTERPRETATION

This section explains the impact of different behavioural biases on investment decision making (IDM) for the retail investors. The section discusses the sample demographics, results of the reliability analysis, validity analysis using CFA, item multi-collinearity, common method bias, hypothesis testing using SEM, IPMA and NCA.

4.1. SAMPLE DEMOGRAPHICS

4.2 BEHAVIOURAL BIAS AND IDM OF RETAIL INVESTORS

The paper includes four categories of biases *(heuristic bias, prospect bias, herding bias and disposition effect)* in the structural framework, where, the heuristic bias is measured with five biases (*anchoring bias, availability bias, gambler's fallacy bias, overconfidence bias and representative bias)*, the prospect bias is measured by three biases (*loss aversion bias, mental accounting bias and regret aversion bias)*, the other biases are *herding bias and disposition effect.* The included biases are measured with the help of different statements included in the instrument. The average score and standard deviation of all the biases is estimated. Table 2 represents the descriptive analysis of the included biases.

Table: Descriptive analysis- Behavioural bias & Investment decision making of retail investors

Behavioural Bias	**Statements**	**Mean (SD)**	**SD**
Overconfidence	OC1- I believe that my skills and knowledge of stock market can help me to outperform the market. Oc2- I trade frequently than other people OC3- I feel more confident in my own investment opinion over the opinion of my colleagues or friends OC4- I know the best time to enter and to exit my investment position from the market	3.560 **(1.050)**	1.050
Anchoring Bias	ANCH1- I rely on my previous experiences in the market for making next investment. ANCH2- I usually invest in a stock which has fallen considerably from its previous closing or all times high. ANCH3- I forecast the changes in stock prices in the future based on recent stock prices. ANCH4- I use the purchase price of stocks as a reference point in trading.	3.496	1.010
Availability Bias	AVB1- I prefer to buy local stocks than trade in international stocks. AVB2-I prefer to invest in stock which has been evaluated by well-known experts. AVB3-My investment decision depends on new and favourable (positive) information released regarding the stock. AVB4-If someone has tells me that a financial crisis is about to happen in a year' time, i would be convinced. AVB5-I prefer to buy stocks on the days when the value of index increases. AVB6-I prefer to sell stocks on the days when the value of index decreases.	3.538	1.032
Gambler's Fallacy Bias	GF1-I am normally able to anticipate the end of good or poor. GF2-I tend to ignore the benefits that can accrue by investing in different investment options. GF3-After a fall in the market for few days consecutively, I believe that now the market will move upwards.	3.527	1.076
Representative Bias	REP1- I prefer to invest only in familiar stocks. REP2- I buy 'hot' stocks and avoid stocks that have performed poorly in the recent past. REP3- I use trend analysis to make investment decisions. REP4- If other stocks of a company are performing well and the same company offers new shares, i will buy the same. REP5- Even if my best researched stock does not perform according to my expectations, still i hold the same.	3.496	0.966
Heuristic Bias		3.523	0.766

Investment Decision Making	IDM1-In general, I feel satisfied with the way i am making investment decisions IDM2-My decision-making helps you to achieve my investment objectives IDM3-I am confident about accuracy of my investment decisions IDM4-My investments decisions can mostly earn higher than average return in the market IDM5-I make all investment decisions on my own IDM6-I consider all possible factors (viz. interest rate, inflation, global factors, political factors etc.) while making investment decisions IDM7-Return on my portfolio justifies my investment decision	3.582	1.013
Loss Aversion Bias	LA1-When faced with a sure gain, I am risk averse. LA2-When faced with a sure loss, I am a risk taker. LA3-I avoid selling shares that have decreased in value and readily sell shares that have increased in value.	3.332	1.068
Mental Accounting Bias	MA1-I tend to treat each element/account in my investment portfolio separately MA2-I sell losing investment from my portfolio MA3-I ignore the connection between different investment possibilities	3.319	1.036
Disposition effect	DE1-I will keep holding stocks even though they are losing and will never think about selling stocks until they balance the losses. DE2-I usually sell profitable stocks to realize gains first when I am in want of money. I buy other stocks and keep holding them to wait for the price of unprofitable stocks to go up. DE3-I don’t have any quick responses to good or bad news and tend sell profitable stocks too early and sell losing stocks too late. DE4-If the stock market index has been surging for a while, I will continue holding unprofitable stocks and will not sell them immediately or buy other stocks DE5-I tend to keep holding an unprofitable stock because I believe that it is a blue –chip investment worthy of long-term preservation. DE6-After selling profitable stocks, I will be upset with those losing ones that have not been sold yet. DE7-I will feel regret and disappointed if the price of the stock I sold keeps growing DE8-I sell profitable stocks because I am afraid that the stock price would fall DE9-I will be satisfied with my decision when I gain profit from the surging price of the stock, I bought	3.403	0.924
Prospect Bias		3.345	0.867
Regret Aversion Bias	RA1 I avoid selling shares that have decreased in value. RA2I sell shares that have increased in value faster. RA3 I feel more sorrow about holding losing stocks too long than about selling winning stocks too soon.	3.385	1.056
Herding Bias	HB1-Other investors’ decisions of choosing stock types have impact on my investment decisions. HB2-Other investors’ decisions of the stock volume have impact on my investment decisions.	3.415	1.065

