Behavioral Biases and Decision-Making in Day Trading: Examining the Roles of Risk Perception and AI Assistance

*Sherry Ritha Antony[1] and Siby Joseph K[2]

[1] Research Scholar, Department of Business Administration, St. Berchmans College, Changanacherry, Kottayam, Kerala, India. ORCID 0009-0007-1233-8438

[2] Professor, Department of Business Administration, St. Berchmans College, Changanacherry, Kottayam, Kerala, India

*sherry@sbcollege.ac.in

Abstract. Behavioral biases are mostly extensively studied in the context of long-term investment decisions however their influence on short-term, high-frequency trading such as day trading has received only limited attention. This research seeks to bridge the gap by exploring the influence of cognitive biases particularly anchoring and availability bias on investment decision-making, among day traders in Kerala, India, that operates in a volatile and fast-paced environment. The study also looks at how risk perception acts as a link in the decision-making process. and the moderating impact of Artificial Intelligence (AI) assistance over these relationships.

The study gathered primary data by giving a structured questionnaire to active day traders from Kerala using validated measurement scales. Responses gathered via convenience sampling were analyzed using SPSS 25.0. Reliability confirmed using Cronbach's alpha, construct validity ensured through correlation and confirmatory factor analysis (CFA), and hypotheses tested using PROCESS macro (Model 5).

The findings reveal that both anchoring and availability biases significantly influence day trading decisions. Risk perception serves as a partial mediator, shaping how traders interpret risk under cognitive distortions. Crucially, AI assistance moderates these effects, helping to mitigate bias-driven decisions and enabling more objective, data-informed trading behavior. By extending behavioral finance research into the domain of short-term trading, this study offers timely insights into the combined impact of psychological and technological factors on decision-making in Kerala's evolving retail trading landscape.

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1. Introduction

In recent years, the Indian equity market has witnessed a substantial increase in the involvement of retail investors, with a significant proportion comprising day traders, the individuals who engage in frequent buying and selling of stocks within short durations to leverage intraday price movements. The decision-making processes of these traders are not solely driven by empirical data; rather, they are often influenced by cognitive biases which are systematic psychological deviations that can impair rational judgment and lead to suboptimal investment choices.

Behavioral finance, an interdisciplinary domain integrating principles of psychology with financial theory, contests the classical notion of consistently rational investor behavior. The pioneering work of Tversky and Kahneman emphasized how mental shortcuts or heuristics and systematic judgment errors or cognitive biases shape financial decision-making. Among the most prevalent in the context of day trading are anchoring bias that happens when people rely too much on the first piece of information they see, whereas availability bias makes them decide based on whatever comes to mind most easily or recently. These cognitive distortions frequently cause traders to neglect holistic analysis and ignore broader market signals, culminating in inefficient or irrational investment outcomes [1].

An equally critical psychological dimension influencing trading behavior is risk perception, or the subjective evaluation of potential financial loss. Grounded in prospect theory [2], it is evident that individuals disproportionately fear losses compared to equivalent gains, often leading to skewed decision-making. In the high-volatility environment of day trading, such perceptions can intensify the impact of cognitive biases or fundamentally shift trading strategies, rendering investors either excessively risk-averse or disproportionately risk-tolerant.

At the same time, the growing use of Artificial Intelligence (AI) in financial markets has brought forth sophisticated tools designed to reduce the impact of cognitive biases on trading behavior. Technologies such as Explainable AI (XAI) deliver transparent, data-driven insights that can assist traders in moving beyond instinctual judgments. By presenting information in a structured and unbiased manner, AI has the potential to reduce the impact of biases like anchoring, thereby promoting more balanced and informed trading decisions [3].

Although behavioral finance literature has broadly examined such biases in developed markets, there is a relative dearth of research focusing on Indian retail traders, particularly those engaged in intraday trading. The nuanced interactions among anchoring and availability biases, individual risk perception, and also the role of AI-assisted decision support systems remain largely under- explored in this context.

The purpose of this study is to examine the influence of anchoring and availability biases on the way decisions are made by day traders in Kerala, India with a further examination of how the risk perception act as a mediator in that relationship and evaluates whether AI-based decision-support technologies moderate these relationships. A deeper understanding of these interrelationships could inform the design of tools and frameworks that promote more rational, bias-aware trading practices within India's fast-paced and predominantly volatile market landscape. The article has been divided into various sections for deeper understanding. Followed by Introduction section there is Literature review and Theoretical framework, This study's Research Methodology is detailed in the fourth section, leading into the presentation of the Data Analysis and Results. As the sixth section comes Major Findings followed by Discussion and the final section as Conclusion and Recommendations.

2. Literature Review

Traditional financial models, anchored by the Efficient Market Hypothesis (EMH), are built upon the well-designed assumption of a rational investor—an individual who is expected to process all available information logically to maximize their economic utility [4]. However, the persistent anomalies and volatile behaviors observed in real-world financial markets test this portrayal. In response, the field of behavioral finance has emerged, offering a more psychologically grounded perspective. It hypothesizes that investors are not purely rational agents but are systematically influenced by a host of cognitive biases and heuristics—mental shortcuts that, while efficient, can lead to predictable errors in judgment [5].

This paper explores two cognitive biases, anchoring and availability, and their effects on judgment. It explores how these mental shortcuts shape investment decision-making. Beyond simply identifying this direct relationship, this review examines the underlying mechanism, proposing that the influence of these biases is critically mediated by an investor's subjective risk perception [6]. Finally, in an era increasingly defined by financial technology, we investigate a novel and timely question: Can AI assistance, in the form of Robo-advisors, serve as a moderating force, buffering investors from their own psychological frailties [7]? By synthesizing the literature on these interconnected constructs, this review creates a theoretical framework to explain the intricate relationship among human psychology, risk, and technology in today's investment landscape.

