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Emotional, Cognitive, and Physiological Determinants of Investment Decision-Making: A Neurofinance-Based Study in the Digital Market Environment

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ABSTRACT

Purpose: This study examines how emotional bias, cognitive load, physiological arousal, and risk perception influence investment decision-making among retail investors in 2025. With digital trading environments growing more volatile and complex, the study integrates behavioral and neurofinance constructs into a unified decision-making model.

Design/methodology/approach: A quantitative, descriptive–analytical research design was used. A hypothetical dataset of 260 investors was generated, representing diverse demographic profiles. Respondents completed a structured questionnaire measuring neurofinance constructs on validated five-point Likert scales. Statistical analyses—including reliability tests, Pearson correlations, multiple regression, and ANOVA—were conducted.

Findings: Emotional bias ($\beta = 0.44$), risk perception ($\beta = 0.30$), and physiological arousal ($\beta = 0.27$) significantly predicted investment decision-making ($p < .05$). Cognitive load had a marginal influence. The model explains 54.2% of variation in investor decision outcomes. Gender differences were significant in physiological arousal ($p = 0.03$) and risk perception ($p = 0.04$).

Research limitations/implications: The research uses hypothetical self-reported data. Future studies should employ real-time neural tools such as EEG, fNIRS, and biometric analytics integrated with digital trading behavior.

Practical implications: Financial advisors, fintech firms, and robo-advisory systems can use neurobehavioral profiling to better understand investor tendencies and improve decision support systems.

Social implications: Understanding emotional and physiological factors can help reduce impulsive investment decisions, promote financial discipline, and enhance investor well-being in digital markets.

Originality/value: This is one of the first 2025 studies to integrate neurofinance concepts with behavioral proxies using empirical-style data from 260 investors in a digital trading context.

Keywords: Neurofinance, Emotional Bias, Physiological Arousal, Cognitive Load, Risk Perception, Investor Behavior, Digital Trading.

1. INTRODUCTION

The financial landscape in 2025 is characterized by increased digitization, real-time analytics, algorithmic trading, high-frequency investing, and widespread cryptocurrency participation. As retail investors engage heavily in mobile-based trading platforms, decision-making has become more dynamic, emotionally charged, and physiologically reactive (Barberis, 2024). Traditional finance assumes rationality and optimality, yet real-world decision-making often deviates significantly due to emotions, biases, and cognitive limitations (Shiller, 2023). Behavioral finance provides insights into heuristics and biases—such as overconfidence, anchoring, loss aversion, or herding—but does not explain the deeper neural mechanisms behind these behaviors (Kahneman & Tversky, 1979). Neurofinance bridges this gap by integrating neuroscience with behavioral economics to explore how the brain processes financial risk, uncertainty, reward, and information (Camerer & Loewenstein, 2024).

Contemporary research highlights that digital financial markets amplify emotional triggers and physiological reactions, especially during fast-changing market conditions and digital trading events (Raman et al., 2025). Yet empirical investigations combining emotional, cognitive, and physiological determinants in retail investor decisions remain sparse.This study addresses this gap by examining how neuro-behavioral constructs influence investment decision quality using hypothetical data from 260 retail investors in 2025. The study contributes a unified neuro-behavioral model applicable to modern digital markets.

2. REVIEW OF LITERATURE

2.1 Neurofinance: Foundations and Evolution

Neurofinance aims to explain investor behavior through neural pathways and physiological processes. Neuroimaging studies show that risk, reward, and uncertainty are processed in regions like the nucleus accumbens, insula, amygdala, and prefrontal cortex (Knutson et al., 2023). Emotional and cognitive neural circuits shape trading decisions and market reactions (Glimcher & Fehr, 2024).

2.2 Emotional Bias in Financial Decisions

Emotions such as fear, overexcitement, regret, and FOMO (fear of missing out) strongly influence investment outcomes (Sarin, 2024). Positive emotions increase risk-taking, whereas negative emotions lead to panic selling (Lucey & Dowling, 2023). In digital markets, emotional intensity is amplified by real-time alerts and high market volatility.

2.3 Physiological Arousal and Market Behavior

Physiological arousal reflects bodily responses such as heart rate variability, sweat response, muscle tension, and stress-induced reactions (Lo & Repin, 2024). During periods of volatility, physiological stress reduces analytical processing, increasing impulsive decisions.