	HB3-Other investors' decisions of buying and selling stocks have impact on my investment decisions. HB4-I usually react quickly to the changes of other investors' decisions and follow their reactions to the stock market		

The result reported the moderate agreement of the equity investors towards presence of biases in their behaviour (mean score of included biases and IDM are greater than 3). The highest agreement found with overconfidence bias in the equity retail investors (mean score =3.56), followed by the availability bias (mean score = 3.538). The next biases with high agreement (mean > 3.5) are Gamber's fallacy bias and heuristic bias. However, in other biases, the investors agreed to have moderate to low presence of biases in their behaviour (mean < 3.5). The standard deviation of the responses estimated for different bias, indicates the presence of moderate variation in the level of agreement against the included biases and investment behaviour.

4.3 Reliability analysis, construct validity, item multicollinearity and common method bias

This section discusses about the results of the different required statistical assumptions about the research instrument, to ensure the valid conclusions drawn from hypothesis testing and statistical analysis including IPMA and NCA. The consistency reliability for each construct in the instrument is evaluated with Cronbach alpha, the construct validity of instrument is examined using CFA, item multicollinearity is examined using VIF and CMB is tested with 'Harman single factor' (HSF) method.

The reliability of the research instrument measuring behavioral biases and IDM is examined using Cronbach alpha. The internal consistency for different behavioral bias and IDM ensures the high correlation among the items/statements measuring the constructs. The Cronbach alpha for each behavioral bias and investment decision making is expected to be greater than 0.7. The result of reliability analysis is reported in table 2. The result reported that the Cronbach alpha for each bias and IDM is greater than 0.8 (*anchoring bias= 0.854, availability bias= 0.916, disposition effect=0.903, Gambler's Fallacy bias= 0.860, herding Bias= 0.870, IDM = 0.913, loss aversion bias = 0.828, mental accounting bias = 0.828, overconfidence bias = 0.881, regret aversion bias = 0.819 and representative bias = 0.873).* Thus, the results ensure the presence of consistency reliability of the instrument and it is concluded that the responses received against the behavioral bias and IDM are reliable.

The construct validity of the research instrument ensures its validity and validity of the conclusions derived from the hypothesis testing and statistical analysis. Here, the construct validity of the inclement incorporating the different behavioral bias and IDM is examined using CFA approach. The construct validity has two dimensions namely the convergent validity and discriminant validity, where the convergent validity ensures the correct measurement of included constructs and discriminant validity ensures the constructs are different from each other as indicated by low correlations among the constructs. The convergent validity examined the relationship between the items and the construct, using item *construct loadings*, required to higher than 0.7, '*composite reliability'* (CR) expected greater than 0.7 and '*average variance extracted'* (AVE) expected greater than 0.7 for each construct in the instrument measuring behavioral bias and IDM. The discriminant validity ensures the presence of moderate or low relationship between the items of different constructs in the instrument measuring the behavioral bias and IDM. The discriminant validity is inspected using cross loadings of the items of different constructs using HTMT ratio and Fornell Larcker criteria. The HTMT indicators of each pair of constructs is expected to be less than 0.85 and in Fornell Larcker criteria, the square root of AVE for each bias and IDM is expected to be higher than its correlation with remaining construct in the instrument. The result of construct validity are reported in tables shown below:

Table: Construct loadings- Heuristics Bias

Item code	**Construct name**	**Construct loadings**	**Cronbach Alpha**	**Composite reliability**	**Average variance extracted**	**VIF**
ANCH1	Anchoring Bias	0.784	*0.854*	*0.854*	*0.593*	1.914
ANCH2		0.792				1.986
ANCH3		0.752				1.948
ANCH4		0.753				1.907
AVAIL1		0.847	*0.916*	*0.916*	*0.647*	2.798
AVAIL2		0.830				2.724