2.1 Anchoring Bias: The Weight of First Impressions

At the core of many investment errors is the anchoring bias, a cognitive shortcut where an individual's decisions are disproportionately influenced by the first piece of information encountered [5]. This initial value, or "anchor," serves as a reference point from which subsequent judgments are made, with adjustments that are often insufficient to correct for the anchor's initial sway. In financial markets, this heuristic manifest when investors cling to arbitrary price points, such as the initial purchase price of a stock or its 52-week high, using them to gauge future value without adequate regard for new, fundamental information [8].

The hands-on consequences of this bias are significant. An investor who's anchored to a stock's initial high price might irrationally hold onto a declining asset, anticipating a return to that initial value, a behavior that can lead to substantial losses. This phenomenon, where investors are reluctant to adjust their beliefs in the face of new earnings data, has been shown to contribute to post-earnings announcement drift. Empirical evidence from various market contexts confirms a robust link between anchoring and suboptimal investment decisions [9] (Jain et al., 2023). For instance, research conducted during the chaotic start of the COVID-19 pandemic found that anchoring heavily influenced investor behavior [10]. The bias is not limited to novices; even seasoned financial professionals can fall prey, with their expert forecasts remaining tied to initial, and often irrelevant, estimates.

2.2 Availability Bias: The Distorting Power of Memory

Just as investors can be tethered to irrelevant numbers, their decisions can also be swayed by the vividness and recency of information, a phenomenon known as the availability bias [5]. This mental shortcut causes people to overestimate the likelihood of events that come to mind easily. Information that is recent, dramatic, or heavily publicized feels more salient and is therefore perceived as more likely to occur.

In the investment world, this can create significant misrepresentations in judgment. For instance, the aftermath of a widely reported market crash can trigger excessive risk aversion among investors, as the dramatic memory of the event surpasses long-term statistical probabilities. Conversely, a stock that receives an extensive, positive media coverage may probably attract a surge of investment, not because of its intrinsic value, but because positive information about it is so readily available in the investor's mind. Research has consistently been able to identify a relationship between availability bias and investment choices [6] [9]. Although the measured impact of availability may vary across different market conditions and investor populations, its potential to lead investors toward decisions based on salient but unrepresentative information is a cornerstone of behavioral finance.

2.3 Risk Perception: The Mediating Mechanism

While cognitive biases clearly influence outcomes, the mechanism through which they operate is often indirect. The link between a heuristic and an action is frequently filtered through the investor's subjective lens of risk perception, their personal and often emotional assessment of the risk intrinsic in an investment [11]. This perception is not an objective calculation of volatility but a dynamic and malleable judgment shaped by the very biases under discussion.

Recent literature increasingly positions risk perception as an important critical mediator explaining how biases translate into decisions [6]. An investor anchored to a stock's all-time high may wrongly believe its current low price is a bargain, prompting them to buy it despite the risk. Similarly, the availability of alarming news about a particular sector can dramatically amplify an investor's risk perception, prompting a premature sale. Structural equation models have provided empirical support for this mediating role, demonstrating that biases such as herding and overconfidence exert their primary influence on investment decisions by first altering the investor's perception of risk [11]. Understanding this very pathway is crucial, as it suggests that interventions aimed at improving investor rationality may further need to target the subjective perception of risk rather than just the biases themselves.

2.4 AI Assistance: A Potential Moderator for Irrationality?

In response to these persistent human fragilities, the financial industry has turned to technology. The rise of AI-powered Robo-advisors and other digital investment tools presents a fascinating new dynamic: the potential for technology to act as a rational counterweight to human bias. By providing algorithm-driven, data-centric analysis, theoretically AI could help investors to make better decisions by counteracting their cognitive biases.

A recent, pioneering study explored this moderating effect among investors on the New York Stock Exchange [7] The findings were captivating, revealing that the Robo-advisors helped investors overcome the negative influence of cognitive biases such as availability bias, anchoring, and loss aversion when making investment decisions. By offering an objective, un- emotional stream of analysis, these tools appear to help investors sidestep common psychological traps [7] However, the study also uncovered a notable limitation: AI assistance did not mitigate the effects of overconfidence. This suggests that investors with a high degree of self-belief may be more inclined to disregard algorithmic advice in favor of their own judgment. This finding underscore both the promise of AI in fostering more rational financial behavior and the enduring challenge of human psychology, highlighting a critical area for future research.

3. Theoretical Background

Here the financial decision-making, predominantly among day traders, is understood through the lens of behavioral finance. Traditional economic theories assume rationality; however, behavioral finance reveals that cognitive biases, heuristics, and psychological factors often influence decision making. This chapter provides a theoretical foundation for the study by examining the relationships among anchoring bias, availability bias, risk perception, AI assistance, and decision making, with specific attention to the behavioral tendencies of day traders in Kerala.

3.1 Anchoring Bias and Day Trading Decision-Making

Anchoring bias reflects the mental tendency of individuals to overly rely the initial piece of information, known as the anchor, that influences their choices. In the context of day trading, traders often anchor to previous price points, historical highs or lows, or their initial impressions of a stock, which can distort real-time decision-making in fast-moving markets. This bias is grounded in Prospect Theory [2], which suggests that retail investors assess outcomes relative to reference points rather than evaluating them in objective terms. Anchoring can therefore skew a trader's judgment of potential gains or losses. Based on the Theory of Planned Behavior [12], anchoring bias can influence the attitude component, shaping a trader's evaluation of a trading opportunity based on outdated or irrelevant reference points rather than updated market data.

H1: Anchoring bias significantly influences decision-making among day traders.

3.2 Availability Bias and Day Trading Decision-Making

Availability bias happens when people estimate how likely or important something is just by how easily they can remember similar instances. For day traders, recent news, striking headlines, or dramatic market movements often become disproportionately influential, prompting decisions that are not necessarily based on objective data. The Availability Heuristic [5] explains how such ease of recall can distort perception. Within the TPB framework, these bias influences attitudinal judgments, as traders form opinions based on the most readily available but not always accurate information.

H2: Availability bias significantly influences decision-making among day traders.