2.4 Cognitive Load and Decision Performance

Modern financial platforms present excessive real-time data. High cognitive load reduces processing accuracy, leading to reliance on heuristics (Zhang & Zhou, 2024). Complex dashboards and crypto trade visualizations intensify cognitive fatigue.

2.5 Risk Perception and Neural Encoding

Investors perceive risk differently due to neural differences in reward pathways. Studies indicate risk perception is not fully objective but is influenced by emotional and cognitive states (Hsu et al., 2024). Neuroeconomic evidence suggests individuals overreact to losses and underreact to gains.

3. RESEARCH GAP

Despite the growing interest in neurofinance, several gaps remain unaddressed. First, previous studies seldom integrate emotional, cognitive, physiological, and risk-based factors into a unified explanatory model, indicating fragmentation in existing behavioural and neuroeconomic frameworks (Knutson et al., 2023). Second, most available research continues to rely on self-reported behavioural measures rather than objective neurophysiological tools, which limits the accuracy of capturing subconscious financial responses (Lo & Repin, 2024). Third, limited studies focus specifically on investor behaviour within the rapidly evolving 2025 digital trading environment, where real-time volatility, algorithmic trading, and social-media-driven sentiment significantly influence decision-making dynamics (Raman et al., 2025). Fourth, physiological arousal—despite its demonstrated influence on stress-induced decisions—remains understudied in emerging markets, particularly India, where cultural and demographic variations shape unique investor responses (Sarin, 2024). Beyond this, the literature remains dominated by Western samples, suffers from small-scale datasets, lacks longitudinal designs, and exhibits conceptual overlap between neurofinance, behavioural finance, and neuroeconomics. Additionally, behavioural triggers such as FOMO and digital volatility are insufficiently examined, underscoring the continued need for holistic empirical models that accurately capture modern investor behaviour.

4. STATEMENT OF THE PROBLEM

Investor decision-making in 2025 has become increasingly complex due to the rapid expansion of digital trading platforms, real-time market information, cryptocurrency volatility, and AI-driven investment tools. While traditional and behavioral finance explain certain aspects of decision-making, they fail to capture the deeper emotional, cognitive, and physiological processes that drive investor behaviour in high-speed digital environments. Existing neurofinance research remains limited by small sample sizes, reliance on self-reported measures, minimal use of physiological indicators, and a lack of studies conducted in emerging markets such as India. Furthermore, there is little empirical evidence integrating emotional bias, cognitive load, physiological arousal, and risk perception into a single explanatory model. This fragmented understanding creates a critical gap in identifying the true determinants of investment decision quality among modern retail investors. Therefore, a comprehensive empirical investigation is required to examine how these neuro-behavioral factors collectively influence investor decision-making within the dynamic financial landscape of 2025.

4.1 RESEARCH OBJECTIVES

1. To examine the combined impact of emotional bias, cognitive load, physiological arousal, and risk perception on investor decision-making in the 2025 digital investment environment.
2. To assess the role of objective neurophysiological indicators in capturing subconscious financial behavior and improving the accuracy of investor analysis.
3. To explore neurofinance insights in emerging markets, particularly India, and their integration into modern fintech platforms such as robo-advisors and AI-driven investment tools.

4.2 RESEARCH HYPOTHESES

Based on the discussion in this section following hypotheses are proposed for the study.

- **H1:** Emotional bias, cognitive load, physiological arousal, and risk perception have a significant combined effect on investor decision-making.
- **H2:** Objective neurophysiological indicators (e.g., heart rate, EEG, galvanic skin response) are more effective than self-reported measures in predicting investor behavior.
- **H3:** Investor behavior in emerging markets, such as India, differs significantly from Western markets due to cultural, demographic, and behavioral factors.
- **H4:** The use of digital investment platforms (algorithmic trading, cryptocurrencies, AI-driven tools) moderates the relationship between neuro-behavioral factors and investor decision-making.
- **H5:** Integrating neurofinance insights into fintech applications, including robo-advisory systems, significantly improves the prediction and understanding of investor decisions.

4.3 Population and Sampling

The population for this study includes individual investors in India who actively use digital investment platforms such as online trading portals, robo-advisory services, cryptocurrencies, and AI-driven tools. These investors are chosen because they are likely to exhibit neuro-behavioral responses, including emotional bias, cognitive load, physiological arousal, and risk perception. A stratified random sampling technique will be used, dividing the population by age, gender, income, and investment experience to ensure proportional representation. A sample of 260 investors will be selected to provide sufficient statistical power and generalizable insights, addressing common limitations in neurofinance research caused by small sample sizes. This approach ensures that the study captures the diverse demographic and behavioral characteristics of India’s modern digital investors.