AVAIL3	Availability Bias	0.764				2.142
AVAIL4		0.827				2.902
AVAIL5		0.770				2.723
AVAIL6		0.784				2.361
OC1	Overconfidence	0.807	*0.881*	*0.881*	*0.649*	2.485
OC2		0.798				2.080
OC3		0.786				2.119
OC4		0.831				2.319
GF1	Gamblers Fallacy	0.801	*0.860*	*0.860*	*0.672*	2.175
GF2		0.807				2.084
GF3		0.851				2.281
REP1	Representative Bias	0.815	*0.873*	*0.873*	*0.580*	2.332
REP2		0.724				1.872
REP3		0.743				1.937
REP4		0.748				1.988
REP5		0.776				2.336

Table: Construct loadings- Prospect bias, disposition effect and herding bias

Item code	**Construct name**	**Construct loadings**	**Cronbach Alpha**	**Composite reliability**	**Average variance extracted**	**VIF**
Dis1	Disposition effect	0.770	*0.903*	*0.903*	*0.509*	2.415
Dis2		0.768				2.131
Dis3		0.624				1.929
Dis4		0.699				2.290
Dis5		0.746				2.225
Dis6		0.717				2.071
Dis7		0.657				2.190
Dis8		0.722				2.057
Dis9		0.708				2.259
HB1	Herding Bias	0.770	*0.870*	*0.870*	*0.626*	2.208
HB2		0.834				2.071
HB3		0.749				1.998
HB4		0.809				2.170

IDM1	Investment Decision Making	0.801	*0.913*	*0.913*	*0.599*	2.510
IDM2		0.777				2.409
IDM3		0.740				2.035
IDM4		0.752				2.232
IDM5		0.798				1.975
IDM6		0.781				2.321
IDM7		0.764				2.675
LA1	Loss Aversion Bias	0.774	*0.828*	*0.828*	*0.617*	2.043
LA2		0.811				1.875
LA3		0.770				1.804
MA1	Mental Accounting Bias	0.807	*0.828*	*0.829*	*0.618*	1.968
MA2		0.752				1.791
MA3		0.798				1.940
REA1	Regret Aversion Bias	0.802				2.067
REA2		0.783	*0.819*	*0.820*	*0.602*	1.853
REA3		0.742				1.682

The result reported that the construct loadings of all the items measuring the behavioral biases and the IDM are greater than 0.7, the CR and AVE of the constructs representing the different biases and the IDM are greater than 0.7 and 0.5 respectively (*anchoring bias: CR=0.854, AVE=0.593, availability bias: CR=0.916, AVE=0.647, disposition effect: CR=0.903, AVE=0.509, Gambler's Fallacy bias: CR = 0.860, AVE=0.672, herding bias: CR = 0.870, AVE=0.626, IDM: CR = 0.913, AVE= 0.599, loss aversion bias: CR= 0.828, AVE=0.617, mental accounting bias: CR = 0.829, AVE=0.618, overconfidence: CR = 0.881, AVE=0.649, regret aversion bias: CR = 0.820, AVE= 0.602 and representative bias: CR = 0.873, AVE=0.580).* The CR and AVE of all the included constructs measuring the biases and IDM of the equity retail investors satisfy the requited criteria of the convergent validity. Thus, the results ensure the presence of convergent validity of the instrument measuring the different behavioral biases and IDM for equity retail investors.

Further, the discriminant validity of the instrument measuring the different biases and IDM for equity retail investors is tested with HTMT ratio and Fornell Larcker criteria. The discriminant ant validity is evaluated from the cross loadings of the items of different factors and reported in the form of HTMT ratio and Fornell Larcker criteria. The results reported that the HTMT indicator for each pair of constructs less than 0.85, and in Fornell Larcker criteria, the square root of AVE for each bias and IDM of equity retail investor is found higher than its correlation with remaining construct in the instrument. The results of HTMT and Fornell Larcker criteria are satisfied by the results, indicating that the discriminant validity of the instrument is ensured. The fulfilment of the both convergent and discriminant validity of the scale measuring the different biases and IDM for equity retail investors ensures the construct validity of the scale.

Table: HTMT ratio for discriminant validity

	Anchoring Bias	Availability Bias	Disposition effect	Gambler's Fallacy Bias	Herding Bias	Heuristic Bias	IDM	Loss Aversion Bias	Mental Accounting Bias	Overconfidence	Prospect Bias	Regret Aversion Bias	Representative Bias
Anchoring Bias													