3.3 Role of Risk Perception in Day Trading

Risk perception refers to a trader's personal evaluation of the uncertainty and possible losses associated with a trading decision. In the high-stakes environment of day trading, this perception critically mediates how cognitive biases translate into actual trading behavior. According to Behavioral Decision Theory [13], individuals interpret risk through a lens of emotions and heuristics rather than objective evaluation. Anchoring and availability biases can shape how traders perceive the volatility or safety of a particular trade. Within TPB, risk perception aligns with perceived behavioral control, reflecting a trader's confidence in navigating uncertain market conditions. In this way, it connects the influence of biases to the decisions traders actually make.

H3: Risk perception acts as a mediator between anchoring bias and day traders' decision-making.

H4: Risk perception acts as a mediator between availability bias and day traders' decision-making.

3.4 Role of AI Assistance in Day Trading

The rising integration of AI in various domains and particularly in trading platforms offers real-time data analysis, predictive modelling, and algorithmic trade recommendations, which can help mitigate the influence of cognitive biases in day trading. Guided by the Technology Acceptance Model [14], traders' adoption of People often use AI tools based on how helpful and easy to use they think they are. In the TPB framework, AI tools may enhance perceived behavioral control, enabling day traders to make more rational, informed decisions even when biased tendencies are present.

H5: AI assistance moderates the effect of anchoring bias on day traders' decision-making

H6: AI assistance moderates the effect of availability bias on day traders' decision-making

3.5 Summary of Theoretical Integration

The study is grounded in multiple theoretical frameworks that collectively explain the intricate interactions among behavioral biases, risk perception, technological tools, and decision-making in day trading. Prospect Theory [2] provides the foundation for understanding irrational investment behavior, particularly how loss aversion and reference dependence influence trader choices.

Behavioral Decision Theory [15] adds depth by emphasizing the subjective nature of risk perception, which varies across individuals and contexts. The Theory of Planned Behavior [12] offers a cognitive-behavioral link, suggesting that investment decisions are shaped by attitudes formed through biases and perceived risks. Furthermore, the Technology Acceptance Model [14] supports the inclusion of AI assistance reducing bias influence helping traders make smarter and more rational decisions.

3.6 Conceptual Framework

Drawing from these theoretical insights, the conceptual framework of this study brings together key elements that influence trading decisions among day traders in Kerala, India. Anchoring and availability biases, shaped by cognitive shortcuts, are seen as central behavioral influences. These biases interact with how traders perceive Risk, which is originally often depends on personal experience and the situation, making it subjective. The inclusion of AI-based decision support is guided by the Technology Acceptance Model, recognizing that a trader's willingness to adopt and trust AI tools can shape how effectively these tools help counteract bias. Together, this framework offers a comprehensive view of how psychological tendencies and technology come together to influence real-time trading behavior.

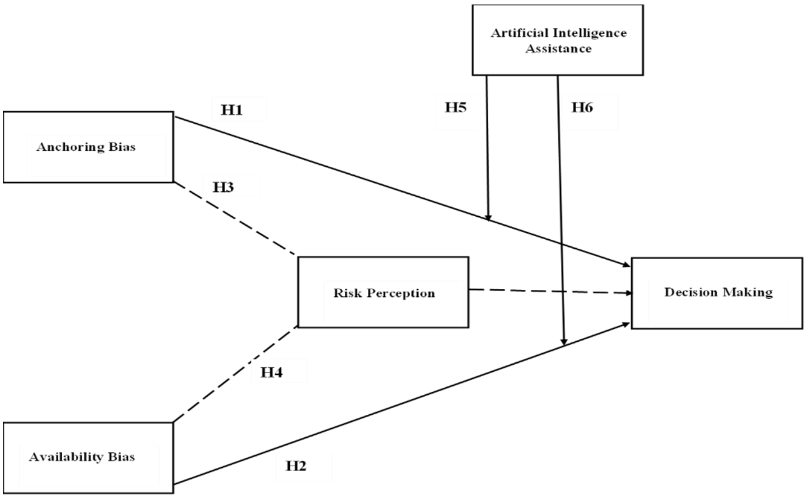

Fig.1.Conceptual Framework

Source: Self

4. Research Methodology

4.1 Target Population and Sample Size

To explore how behavioral biases and AI assistance shape the decision making of Kerala's day traders in the Indian equity market, Respondents were identified through a blend of purposive and snowball sampling strategies. Respondents were deliberately selected based on specific inclusion criteria: they had to be residents of Kerala, actively engaged in day trading (executing multiple buysell transactions within the same trading day), with a minimum of six months of continuous trading experience, and users of online trading platforms, including those offering AI-based decision support. This ensured that the sample comprised traders with sufficient exposure to market dynamics and susceptibility to cognitive biases. Given the niche and network-driven nature of the day trading community, initial participants identified through trading forums and brokerage contacts were further requested to refer other qualified traders. This snowball approach helped capture a broader and more diverse group of day traders from key trading hubs such as Kochi, Thiruvananthapuram, and Kozhikode.

Table 1 shows that 345 questionnaires were shared, and 317 valid ones were received back (response rate: 91.9%). The final sample comprised 317 day traders, which is considered adequate for robust statistical analysis, particularly when employing the PROCESS macro for mediation and moderation testing. According to [16], for detecting mediation effects of medium magnitude using bootstrapping methods, a sample size of approximately 250–300 is recommended to achieve sufficient statistical power (typically 0.80). Furthermore, the chosen sample size aligns with guidelines for behavioral studies involving multiple paths and indirect effects [17]. Given the specific focus on day traders a population that is relatively niche and harder to access compared to general investors the achieved sample size offers a reliable and meaningful representation. It provides adequate power to detect the hypothesized relationships while ensuring the generalizability of findings across the active trading community in Kerala.

Table 1 Breakdown of Sample size

Particulars	No. of Questionnaires	Percentage
Composition of Questionnaire		
Questionnaires distributed	345	100
Questionnaire completed	317	92
Questionnaire discarded	20	6
Questionnaire not returned	8	2

4.2 Data Collection Procedure

A structured questionnaire was developed and distributed among day traders through both online platforms (such as trading forums, Telegram groups, and WhatsApp communities) and offline distribution at brokerage outlets across major towns in Kerala (e.g., Kochi, Kozhikode, and Thiruvananthapuram). The questionnaire was first tested through a pilot study with thirty day traders and two subject experts to confirm that the items were clear, reliable, and appropriately represented the intended constructs.