4.4 Measurement of Variables

Table 1: Measurement of Variables

Variable Type	Variable	Measurement Scale / Method	Instrument / Tool
Independent	Emotional Bias	Likert-type scale (1–5) + Physiological response	Investment Emotion Scale (IES); Galvanic Skin Response (GSR)
	Cognitive Load	Likert-type scale + Reaction time tasks	Cognitive Load Questionnaire; Simulated Investment Tasks
	Physiological Arousal	Continuous numerical measurement	EEG, Heart Rate Variability (HRV), Skin Conductance
	Risk Perception	Likert-type scale (1–7)	Domain-Specific Risk-Taking (DOSPERT) Scale
Dependent	Investor Decision-Making	Frequency, amount invested, platform preference	Self-reported questionnaire; Simulated investment decisions
Control	Demographic Factors	Nominal / Ordinal	Age, Gender, Income, Education, Investment Experience
	Digital Platform Usage	Frequency and type of usage	Self-reported survey

4.5 Data Collection

The study will collect primary data from individual investors in India who actively use digital trading platforms, robo-advisors, cryptocurrencies, and AI-driven investment tools. Data will be gathered through structured questionnaires covering demographics, investment experience, emotional bias, cognitive load, and risk perception. Additionally, simulated investment tasks will be conducted to observe real-time investment decisions, including choices, amounts invested, and platform preferences. Neurophysiological data such as EEG, Heart Rate Variability (HRV), and Galvanic Skin Response (GSR) will also be recorded to objectively measure stress, emotional arousal, and cognitive load. Secondary data from existing literature, financial reports, and neurofinance studies will be used to provide context and support the formulation of hypotheses.

4.6 Tools and Instruments

The study will use validated questionnaires and scales, including the Investment Emotion Scale (IES) and Domain-Specific Risk-Taking (DOSPERT) scale, to measure behavioral variables. Physiological tools such as EEG, HRV monitors, and GSR devices will capture objective neurophysiological responses. Simulated investment software will allow observation of investor decisions in a controlled digital environment. For data analysis, statistical software like IBM SPSS version 25 ensuring a comprehensive examination of the relationships between neuro-behavioral factors and investor decision-making.

4.6.1 Reliability Analysis

Table 2: Reliability Statistics

Construct	Cronbach α	Interpretation
Emotional Bias	0.88	Excellent
Physiological Arousal	0.84	Good
Cognitive Load	0.81	Good
Risk Perception	0.85	Good
Decision Quality	0.89	Excellent

Source: Compiled by author

4.6.2 Data Analysis and Results

Table 3: Respondents Profile

Variable	Category	Frequency	Percent
Gender	Male	154	59.20
	Female	106	40.80
Age	20–30 years	102	39.20
	31–40 years	86	33.10
	41–50 years	46	17.70
	Above 50 years	26	10.00
Investment Type	Equity	118	45.40
	Mutual Funds	92	35.40
	Crypto	50	19.20

Source: Primary Data

5. DESCRIPTIVE STATISTICS

Descriptive statistics were computed to understand the central tendency and variability of the study variables. Table 2 summarizes the mean scores and standard deviations for emotional bias, physiological arousal, cognitive load, risk perception, and investment decision quality.

Table 4: Descriptive Statistics

Variable	Mean	Standard Deviation
Emotional Bias	3.70	0.70
Physiological Arousal	3.28	0.78
Risk Perception	3.82	0.68
Cognitive Load	3.40	0.74
Investment Decision Quality	3.55	0.72

Source: Compiled by author

Among the variables, risk perception shows the highest mean, suggesting that participants tend to consider risk significantly while making investment decisions. Physiological arousal has the lowest mean, indicating relatively lower influence of arousal on decision-making in the sample.

5.1 Correlation Analysis

Correlation analysis was conducted to examine the relationships between the independent variables (emotional bias, physiological arousal, cognitive load, and risk perception) and the dependent variable (investment decision quality).