Availability Bias	0.532												
Disposition effect	0.210	0.179											
Gambler's Fallacy Bias	0.452	0.496	0.235										
Herding Bias	0.248	0.198	0.212	0.318									
IDM	0.833	0.859	0.262	0.772	0.318								
Loss Aversion Bias	0.485	0.441	0.431	0.516	0.607	0.604							
Mental Accounting Bias	0.294	0.277	0.130	0.283	0.398	0.326	0.506						
Overconfidence	0.271	0.250	0.201	0.244	0.507	0.328	0.526	0.572					
Regret Aversion Bias	0.536	0.424	0.197	0.536	0.211	0.790	0.425	0.214	0.235				
Representative Bias	0.316	0.299	0.209	0.333	0.538	0.383	0.602	0.952	0.962	0.261			
Anchoring Bias	0.238	0.233	0.199	0.321	0.463	0.321	0.500	0.640	0.666	0.216	0.991		
Availability Bias	0.557	0.524	0.205	0.514	0.282	0.857	0.479	0.194	0.259	0.497	0.276	0.248	

Table: Fornell Larcker criteria for discriminant validity

	Anchoring Bias	Availability Bias	Disposition effect	Gambler's Fallacy Bias	Herding Bias	Heuristic Bias	IDM	Loss Aversion Bias	Mental Accounting Bias	Overconfidence	Prospect Bias	Regret Aversion Bias	Representative Bias
Anchoring Bias	0.770												
Availability Bias	0.533	0.804											
Disposition effect	0.209	0.178	0.714										
Gambler's Fallacy Bias	0.452	0.497	0.236	0.820									

Herding Bias	*0.250*	*0.200*	*0.212*	*0.318*	*0.791*								
IDM	*0.832*	*0.858*	*0.262*	*0.776*	*0.320*	*0.608*							
Loss Aversion Bias	*0.485*	*0.441*	*0.433*	*0.516*	*0.608*	*0.605*	*0.774*						
Mental Accounting Bias	*0.293*	*0.277*	*0.130*	*0.282*	*0.399*	*0.326*	*0.506*	*0.785*					
Overconfidence	*0.270*	*0.250*	*0.201*	*0.244*	*0.506*	*0.327*	*0.526*	*0.573*	*0.786*				
Regret Aversion Bias	*0.536*	*0.424*	*0.198*	*0.537*	*0.212*	*0.788*	*0.425*	*0.214*	*0.233*	*0.806*			
Representative Bias	*0.314*	*0.299*	*0.209*	*0.333*	*0.539*	*0.383*	*0.602*	*0.948*	*0.961*	*0.260*	*0.664*		
Anchoring Bias	*0.237*	*0.235*	*0.200*	*0.322*	*0.466*	*0.321*	*0.500*	*0.641*	*0.665*	*0.215*	*0.993*	*0.776*	
Availability Bias	*0.558*	*0.524*	*0.206*	*0.515*	*0.282*	*0.856*	*0.478*	*0.193*	*0.259*	*0.497*	*0.276*	*0.248*	*0.762*

Item multicollinearity and CMB: The different items are included in instrument to measure the different biases and IDM for equity retail investors and it expected that the included items are not similar or highly correlated. The presence of item multicollinearity is not desirable in the responses, as it leads to redundant responses. The item multicollinearity is examined using VIF measure, which is considered as satisfactory, if found less than 5, and excellent if found less than 3. The result of the VIF for all the items included in instrument is shown in table 2. The result reported that the estimated value of VIF for all the items are found less than 3, indicating that the items are free from multicollinearity problem. Further, it is also expected that the responses received against the items measuring the different biases and IDM for equity retail investors in the study were not biased, as the biased responses leads to biased conclusions. The CMB is examined with HSF method, where the 'exploratory factor analysis' is applied on the included items in the instrument, with the restriction of single factor to be extracted. The result of CMB with HSF method found that the extracted single factor explains just 26.822% of the variance of the entire data and less than the cut-off value of 50%, indicating that the instrument is from CMB and the conclusions made in the paper are unbiased.