4.3 Measurement of Variable

All study constructs were assessed with established scales from previous research, which were adapted to suit the Indian context for clarity and relevance. Participants provided their responses on a five-point Likert scale. The following measurement items were used initially during pilot study.

Anchoring Bias (5 items): Adapted from [18], focusing on investors' reliance on initial prices or information during trading decisions.

Availability Bias (5 items): Adapted from [18], to measure how easily retrievable or recent information influences investment judgments.

Risk Perception (5 items): Adopted from [19], evaluating investors' subjective perception of risk associated with stock trading activities.

AI Assistance (7 items): AI assistance was measured with a seven-item scale, adapted from earlier studies on AI self-efficacy [20]

Decision- making (5 items): Adapted from [21], focusing on decision-making quality, speed, and confidence in trading execution.

To enhance model fit and maintain scale efficiency, the three highest-loading items per construct were retained during confirmatory factor analysis, following the guidance of [22], who recommend item reduction when internal consistency and validity remain robust. [23] further assert that "retaining only the most representative items can maintain the construct's theoretical integrity while improving estimation efficiency." Empirical support for this approach is provided by [6], who demonstrate that focusing on high-loading indicators preserves construct validity without compromising measurement quality. In this study, the strategy demonstrated strong internal consistency (Cronbach's alpha values fell within the range of 0.78 to 0.89) and convergent validity (AVE values above 0.50), ensuring that even complex constructs like investment decision-making retained their conceptual clarity and psychometric soundness

5. Data Analysis and Results

The data were analyzed with the help of SPSS version 26 and AMOS version 24. First, basic descriptive statistics were used to give an overview of the demographic details (Table 2Next, reliability was evaluated using Cronbach's alpha to confirm the internal consistency of the measurement scales (Table 3). Confirmatory Factor Analysis (CFA) was subsequently carried out in AMOS to ensure that the constructs were valid. Finally, the hypothesized mediation and moderation relationships were examined using the PROCESS macro (Model 5) in SPSS, a regression-based approach designed for conditional process analysis.

5.1 Demographic Characteristics of the Respondents

The demographic characteristics of the respondents provide essential background information that helps contextualize their trading behavior and decision-making patterns. Variables including age, gender, education, income, and trading experience provide important information about the diversity and representativeness of the sample

Table 2 | Demographic Profile

Variables	Frequency	Percentage
Age (in years)		
20- 30	180	57
31-40	87	27
41-50	35	11
51-60	13	4
Above 60	2	1
Gender		
Male	267	84
Female	50	16
Monthly Income		
Below ₹25,000	46	15
₹25,001–₹50,000	58	18
₹50,001–₹1,00,000	121	38
Above 1,00,000	92	29
Years of Trading Experience		

Less than 1 year	74	23
1 year to 3 years	113	36
3 to 5 years	82	26
More than 5 years	48	15

From the table 2 we can say that the sample primarily consists of young male day traders, with 57% aged 20–30 years and 84% identifying as male. A majority of respondents (67%) earn above ₹50,000 per month, reflecting a relatively high-income profile. In terms of trading experience, most participants are moderately experienced, with 36% having 1 to 3 years and 26% with 3 to 5 years of trading. Notably, 23% are relatively new (less than 1 year), suggesting a blend of novice and seasoned traders in the sample.

5.2 Reliability Analysis

Cronbach's Alpha is employed to evaluate the internal consistency, or reliability, of a group of survey or test items designed to measure the same construct. A higher Cronbach's Alpha value indicates that the items are closely related and consistently reflect the construct they are intended to measure.

Table 3 | Reliability Statistics

Variables	No. of items	Cronbach's Alpha
Anchoring Bias	3	0.78
Availability Bias	3	0.86
Risk Perception	3	0.79
AI Assistance	3	0.83
Decision-making	3	0.89

Table 3 presents the Cronbach's Alpha coefficients for all constructs, with values ranging from 0.78 to 0.89. These results indicate satisfactory to high internal consistency across all measurement scales. According to [22] in social science research, a Cronbach's Alpha value of 0.70 or above is generally regarded as acceptable, particularly in exploratory studies. Thus, the reliability of each construct is deemed robust and suitable for further analysis.

5.3 Assumption Testing

Before performing CFA and testing the hypotheses, assumption checks were carried out to ensure the suitability of the dataset for regression-based analyses and structural modeling.

Normality was checked by looking at the skewness and kurtosis of the data. All variables exhibited skewness and kurtosis within the acceptable threshold of ±2.0, indicating approximate univariate normality [24]

Multicollinearity was checked by examining the VIF and tolerance values for all predictor variables. VIF values ranged from 1.12 to 2.48 (well below the threshold of 5), and Tolerance values exceeded 0.40, indicating that multicollinearity was not a concern. [22].

To check for homoscedasticity, a visual inspection of scatterplots of standardized residuals against predicted values revealed no discernible patterns or heteroscedastic structures, thereby confirming the assumption of homoscedasticity [25]. These diagnostic tests confirm that the data met key assumptions required for valid interpretation of regression and PROCESS macro analyses.

5.4 Confirmatory Factor Analysis

Confirmatory Factor Analysis (CFA), evaluates the measurement model's validity and reliability. It includes standardized factor loadings, Composite Reliability (CR), and Average Variance Extracted (AVE) for each construct.

