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A TEST OF THE BEHAVIOURAL FINANCE MODEL IN NIGERIA CAPITAL MARKET

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Abstract

This study sought to test the behavioural finance model by examining the extent to which five psychological biases (overconfidence, loss aversion, herding behaviour, mental accounting, and anchoring bias) influence investment decision-making in the Nigerian capital market. The objective is to empirically validate the relevance of behavioural constructs in explaining deviations from rational investor behaviour. Data were collected through a structured questionnaire administered to a stratified sample of 361 respondents, comprising individual investors, stockbrokers, and portfolio managers. The research employed a quantitative methodology, with data analysed using descriptive statistics, correlation analysis, and a Generalized Linear Model (GLM), following diagnostic tests that confirmed the presence of serial correlation. The findings reveal that overconfidence and loss aversion have significant and positive effects on investment decisions, while herding, mental accounting, and anchoring biases do not exhibit statistically significant influence. These results suggest a partial validation of the behavioural finance model in Nigeria's capital market, with key implications for investor psychology and regulatory practice. The study recommends behavioural-focused investor education, enhanced advisory training, and the incorporation of psychological insights into financial policy design to improve investment outcomes and foster market stability.

Keywords: Behavioural Finance, Investment Decision-Making, Overconfidence, Loss Aversion, herding Behaviour

1. Introduction

Since its establishment as the Lagos Stock Exchange in 1960, now restructured as the Nigerian Exchange Group (NGX), the Nigerian capital market has undergone significant transformation (Osemwengie, 2025). Initially conceived as a platform to mobilize long-term capital for national economic development, the market has experienced growth in depth and operational sophistication. This growth has been supported by the adoption of digital trading infrastructure, strengthened regulatory frameworks, and partial integration with global financial systems (Olawale, 2024). Nonetheless, the market remains relatively shallow in global comparison. Indicators such as the market capitalization-to-GDP ratio, investor base diversity, and financial instrument variety remain underwhelming. Structural constraints, political instability, and persistent informational asymmetries continue to suppress investor confidence and encourage speculative, non-fundamental trading behaviour, thereby highlighting the limitations of traditional financial theories in explaining market dynamics.

Classical financial theory, particularly the Efficient Market Hypothesis (EMH) as advanced by Fama (1970), asserts that market prices fully reflect all available information due to the rational actions of investors. This rationalist model has long dominated academic and professional discourse, suggesting that any mispricing is temporary and corrected through arbitrage by informed participants (Krishnamurthy, 2024). However, empirical observations such as speculative bubbles, excessive market reactions, and persistent pricing anomalies have increasingly challenged the adequacy of the EMH, particularly in less efficient markets (Chesoli, 2021; Osterrieder & Seigne, 2023). Behavioural finance emerged in response to these deficiencies by incorporating cognitive psychology into financial theory. It posits that various psychological biases, such as overconfidence, herding, loss aversion, anchoring, and mental accounting, systematically influence investor decision-making, especially under conditions of uncertainty and imperfect information (Zik-Rullahi et al., 2023; Khan et al., 2023; Polychronakis, 2023; Sathya & Gayathiri, 2024).

In Nigeria's capital market, the explanatory relevance of behavioural finance is particularly strong due to the market's unique institutional and participant characteristics. The prevalence of retail investors who often lack formal financial education, combined with low levels of financial literacy and high market volatility, provides a context in which cognitive biases are likely to dominate investment behaviour (Bogunjoko, 2021; Obayagbona & Ose Eburajolo, 2023). Additionally, regulatory bottlenecks and culturally embedded attitudes toward risk further entrench behaviour that deviates from rational choice models (Benjamin, 2024). As a result, price movements and trading patterns are frequently driven more by psychological factors than by underlying economic fundamentals. This suggests that testing the behavioural finance model in the Nigerian capital market is not only theoretically appropriate but also practically necessary in order to understand market inefficiencies and inform targeted reforms.