4.4. Hypothesis testing

The representativeness, anchoring, availability bias, and gamblers' fallacy, to simplify their decision-making processes, however often result in systematic errors and suboptimal outcomes (Kahneman & Tversky, 1979; Baker & Nofsinger, 2010; Chen et al., 2007; Kliger & Kudryavtsev, 2010; Matsumoto et al., 2013; Riaz & Iqbal, 2015; Tekçe et al., 2016; Ullah et al., 2017). Existing literature found significant influence of psychological biases on investment decision-making of equity investors, often leading to deviations from rational behavior and contributing to inefficiencies in financial markets. Overconfidence leads investors to overestimate their knowledge, making decisions based on limited or biased information, while the availability heuristic causes them to overemphasize recent or memorable events, contributing to market mispricing (Shleifer, 2000; Hirshleifer, 2001). Beyond heuristics, prospect theory has been extensively studied, particularly in relation to biases such as regret aversion, loss aversion, mental accounting, and the disposition effect, all of which significantly influence investment decisions (Kahneman & Tversky, 1979; Waweru et al., 2008; Richards et al., 2011; Zona, 2012). These biases, particularly loss aversion, often cause investors to react irrationally to short-term losses, leading to excessive trading and poor portfolio management (Benartzi & Thaler, 1995). The disposition effect, which describes the tendency of investors to sell winning investments too early and hold onto losing investments for too long, further complicates investment strategies and outcomes (Shefrin & Statman, 1985). Moreover, herding behavior—where investors mimic the actions of others rather than relying on independent judgment—amplifies market inefficiencies and volatility, further undermining market efficiency (Dennis & Strickland, 2002; Caparrelli et al., 2004; Lee et al., 2004; Lim, 2012; Kengatharan & Kengatharan, 2014). Individual biases, such as anchoring (Andersen, 2010), availability bias and loss aversion (Khan, 2017), and gamblers' fallacy (Rakesh, 2013), have also been specifically studied for their unique impacts on decision-making. Collectively, these psychological biases contribute to predictable errors and deviations from rational investment decision-making, emphasizing the need for a comprehensive understanding and mitigation of these biases to improve investment outcomes and enhance market efficiency (Fama, 1998; Thaler & Sunstein, 2008).

In the study the structural model indicating the relationship between psychological bias and investment decision making of retail investors is developed and tested with the help of SEM approach using SmartPLS software. The four psychological biases namely *disposition effect*, *herding bias, heuristic bias, prospect bias* are included in the structural model as independent constructs and investment decision making as dependent construct. The heuristic bias and prospect biases are second order construct initially, however, transformed as lower order after estimating the scores of lower order constructs measuring the heuristic and prospect biases. The following hypothesis are examined using SEM method:

Hypothesis (H1a): *"Heuristic biases in equity retail investors significantly influences their investment decision making"*

Hypothesis (H1b): *"Prospect biases in equity retail investors significantly influences their investment decision making"*

Hypothesis: (H1c) *"Disposition effect in equity retail investors significantly influences their investment decision making"*

Hypothesis (H1d): *"Herding biases in equity retail investors significantly influences their investment decision making"*

The structural model is shown below in figure and the results of hypothesis testing are reported in table:

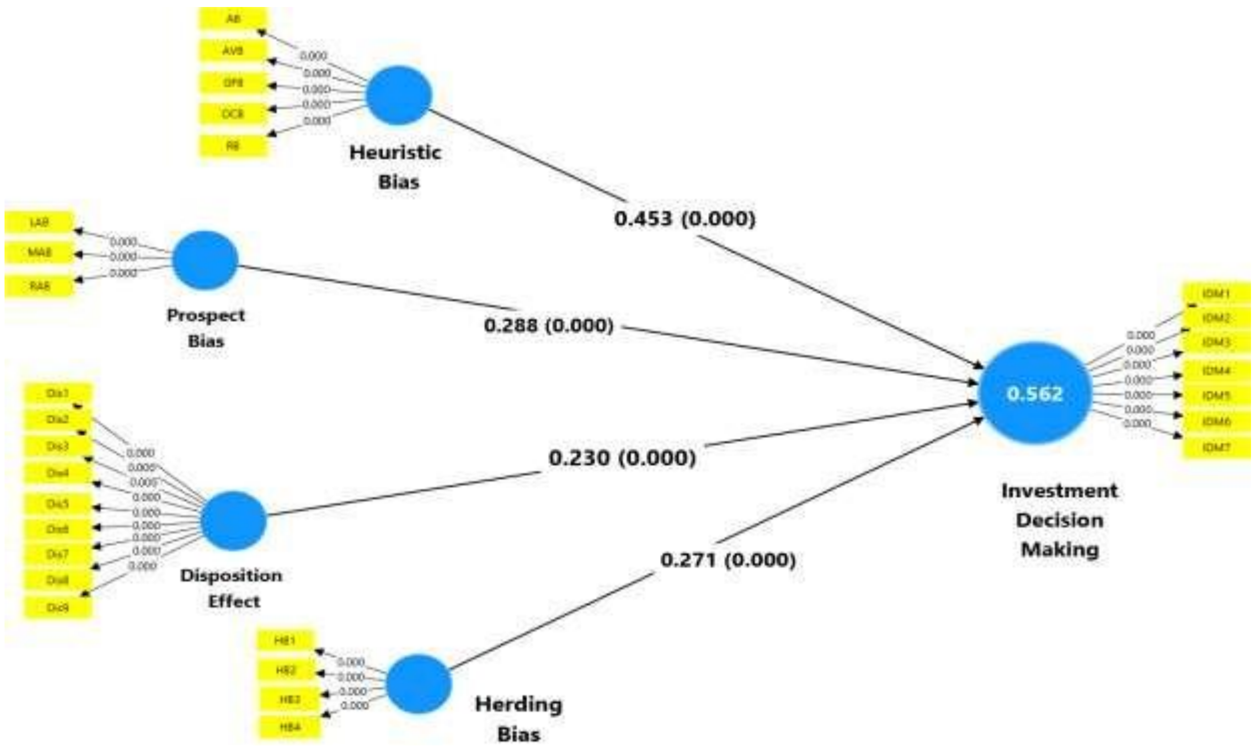


Table: Hypothesis testing using SEM

Independent Construct	Dependent Construct	Path Coefficient	Standard error	T stats	P values	F square	R Square
Disposition Effect	Investment Decision Making	0.231	0.030	7.663	0.000	0.096	56.6%
Herding Bias		0.270	0.028	9.721	0.000	0.142	
Heuristic Bias		0.453	0.037	12.291	0.000	0.225	
Prospect Bias		0.288	0.033	8.586	0.000	0.103	

The result of SEM analysis supported the influence of all the included psychological biases on the investment decision making of equity investors. In case of heuristic biases, the results supported the hypothesis that *"Heuristic biases in equity* *retail investors significantly influences their investment decision making" (path coefficient =0.453, t stats = 12.291).* The results reported that higher heuristic biases have the highest significant influence on the investment decision making of equity retail investors. This is followed by higher and significant effect of the prospect bias on the investment decision making of equity retail investors. The results supported the hypothesis that *"Prospect biases in equity retail investors significantly influences their investment decision making" (path coefficient =0.288, t stats = 8.586).* The prospect bias is found to have significant influence on the investment decision making of equity retail investors. The result also significantly support the hypothesis that *"Disposition effect in equity retail investors significantly influences their investment decision making" (path coefficient =0.231, t stats = 7.663) and "Herding biases in equity retail investors significantly influences their investment decision making" (path coefficient =0.270, t stats = 9.721).* Thus, it can be concluded that the included psychosocial biases have the significant impact of investment decision making of equity retail investors. The explanatory power of the structural model is evaluated with the help of r square, which is found to be 56.6%. Thus, it can be concluded that the model has sufficient explanatory power and 56 percent of the variance in the investment decision making can be explained with the help of structural model.

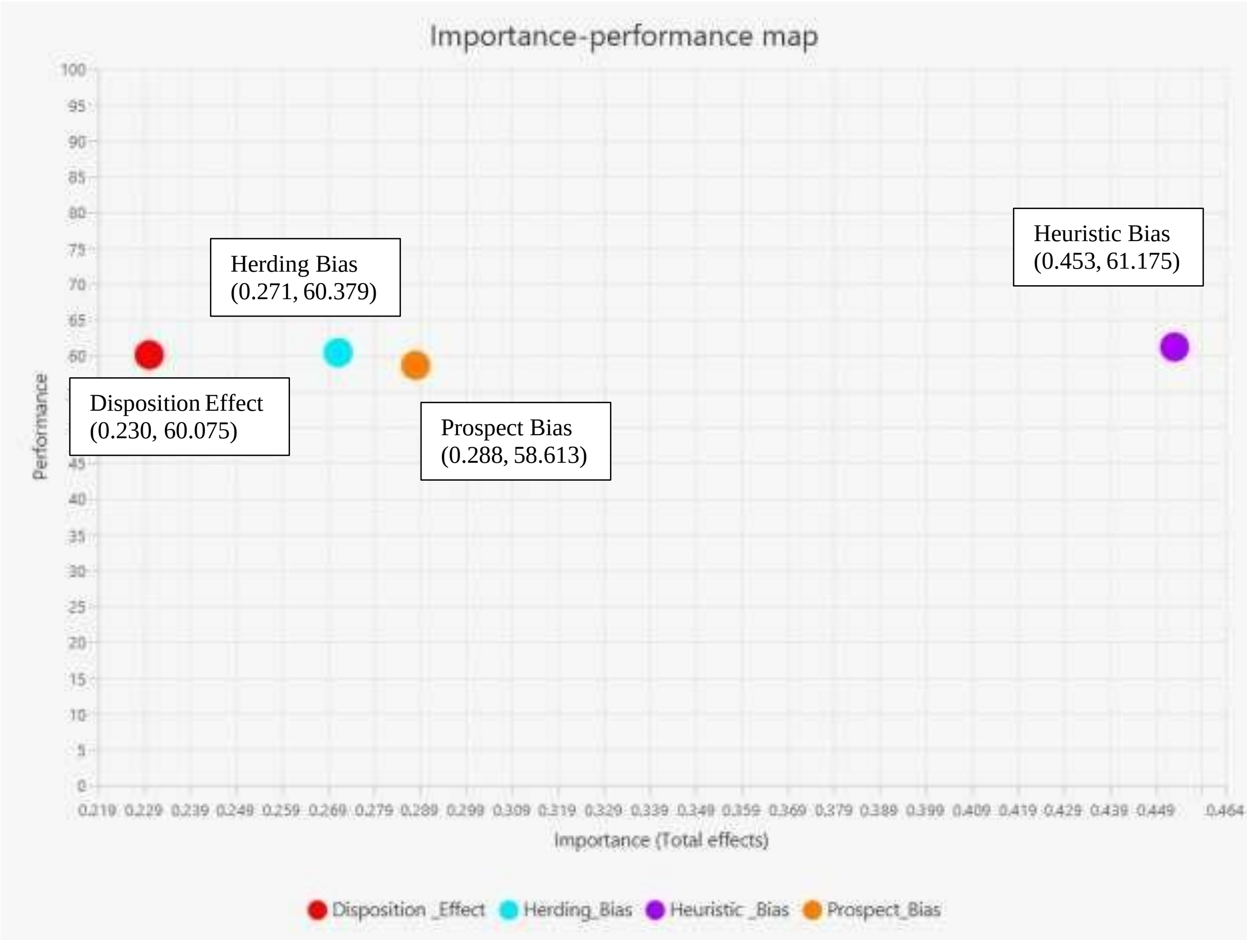
Importance and performance analysis (IPMA)