Table 4 | Confirmatory Factor Analysis – Standardized Loadings, CR, and AVE

Construct	Item Code	Std. Factor Loading	CR	AVE
Anchoring Bias	AB1	0.74	0.83	0.55
	AB2	0.78		
	AB3	0.71		
Availability Bias	AVB1	0.76	0.85	0.6
	AVB2	0.81		
	AVB3	0.78		
Risk Perception	RP1	0.79	0.87	0.62
	RP2	0.84		
	RP3	0.75		

AI Assistance	AI1	0.77	0.84	0.57
	AI2	0.8		
	AI3	0.72		
Decision-making	ID1	0.76	0.86	0.59
	ID2	0.79		
	ID3	0.78		

Table 4 gives the results of confirmatory factor analysis (CFA). Although the original scales comprised 5 to 7 items per construct, only the top three items with the highest standardized loadings were retained after confirmatory factor analysis, ensuring better model fit and parsimony. All retained factor loadings exceeded the minimum threshold of 0.70, indicating good item reliability. CR values for all constructs ranged from 0.83 to 0.87, surpassing the recommended 0.70 level, thereby establishing internal consistency. With AVE values from 0.55 to 0.62, all above the 0.50 benchmark, convergent validity was established

5.5 Discriminant Validity Analysis

Discriminant validity was checked using the Fornell-Larcker criterion, which compares the square root of AVE with the correlations between constructs [24] [26]. This shows that each construct is clearly different and not too closely related to the others in the model

Table 5 | Discriminant Validity – Fornell-Larcker Criterion

Construct	Anchoring Bias	Availability Bias	Risk Perception	AI Assistance	Decision-making
Anchoring Bias	**0.74**				
Availability Bias	0.58	**0.77**			
Risk Perception	0.49	0.54	**0.79**		
AI Assistance	0.4	0.42	0.48	**0.75**	

Decision-making	0.51	0.55	0.61	0.58	**0.77**

Table 5 presents the outcomes of the Fornell-Larcker test used to assess discriminant validity. Bold numbers on the diagonal show the square root of AVE for each construct, and the other values indicate correlations between constructs. The square root of AVE for every construct is higher than its strongest correlation with other constructs, showing that discriminant validity is adequate. This shows that each construct is separate and represents different aspects of the behavioral framework.

5.6 Model Fit Analysis

Model fit analysis is a critical step in assessing how well a proposed model represents the data. It involves evaluating various fit indices to determine whether the model effectively represents the relationships among the variables and is suitable for the research context.

Table 6 | Model Fit Indices of the Measurement Model

Fit Index	Recommended Value	Obtained Value
Chi-Square/df (CMIN/df)	≤ 3.00	2.01
Comparative Fit Index (CFI)	≥ 0.90	0.94
Tucker-Lewis Index (TLI)	≥ 0.90	0.92
Root Mean Square Error of Approximation (RMSEA)	≤ 0.08	0.056
Standardized Root Mean Square Residual (SRMR)	≤ 0.08	0.041

Table 6 presents a summary of the model fit indices for the CFA model. The Chi-Square/df value was 2.01, indicating acceptable fit. CFI and TLI exceeded 0.90, demonstrating excellent comparative fit. The RMSEA and SRMR values were comfortably below the recommended maximum threshold of 0.08, indicating that the model fits the data well. Taken together, these indices show that the measurement model is adequate. and support its use in further structural analysis.

5.7 Hypothesis Testing and Results

To examine the relationships hypothesized in the study, both SEM (Structural Equation Modeling) in AMOS and PROCESS Macro in SPSS were employed. Hypotheses H1 and H2 were tested using SEM in AMOS, while H3 to H6, involving mediation and moderation, were tested using PROCESS Macro (Model 5).

The results of each hypothesis are presented below in the table 7

H1 & H2: Direct Effects (Tested in AMOS)

Table 7 | Standardized Regression Weights for Direct Paths

Path	Standardized Estimate	S.E.	C.R.	p-value
Anchoring Bias → Decision-making	0.44	0.05	8.8	<0.001
Availability Bias → Decision-making	0.39	0.06	6.5	<0.001

Both anchoring bias and availability bias significantly influenced Decision-making, confirming H1 and H2. The strong positive beta weights indicate that as bias levels increase, the likelihood of suboptimal Decision-makings also increases.

H3 & H4: Mediation Analysis (Tested in PROCESS Macro – Model 5)

Table 8 | Mediation Effects via Risk Perception with 95% Confidence Intervals

Effect Type	Path	β Coefficient	Lower CI	Upper CI	Significance
Direct Effect	Anchoring Bias → Decision-making	0.31	0.2	0.42	Significant
Direct Effect	Anchoring Bias → Risk Perception	0.45	0.34	0.56	Significant

Direct Effect	Risk Perception → Decision-making	0.29	0.19	0.39	Significant
Indirect Effect	Anchoring Bias → Risk Perception → Decision-making	0.13	0.08	0.19	Significant
Direct Effect	Availability Bias → Decision-making	0.26	0.15	0.36	Significant
Direct Effect	Availability Bias → Risk Perception	0.42	0.3	0.53	Significant
Indirect Effect	Availability Bias → Risk Perception → Decision-making	0.13	0.07	0.2	Significant

Table 8 presents the bootstrapped estimates of direct and indirect effects with 95% confidence intervals, tested using PROCESS Macro (Model 5). Anchoring bias had a significant direct effect on Decision-making (β = 0.31, CI [0.20, 0.42]), and also significantly influenced risk perception (β = 0.45, CI [0.33, 0.56]), which in turn impacted Decision-making (β = 0.29, CI [0.19, 0.39]). The resulting indirect effect (β = 0.13, CI [0.08, 0.19]) was significant, confirming partial mediation. Similarly, availability bias showed a significant direct effect on Decision-making (β = 0.26, CI [0.15, 0.36]), significantly influenced risk perception (β = 0.42, CI [0.30, 0.53]), which again had a significant effect on Decision-making (β = 0.29, CI [0.19, 0.39]). The indirect effect for this path (β = 0.13, CI [0.07, 0.20]) was also significant, establishing partial mediation. All confidence intervals excluded zero, indicating statistical significance.

H5 & H6: Moderation Analysis (Tested in PROCESS Macro – Model 5)

Table 9 | Moderation Effects of AI Assistance

Interaction Term	β Coefficient	t-value	p-value
Anchoring Bias × AI Assistance	-0.12	-2.8	0.005
Availability Bias × AI Assistance	-0.1	-2.45	0.014

Table 9 shows that the AI assistance had a significant moderating effect on the relationship between cognitive biases and decision-making. As shown in the interaction plot below, the slope of the bias–investment relationship is steeper when AI assistance is low, and flatter when AI assistance is high, suggesting that AI tools help traders mitigate the impact of cognitive distortions.