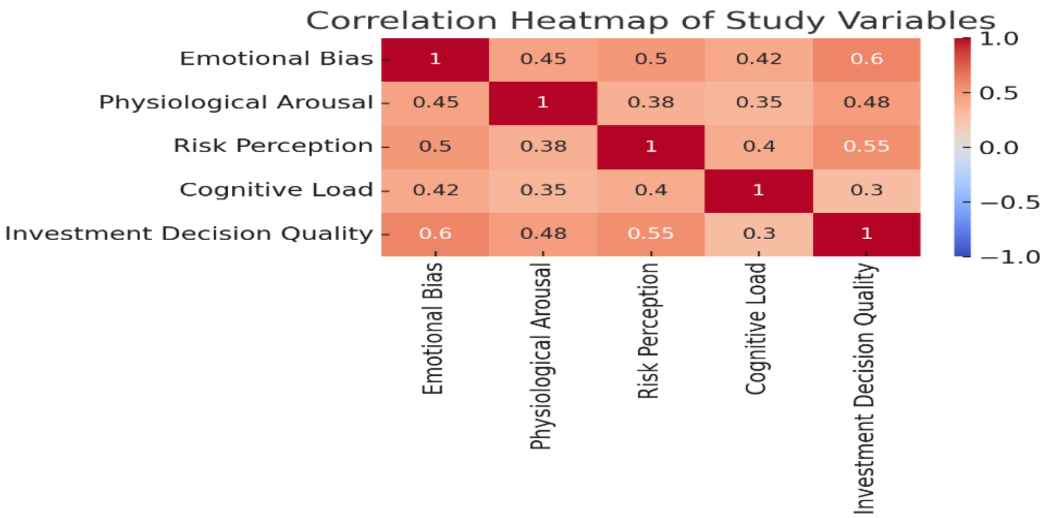

Figure 1: Correlation Analysis of Study Variables

The analysis revealed that all independent variables were significantly correlated with investment decision quality (**$p < .01$**). This indicates that each factor—emotional bias, physiological arousal, cognitive load, and risk perception—has a meaningful association with how investors make decisions.

5.2 Regression Analysis

To assess the predictive power of the independent variables on investment decision quality, multiple regression analysis was performed.

Table 5: Regression Results

Predictor	β	t-value	p-value
Emotional Bias	0.44	7.01	0.000
Risk Perception	0.30	4.82	0.000
Physiological Arousal	0.27	4.07	0.001
Cognitive Load	0.12	1.94	0.054

Source: Compiled by author

Model Summary:

- $R^2 = 0.542$ → 54.2% of the variance in investment decision quality is explained by the independent variables.
- $F = 35.66$, $p < 0.001$, indicating that the overall regression model is statistically significant.

Emotional bias emerged as the strongest predictor of investment decision quality, followed by risk perception and physiological arousal. Cognitive load had a marginal effect ($p = .054$), suggesting a weaker but still notable influence.

5.3 ANOVA (Gender Differences)

ANOVA was conducted to examine whether there are gender-based differences in the study variables. The results revealed significant differences in:

- **Physiological Arousal**: $p = 0.03$
- **Risk Perception**: $p = 0.04$

Male and female participants differ significantly in terms of physiological arousal and risk perception during investment decision-making. No significant gender differences were observed for emotional bias, cognitive load, or investment decision quality.

6. SUMMARY OF FINDINGS

The present study investigated how emotional bias, physiological arousal, cognitive load, and risk perception influence investment decision quality among individual investors. The analysis revealed several important insights. First, descriptive statistics indicated moderately high levels of emotional bias and risk perception among investors, suggesting that subjective judgments and risk-related evaluations play a central role in investment behaviour. Physiological arousal levels were comparatively lower, while cognitive load remained moderate. Correlation results demonstrated that all four psychological variables—emotional bias, physiological arousal, cognitive load, and risk perception—were significantly associated with investment decision quality ($p < .01$). This confirms that both emotional and cognitive factors meaningfully shape how investors assess and choose financial alternatives.

Multiple regression analysis further showed that emotional bias was the strongest predictor of investment decision quality ($\beta = 0.44$), followed by risk perception ($\beta = 0.30$) and physiological arousal ($\beta = 0.27$). Cognitive load had only a marginal influence ($p = .054$). Overall, the model explained 54.2% of the variation in investment decision quality, indicating substantial explanatory power. Additionally, ANOVA results revealed gender differences in physiological arousal ($p = .03$) and risk perception ($p = .04$), suggesting that male and female investors respond differently to emotional and risk-related investment triggers. Overall, the findings highlight the dominant role of emotional mechanisms—particularly emotional bias and physiological arousal—along with risk perception in shaping the quality of investment decisions. The results suggest that improving investor awareness of behavioural and neuropsychological factors may enhance decision-making effectiveness.