The IPMA analysis is also performed on the structural model explains. The IPMA method discusses about the "*importance*" and "*performance*" dimensions for the relationship between the included psychosocial biases and investment decision making of equity retail investors. The performance analysis represents the ***agreement level*** of the equity investors and the importance analysis represents the impact of different included psychosocial biases on the investment decision making of equity retail investors. The agreement analysis in IMPA depicts the average agreement level of equity retail investor in the scale of 1 to 100 for all the included psychosocial biases and investment decision making of equity retail investors. The higher performance indicator represents higher agreement of the equity retail investor. On the other hand, the importance analysis explains the impact of different included psychosocial biases on the investment decision making of equity retail investors as dependent factor. The results of IPMA analysis applied in the study is shown in fig and tables:

Table: IPMA

Nature of variable		Importance Analysis	Performance Analysis
Dependent Variable	Investment Decision Making	---	64.546
Independent Variable	Disposition Effect	0.230	60.075
Independent Variable	Herding Bias	0.271	60.379
Independent Variable	Heuristic Bias	0.453	61.175
Independent Variable	Prospect Bias	0.288	58.613

The result reported that the level of agreement of the investors is found to be highest in case of investment decision making, the outcome variable of the model. This is followed by the heuristic bias and almost same level of agreement is found in case of other biases. On the other side, the highest impact of the heuristic bias is found on the investment decision making (path coefficient=0.453), followed by prospect bias (path coefficient= 0.288). The other two biases namely the disposition effect and herding bias are found to have least but significant positive effect on the investment decision making of retail investors. The IPMA graph indicating the importance and performance level of the biases included in the model is shown below:



Necessary Condition Analysis

The investment decision making of the retail investors is found to be influences by the different Behavioural biases, however the magnitude of the influence is found different. One of another perspective to examine the influence of the biases on the investment decision making is with the perspective of sufficiency and necessity aspects. Here, the NCA methodology is used to examine the included biases as the necessary (must have logic) and sufficient perspective (should have logic) to influence the investment decision making. Here, the sufficient biases influence the IDM after the necessary biases initiates influencing the IDM of retail investors. The NCA approach is used on PLS SEM algorithm to examine the sufficient biases and the necessary biases influencing the IDM of retail investors. The combined approach of PLS-SEM and NCA has high potential to theory development and the generation of application in different perspectives. The results of the NCA approach applied on the collected responses are discussed below:

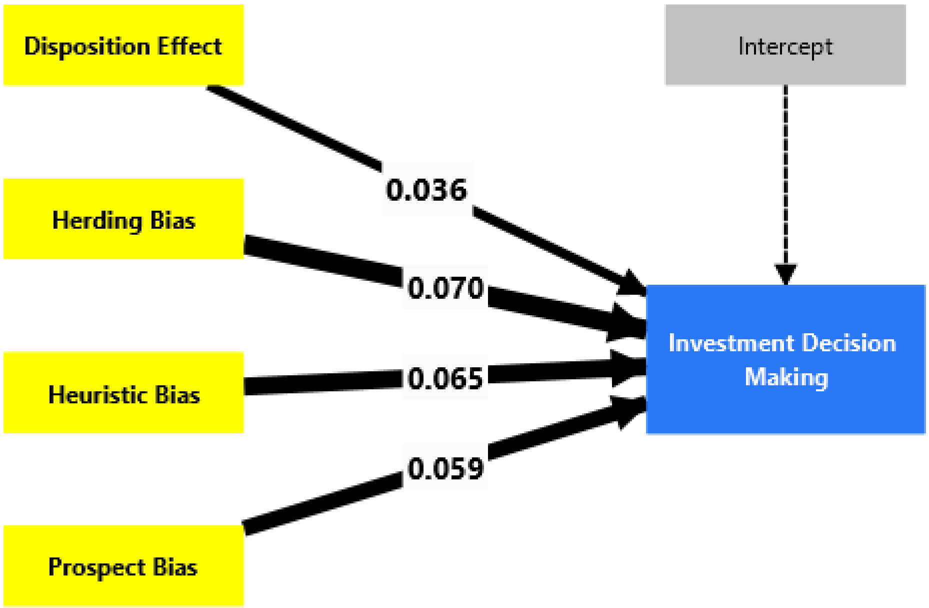


Table: NCA bottleneck table

	Investment Decision Making	***Disposition Effect***	***Herding Bias***	***Heuristic Bias***	***Prospect Bias***
0.000%	*1.275*	*0.000*	*0.000*	*0.000*	*0.000*
10.000%	*1.633*	*0.000*	*0.000*	*0.000*	*0.000*
20.000%	*1.990*	*0.000*	*0.000*	*0.000*	*0.000*
30.000%	*2.348*	*0.000*	*0.000*	*0.000*	*0.000*
40.000%	*2.706*	*0.000*	*0.000*	*0.000*	*0.000*
50.000%	*3.063*	*0.000*	*0.000*	*0.000*	*0.000*
60.000%	*3.421*	*0.000*	*0.000*	*0.000*	*0.000*
70.000%	*3.779*	*0.000*	*0.000*	*0.426*	*0.000*
80.000%	*4.136*	*0.000*	*0.000*	*0.426*	*0.000*
90.000%	*4.494*	*5.824*	*21.165*	*4.261*	*0.284*
100.000%	*4.852*	*54.545*	*98.295*	*79.403*	*99.432*

The results of NCA-PLS Sem reported in the table that the most necessary biases influence the IDM of the retail investors is prospect bias. Once the prospect bias stats influencing the investment decision making, the next bias *"Herding bias"* becomes active and starts affecting the IDM of the investors. Thus, on the basis of NCA analysis, the prospect bias and herding bias are found to be the necessary biases required to influence the IDM of the retail investors. Once, these biases becomes active in the retail investors, it is followed by the heuristic bias and disposition effect comes into picture and starts influencing the decision making of the retail investors. The effect size of the different biases and the accuracy level is reported in table shown below:

Table: Effect size and accuracy

	Effect size	*Accuracy*
Disposition Effect	*0.037*	*98.153*
Herding Bias	*0.063*	*98.011*
Heuristic Bias	*0.075*	*98.153*
Prospect Bias	*0.052*	*98.864*

The results reported that the highest effect size is found in case of heuristic bias, followed by herding bias, and the least effect size is found in case of disposition effect. The accuracy level of all the biases are found higher than 98% for all the biases.

5. CONCLUSION, DISCUSSION AND IMPLICATION

The role of behavioral biases in shaping the investment decision-making (IDM) of equity retail investors is an important focus of this study. The findings show that biases such as heuristic bias, prospect bias, herding bias, and the disposition effect strongly influence how investors make decisions, often leading them away from rational choices. Among these, heuristic bias was found to be the most impactful, meaning that mental shortcuts like overconfidence, availability bias, and anchoring play a big role in decision-making. This is supported by Jain et al. (2023), who explained that heuristic biases often lead to errors in judgment when investors face uncertainty.

There is a strong influence of prospect bias, driven by emotional factors such as loss aversion, regret aversion, and mental accounting. These findings align with Kahneman and Tversky's (1979) Prospect Theory, which explains that people value losses more strongly than gains, leading them to make decisions that are not always logical. Herding bias was another important factor, showing that investors often copy others' actions to avoid regret or take advantage of trends. Sood and Pathak (2022) also identified herding as a cause of instability and inefficiency in financial markets. While the disposition effect was less influential, it still showed that many investors hold on to losing stocks for too long and sell winning stocks too quickly, which agrees with earlier research by Thaler (1980) and Barberis and Thaler (2003).

The study also provides evidence of the interconnectedness of these biases, showing that their simultaneous presence can amplify their individual effects on IDM therefor, heuristic bias can make emotional biases like those in prospect theory even stronger, and herding behavior can worsen mistakes caused by loss aversion, especially during unstable market conditions

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