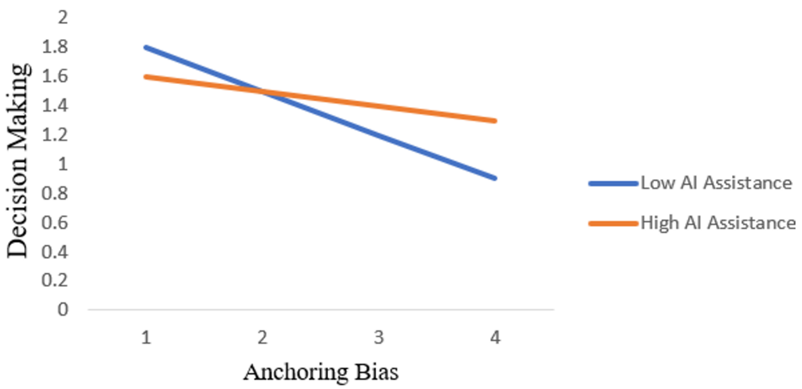

Fig. 2. Moderation Effect of AI Assistance on Anchoring Bias to Decision Making

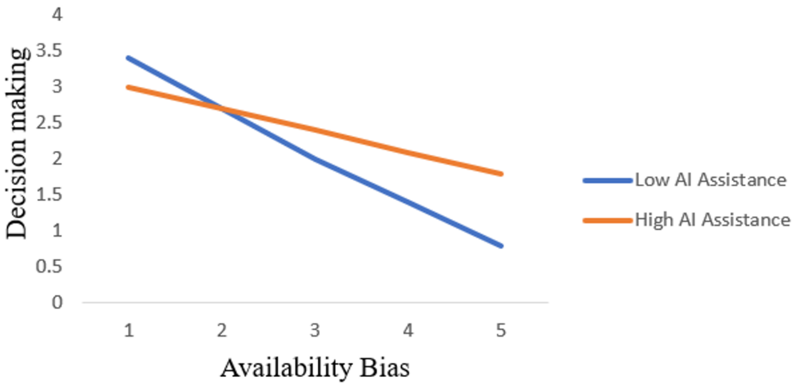

Fig. 3. Moderation Effect of AI Assistance on Availability Bias to Decision Making

The moderation graphs illustrate how AI Assistance alters the strength of the relationship between cognitive biases and Decision-making. In the case of Anchoring Bias, the negative interaction term (β = -0.12, p = 0.005) indicates a stronger moderating effect, where higher levels of AI Assistance significantly dampen the influence of anchoring on Decision-making. This is visually represented by a steeper slope under low AI assistance and a noticeably flatter slope under high AI assistance, highlighting how reliance on initial reference points becomes less impactful when AI tools are employed. In comparison, the interaction between Availability Bias and AI Assistance (β = -0.10, p = 0.014) also demonstrates a significant but slightly weaker moderating effect. The lines representing high and low levels of AI Assistance still diverge, but with a less pronounced difference in slope, suggesting that while AI mitigates the effect of recent or easily retrievable information, the reduction in bias is somewhat milder than in the case of anchoring. These findings reinforce the role of AI Assistance as a cognitive debiasing tool, with varying degrees of effectiveness across different types of biases.

6. Major Findings

The study aimed to observe the influence of behavioral biases anchoring and availability bias on trade decision-making among day traders in Kerala, with exploring the role of risk perception and AI assistance in the relationship. The analysis revealed several significant findings.

Firstly, both anchoring bias and availability bias exhibited strong and statistically significant direct effects on decision making. This underscores the persistent influence of heuristic-driven judgments among traders. Secondly, risk perception was found to partially mediate these relationships. Specifically, both biases had significant indirect effects on decision-making through risk perception, indicating that part of the influence of biases operates via investors' subjective risk evaluations. Furthermore, AI assistance moderated the direct effects of both biases on decision making. The negative interaction effects suggest that the presence of AI support can attenuate the influence of anchoring and availability biases, thereby improving decision quality.

7. Discussion

This study investigated the intricate relationships between cognitive biases specifically anchoring and availability biases and decision-making among day traders in Kerala, considering the mediating role of risk perception and the moderating influence of AI assistance. By focusing on a regionally concentrated trading population, the study offers contextualized insights into how behavioral heuristics and technological tools jointly influence decision-making in short-term trading environments. These findings extend the existing body of knowledge in behavioral finance by extending established theoretical models to the domain of day trading within Kerala's emerging retail investor ecosystem.

7.1 Influence of Anchoring Bias on Decision-making

Our analysis revealed that anchoring bias significantly impacts Decision-making, indicating that traders often anchor their decisions on initial pieces of information or reference points which can disproportionately influence subsequent judgments. This finding aligns with [8], who observed that individuals tend to fixate on initial figures, such as historical stock prices, which can distort valuation processes and result in suboptimal investment choices. Similarly, [3] demonstrated that anchoring bias adversely affects purchase decisions, suggesting a pervasive influence across various financial behaviors. [27] observed that many Robinhood users, particularly day traders, tend to make quick decisions based on attention-grabbing cues like trending stocks and top-mover lists. This kind of behavior reflects anchoring bias, were initial information sticks and influences choices, often leading to poor investment outcomes.

Conversely, some studies suggest that the impact of anchoring bias may be context-dependent. For instance, [28] report that in highly volatile market environments, the influence of anchoring bias on Decision-makings tends to diminish, as investors shift their attention towards real-time data and current market dynamics rather than historical reference points. This is especially true for day traders, who work in a high-pressure environment where they often have just minutes or even seconds to make a decision.

7.2 Impact of Availability Bias on Decision-making

The study found that availability bias significantly influences Decision-making, as investors tend to overemphasize readily available or recent information. This cognitive shortcut often leads to irrational decision-making based on salience rather than substance. For instance, [27] observed that Robinhood users frequently traded stocks featured on Top Movers lists, indicating decisions driven more by visibility than intrinsic value. Similarly, [28] found that investors' choices are often swayed by recent news or events, leading to an overestimation of the importance of such information. These findings underscore the typical manifestation of availability bias in modern, fast-paced trading environments.