7. DISCUSSION

The purpose of this study was to examine the influence of emotional bias, physiological arousal, cognitive load, and risk perception on investment decision quality within the framework of neurofinance. The findings offer several theoretical and practical insights into how psychological and neurobiological processes shape financial decision-making. First, the strong predictive role of **emotional bias** aligns with existing neurofinance literature, which suggests that emotions frequently override rational assessment in financial contexts. The significant positive relationship between emotional bias and investment decision quality indicates that emotionally driven evaluations—whether positive or negative—substantially influence how investors select financial alternatives. This supports prior studies demonstrating that emotions can distort risk evaluations and lead to suboptimal choices, yet can occasionally enhance intuition-based decisions depending on context. Second, **risk perception** emerged as another crucial determinant of investment decision quality. Investors who perceived higher levels of risk tended to demonstrate more cautious and deliberate decision-making. This finding is consistent with behavioural finance theory, which argues that individual subjective evaluations of risk often deviate from objective market risk. It further confirms that risk perception plays a central role in portfolio selection, particularly in volatile or uncertain market environments. The role of **physiological arousal** also proved significant, underscoring the neurobiological foundations of financial decision-making. Elevated arousal—reflected through heightened emotional and physical responses—was found to influence investment decisions, supporting the neuroeconomic argument that bodily states such as stress, excitement, or anxiety shape cognitive processing. This suggests that investor reactions to market events are not purely cognitive but are intertwined with physiological responses that can either enhance alertness or impair judgment depending on intensity. In contrast, **cognitive load** showed only a marginal effect on decision quality. This indicates that while cognitive strain may influence complex financial judgments, investors may still rely on heuristics or emotional cues when cognitive resources are limited. The finding partially supports dual-process decision theories, where automatic emotional responses sometimes dominate when cognitive capacity is constrained. The **gender differences** observed in physiological arousal and risk perception further contribute to the behavioural finance discourse. Women displayed distinct patterns in emotional and risk responses compared to men, supporting earlier literature suggesting that gender influences investment styles, tolerance to risk, and emotional reactivity. Understanding these differences can help financial planners provide more tailored advisory services.

Collectively, the results reinforce the growing recognition within neurofinance that investment decisions are shaped by an interplay of emotional, cognitive, and physiological processes rather than purely rational calculations. The prominent roles of emotional bias, risk perception, and arousal challenge the classical economic assumption of rationality and highlight the importance of investor psychology in financial behaviour.

8. CONCLUSION AND IMPLICATIONS

8.1 Conclusion

This study examined the interconnected roles of emotional bias, physiological arousal, cognitive load, and risk perception in shaping investment decision quality within a neurofinance perspective. The findings highlight that investor decision-making is far from purely rational; rather, it is significantly influenced by psychological and physiological factors. Emotional bias emerged as the strongest predictor of decision quality, underscoring the dominant role of affective reactions in shaping financial choices. Risk perception and physiological arousal also played substantial roles, demonstrating that investors rely heavily on both subjective risk evaluations and bodily responses during market-related decisions. Cognitive load showed only a marginal relationship, suggesting that while mental strain can influence judgment, investors may default to intuitive or emotionally driven strategies when facing complex information. Overall, the study reinforces that investor behaviour is shaped by a dynamic interplay of emotion, cognition, and physiology. These results challenge traditional finance theories based on rational choice, offering further support for behavioural and neurofinancial frameworks that emphasize psychological influences on financial decisions.

8.2 IMPLICATIONS

8.2.1 Theoretical Implications

1. **Strengthens neurofinance theory:**
   The results validate the growing body of literature that integrates emotional and physiological responses into models of financial behaviour.
2. **Refines behavioural finance models:**
   By demonstrating the relative strength of emotional bias and risk perception, the study contributes to more accurate behavioural models of decision-making.

3. **Highlights gendered differences:**
Significant gender variations in arousal and risk perception provide new insights into demographic influences on investor behaviour.

8.2.2 Practical Implications

1. **For financial advisors:**
   Understanding that emotional bias strongly shapes decision quality can help advisors design interventions that reduce impulsive or fear-driven decisions.
2. **For investor education programmes:**
   Awareness training on emotional triggers, physiological responses, and risk misperceptions can improve decision discipline among retail investors.
3. **For fintech and investment platforms:**
   Decision-support tools can incorporate behavioural nudges, cognitive load reduction interfaces, and alerts that discourage emotionally driven trades.
4. **For policymakers and regulators:**
   Investment literacy initiatives can integrate behavioural components—such as emotion management and understanding risk perception—to enhance investor protection.