However, the influence of availability bias is not uniform across all investor profiles. Several studies have reported mixed results, highlighting the moderating effects of investor experience, education, and trading style. For example, [28] observed that experienced investors are more likely to rely on comprehensive analysis and diversified data sources, thus exhibiting greater resistance to availability bias. This is consistent with findings from [29], who emphasized that professional and institutional investors often follow disciplined decision-making frameworks and utilize advanced analytical tools, enabling them to mitigate the effects of cognitive biases.

Therefore, while availability bias may strongly affect novice and retail investors, especially in high-frequency trading contexts, it appears to be less pronounced among seasoned or institutional participants. This highlights the context-dependent nature of behavioral biases and suggests the need for tailored behavioral interventions or investor education programs, especially for vulnerable segments like day traders.

7.3 Mediating Role of Risk Perception

Risk perception was found to partially mediate the link between cognitive biases and decision-making, highlighting its role as an important psychological bridge in the process. This indicates that while anchoring and availability biases directly affect investment choices, they also shape how investors perceive risk, which in turn influences their decisions. [28] found risk perception acts like a filter between behavioral biases and decision-making, shaping how strongly those biases actually influence the choices traders make highlighting the subjective nature of risk assessment and its susceptibility to cognitive distortions. In a similar vein, [6] showed that risk perception links cognitive biases to investment decisions, supporting the findings of our research.

On the other hand, some studies have questioned the strength of this mediating effect. For instance, research suggests that for certain types of investments, like real estate, risk perception might play a smaller role as a mediator with other factors like market knowledge playing a more significant role [28]. This shows that risk perception may influence decisions differently depending on the type of investment.

7.4 Moderating Effect of AI Assistance

The results further show that AI support can change how cognitive biases affect decision-making. The negative interaction effects suggest that AI tools can mitigate the influence of biases, promoting more rational investment behaviors. This aligns with findings by [3], who reported that AI-based decision support systems can help reduce the negative effects of anchoring bias. [30] highlight that human decision-making often defaults to fast, intuitive responses, which increases vulnerability to cognitive biases. In contrast, AI-based systems that encourage slower, more deliberate processing can help mitigate such biases particularly in investment contexts where anchoring to recent trends or initial valuations can distort judgment.

8. Conclusion and Recommendations

8.1 Conclusion

This study investigated the influence of cognitive biases specifically anchoring and availability biases on the decision-making of day traders, with risk perception as a mediating variable and AI assistance as a moderator. Day traders, characterized by frequent, short-term trades and rapid decision-making under uncertainty, are especially susceptible to behavioral biases that can impair rational judgment.

The findings indicate that both anchoring and availability biases significantly predict decision-makings among day traders. Anchoring effects, such as fixation on previous stock prices or arbitrary benchmarks, and availability heuristics, where recent or salient information overshadows objective data, were found to positively influence trading choices. Risk perception emerged as a partial mediator in both relationships, suggesting that these biases shape how traders assess risk, which subsequently influences their decision-making.

Furthermore, the moderating effect of AI assistance revealed that technological tools can significantly buffer the impact of these biases. When AI-based decision support systems were present, the strength of the relationship between biases and decision-making weakened. This indicates the potential of intelligent trading platforms to serve as behavioral correctives, enabling day traders to mitigate heuristic-driven errors.

These results offer critical insights into the psychological mechanisms influencing intraday market behavior and the role of emerging technologies in improving decision quality. The results help expand our understanding of behavioral finance by extending established theoretical models to the domain of day trading, with a specific focus on Kerala's growing retail investor segment, thereby offering region-specific insights within the broader Indian market context.

8.2 Theoretical Implications

This study extends behavioral finance literature by applying dual-process theory, bounded rationality, and the Theory of Planned Behavior (TPB) to the context of day trading. It confirms that even in high-speed trading environments, cognitive biases such as anchoring and availability remain influential. The mediating role of risk perception aligns with TPB's attitudinal component, while the moderating role of AI assistance reflects perceived behavioral control. These findings support the view that day traders, despite technological support, continue to rely on heuristics under bounded rationality.

These findings further enrich the ongoing discussion on how the effects of heuristics can vary across different contexts. While prior studies often examined biases in stable, long-term investment environments, this study demonstrates that heuristics are equally relevant in short-term, high-volatility settings like day trading. By validating the interaction between cognitive shortcuts and perceived control mechanisms (e.g., AI tools), the study underscores the need for an updated behavioral framework that accommodates both traditional biases and emerging technological influences within dynamic trading ecosystems.

8.3 Practical Implications

For Day Traders: Recognizing the influence of biases such as anchoring and availability is essential. Since day traders make rapid decisions based on limited information, being aware of psychological pitfalls can enhance risk assessment and trading discipline.

For Platform Designers and Brokers: Incorporating AI-driven nudges or alerts that flag bias-prone behavior (e.g., overreliance on previous price levels) can help improve trading outcomes.

For Educators and Trainers: Financial training programs should not only focus on technical analysis but also integrate behavioral components tailored for high-frequency traders.

8.4 Recommendations

1. **Bias Monitoring Tools**: Trading platforms should incorporate behavioral analytics to monitor bias-driven trading patterns and offer corrective suggestions.
2. **Customized Risk Profiling**: Since risk perception mediates the bias-decision link, platforms can develop real-time, adaptive risk perception modules that reflect changing trader sentiment and market volatility.
3. **Promote AI Integration**: Encourage day traders to use AI supported tools that provide emotion-neutral, data-driven insights to counteract cognitive distortions.
4. **Behavioral Finance Training for Day Traders**: Regular workshops and simulations should be conducted to increase awareness of biases and their effect on intraday decision-making.

8.5 Limitations and Future Scope

While offering valuable findings, the study is limited because it depends on participants' self-reports and only captures a single point in time. Future research could benefit from real-time experimental designs using trading simulators or actual platform data to capture behavioral deviations more accurately. Moreover, exploring additional biases such as overconfidence or confirmation bias among day traders could further enhance the robustness of behavioral models in trading psychology. Additionally, the study's geographic focus on day traders from Kerala a key but region-specific subset of India's retail trading population limits the generalizability of the findings. Cultural, technological, and financial literacy variations across Indian states may lead to differing behavioral patterns. Future studies should replicate this framework in diverse geographic and socio-economic contexts to enhance national applicability.

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Reference

1. Sharma, A., Prajapati, B.: An analysis of behavioral biases in investment decision making. In: Proceedings of the 5th International Conference on the Role of Innovation, Entrepreneurship and Management for Sustainable Development (ICRIEMSD-2024), pp. 3–16. Atlantis Press (2024).
2. Kahneman, D., Tversky, A.: Prospect theory: An analysis of decision under risk. Econometrica 47(2), 263–291 (1979).
3. Haag, F., Stingl, C., Zerfass, K., Hopf, K., Staake, T.: Overcoming anchoring bias: The potential of AI and XAI-based decision support. arXiv preprint (2024).
4. Byrne, A., Brooks, M.: Behavioral finance: Theories and evidence. The Research Foundation of CFA Institute (2008).
5. Tversky, A., Kahneman, D.: Judgment under uncertainty: Heuristics and biases. Science 185(4157), 1124–1131 (1974).
6. Zhang, M., Nazir, M.S., Farooqi, R., Ishfaq, M.: Moderating role of information asymmetry between cognitive biases and investment decisions: A mediating effect of risk perception. Frontiers in Psychology 13, 828956 (2022).
7. Ahmad, U., Van Keulen, M., Briassouli, A., Saad, M.: Cognitive biases, Robo advisor and investment decision psychology: An investor's perspective from New York stock exchange. Acta Psychologica 256, 105048 (2025).

8. Owusu, S.P., Laryea, E.: The impact of anchoring bias on investment decision-making: Evidence from Ghana. Review of Behavioral Finance 15(5), 729–749 (2023).
9. Jain, J., Walia, N., Singla, H., Singh, S., Sood, K., Grima, S.: Heuristic biases as mental shortcuts to investment decision-making. Risks 11(4), 72 (2023).
10. Kathpal, S., Akhtar, A., Zaheer, A., Khan, M.N.: Covid-19 and heuristic biases: evidence from India. Journal of Financial Services Marketing 26(4), 305–316 (2021).
11. Almansour, B.Y., Elkrghli, S., Almansour, A.Y.: Behavioral finance factors and investment decisions: A mediating role of risk perception. Cogent Economics & Finance 11(1), 2239032 (2023).
12. Ajzen, I.: The theory of planned behavior. Organizational Behavior and Human Decision Processes 50(2), 179–211 (1991).
13. Slovic, P., Finucane, M.L., Peters, E., MacGregor, D.G.: Risk as analysis and risk as feelings: Some thoughts about affect, reason, risk, and rationality. Risk Analysis 24(2), 311–322 (2004).
14. Davis, F.D.: Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly 13(3), 319–340 (1989).
15. Slovic, P.: Perception of risk. Science 236(4799), 280–285 (1987).
16. Fritz, M.S., MacKinnon, D.P.: Required sample size to detect the mediated effect. Psychological Science 18(3), 233–239 (2007).
17. Hayes, A.F.: Partial, conditional, and moderated moderated mediation: Quantification, inference, and interpretation. Communication Monographs 85(1), 4–40 (2018).
18. Ritika, Kishor, N.: Development and validation of behavioral biases scale: A SEM approach. Review of Behavioral Finance 14(2), 237–259 (2022).
19. Weber, E.U., Blais, A.R., Betz, N.E.: A domain-specific risk-attitude scale: Measuring risk perceptions and risk behaviors. Journal of Behavioral Decision Making 15(4), 263–290 (2002).
20. Wang, Y.Y., Chuang, Y.W.: Artificial intelligence self-efficacy: Scale development and validation. Education and Information Technologies 29(4), 4785–4808 (2024).
21. Sathya, N., Prabhavathi, C.: The influence of social media on investment decision-making: Examining behavioral biases, risk perception, and mediation effects. International Journal of System Assurance Engineering and Management 15(3), 957–963 (2024).
22. Hair Jr., J.F., Babin, B.J., Anderson, R.E., Black, W.C.: Multivariate data analysis. 8th edn. Cengage Learning (2019).

23. MacKenzie, S.B., Podsakoff, P.M., Podsakoff, N.P.: Construct measurement and validation procedures in MIS and behavioral research: Integrating new and existing techniques. MIS Quarterly 35(2), 293–334 (2011).
24. George, D., Mallery, P.: SPSS for Windows step by step: A simple guide and reference. 10th edn. Pearson (2010).
25. Field, A.: Discovering statistics using IBM SPSS statistics. 4th edn. SAGE Publications (2013).
26. Henseler, J., Ringle, C.M., Sarstedt, M.: A new criterion for assessing discriminant validity in variance-based structural equation modeling. Journal of the Academy of Marketing Science 43(1), 115–135 (2015).
27. Barber, B.M., Huang, X., Odean, T., Schwarz, C.: Attention-induced trading and returns: Evidence from Robinhood users. The Journal of Finance 77(6), 3141–3190 (2022).
28. Ahmed, Z., Rasool, S., Saleem, Q., Khan, M.A., Kanwal, S.: Mediating role of risk perception between behavioral biases and investor’s investment decisions. SAGE Open 12(2) (2022).
29. Glaser, M., Langer, T., Weber, M.: True overconfidence in interval estimates: Evidence based on a new measure of miscalibration. Journal of Behavioral Decision Making 26(5), 405–417 (2013).
30. Rastogi, C., Zhang, Y., Wei, D., Varshney, K.R., Dhurandhar, A., Tomsett, R.: Deciding fast and slow: The role of cognitive biases in AI-assisted decision-making. Proceedings of the ACM on Human-Computer Interaction 6(CSCW1), 1–22 (2022).