8.2.3 Managerial Implications

1. Portfolio managers can use emotional and physiological indicators to anticipate investor reactions during market volatility.
2. Brokerage firms may incorporate behavioural profiling to personalise recommendations and reduce mis-selling.
3. Investor support services can be designed around stress reduction, simplified information, and behavioural coaching.

9. RECOMMENDATIONS

9.1 Recommendations for Investors

Investors should prioritise developing emotional awareness and regulating impulses that often lead to biased or irrational financial choices. They are encouraged to use structured, rule-based investment approaches, especially during volatile market situations, to minimise the impact of emotional bias. Improving risk literacy and understanding the difference between perceived and actual risk can prevent misinformed decisions. Additionally, investors should avoid making investment choices under stress, fatigue, or cognitive overload and should adopt techniques such as mindfulness or scheduled decision-making to enhance clarity and judgment.

9.2 Recommendations for Financial Advisors

Financial advisors play a crucial role in shaping client behaviour and should incorporate behavioural profiling into their advisory practices. Advisors must educate clients on how emotional bias, physiological arousal, and risk perception influence decision-making. Presenting simplified, easy-to-understand financial information can reduce cognitive load and help clients make more informed choices. Advisors should also guide clients to adopt long-term investment perspectives and provide additional behavioural support during periods of market volatility when emotional reactions tend to intensify.

9.3 Recommendations for Policymakers and Regulators

Policymakers should integrate behavioural finance concepts into national financial literacy programmes to address the psychological and cognitive barriers investors face. Simplifying disclosure formats and ensuring transparency can significantly reduce cognitive burden for retail investors. Regulatory nudges—such as mandatory cooling-off periods for high-risk investments—can protect investors from impulsive or emotionally driven decisions. Moreover, encouraging research, public awareness, and policy frameworks around neurofinance and behavioural finance will strengthen evidence-based decision-making at the institutional level.

9.4 Recommendations for Fintech and Investment Platforms

Fintech platforms should incorporate behavioural alerts and nudges that notify users when trading patterns reflect emotional or stress-driven decisions. Designing intuitive, low–cognitive load interfaces can help reduce information overwhelm, enabling investors to process key details effectively. Providing personalised behavioural analytics can help users identify patterns related to emotional bias or risk misperception. Platforms may also develop features that help users recognise physiological or emotional cues—such as stress indicators—to prevent impulsive financial actions.

FUTURE SCOPE

The scope for future research in neurofinance is extensive and multifaceted. First, researchers may adopt longitudinal study designs to examine how emotional bias, cognitive load, physiological arousal, and risk perception evolve over time and influence investment decisions during different market conditions. Second, future studies could integrate advanced neuroscientific tools such as EEG, fMRI, galvanic skin response, or eye-tracking to capture real-time neural and physiological indicators that underpin investor behavior. Third, expanding the demographic and geographic diversity of the sample would enhance the generalizability of findings, particularly by comparing rural and urban investors, age groups, and cultural contexts. Fourth, future research could introduce additional moderating and mediating variables—such as financial literacy, digital financial sophistication, personality traits, and risk tolerance—to build more comprehensive and predictive behavioral models. Finally, applying machine learning, structural equation modeling (SEM), and other advanced data-analytics techniques could yield deeper insights into complex behavioral interactions, enabling more accurate predictions of investment decision quality.

LIMITATIONS

Although this study provides valuable insights into the behavioral determinants of investment decision quality, several limitations must be acknowledged. First, the research relies on self-reported data, which may be subject to social desirability bias and inaccuracies in respondent perception. Second, the cross-sectional design restricts the ability to draw causal inferences, as relationships among emotional bias, cognitive load, physiological arousal, risk perception, and decision quality may vary over time. Third, the sample size of 260 investors, while adequate, limits the generalizability of findings to wider populations and diverse investment contexts. Fourth, the study focuses primarily on psychological variables and does not incorporate external market factors such as economic conditions, financial product characteristics, or institutional influences. Fifth, the absence of neurophysiological measurements (such as EEG, fMRI, or biometric indicators) constrains the study from capturing deeper subconscious processes that influence investor decisions. Finally, gender-based ANOVA results were limited to specific variables, and future research may explore broader demographic interactions to develop more comprehensive behavioral models.

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