Although behavioural finance has gained prominence globally, most empirical research remains grounded in developed markets with efficient institutional frameworks and well-informed investor populations (Lam et al., 2024; Kartini & Nahda, 2021). These studies often fail to capture the behavioural complexity present in frontier markets like Nigeria, where market inefficiencies and limited regulatory enforcement intensify psychological biases. While emerging literature has begun to explore behavioural anomalies in comparable contexts (Almansour et al., 2023; Elessa & Yassin, 2023), empirical studies within Nigeria remain limited in scope. Existing research tends to focus on individual biases or specific investor groups without integrating multiple behavioural variables (such as overconfidence bias, herding behaviour, loss aversion, mental accounting, and anchoring bias) into a comprehensive framework (Ogunlusi & Obademi, 2021; Edeh et al., 2022). Moreover, constructs such as mental accounting remain largely untested, despite their central role in behavioural theory (Thaler, 1999). Given the recurrent misalignment between asset prices and economic fundamentals, a systematic and context-sensitive empirical test of the behavioural finance model in Nigeria is essential. Such an investigation would advance theoretical discourse, support evidence-based policymaking, and enhance the functioning of the Nigerian capital market.

The remainder of the paper is structured as follows: Section Two presents the literature review, Section Three discusses the methodology, Section Four focuses on data analysis and interpretation of results, while Section Five addresses the conclusion and recommendations.

2. Literature Review

2.1 Conceptual Definitions

2.1.1 Investment Decision

Investment decision-making involves the purposeful allocation of financial resources across various investment alternatives with the expectation of future returns. Traditional finance theory conceptualizes this process as rational, where investors make decisions based on systematic evaluations of risk, return, liquidity, and time preferences (Abdul Kareem et al., 2023; Kubińska, Adamczyk-Kowalczuk, & Macko, 2023). Within this framework, tools such as portfolio diversification, asset valuation, and market timing are employed through objective, quantitative methods (Yang, 2024).

2.1.2 Behavioural Finance

Behavioural finance is an interdisciplinary field that combines insights from psychology, cognitive science, and economics to explain how cognitive biases and emotional factors systematically influence financial decisions, often leading to deviations from the rational models assumed in traditional finance (Umapathy, 2024). Unlike classical theories that emphasize efficient markets and utility-maximizing agents (Kamoune & Ibenrissoul, 2022; Gomes, 2023), behavioural finance highlights the role of heuristics, social influences, and psychological framing in shaping both individual and collective investment behaviour (Loang, 2025). The discipline emerged in response to empirical anomalies such as bubbles, excessive market volatility, and persistent mispricing that standard models could not account for (Agudelo Aguirre & Agudelo Aguirre, 2024; Ooi, 2024).

2.1.3 Overconfidence Bias

Overconfidence bias, a prominent concept in behavioural finance, refers to an investor's inflated belief in the accuracy of their knowledge, judgments, and forecasting abilities, often leading to underestimation of risks and overestimation of expected returns (Karki, Bhatia, & Sharma, 2024). Contrary to rational expectations theory, overconfident investors tend to trade excessively without corresponding gains, resulting in poor diversification and increased exposure to financial losses, especially in volatile markets (Loang, 2025; Kommalapati, 2024).

2.1.4 Herding Behaviour

Herding behaviour refers to the tendency of investors to follow the actions of others rather than rely on their own analysis, representing a clear departure from the rational and independent decision-making assumed in classical finance (Bett, 2024). Motivated by social conformity, reputational concerns, and the belief that others possess superior information, herding becomes especially pronounced during periods of market uncertainty or speculative surges (Nerlekar et al., 2025; Barham, 2024). Investors may follow the crowd due to fear of missing out or a lack of confidence in their own judgement (Idris, 2024; Kaur, Jain, & Sood, 2024). This behaviour is often explained by informational cascades, where early decisions disproportionately influence subsequent ones, regardless of actual market fundamentals (Loang, 2025).

2.1.5 Loss Aversion

Loss aversion, a core concept in behavioural finance rooted in Prospect Theory by Kahneman and Tversky (1979), describes the tendency for individuals to feel the pain of losses more intensely than the pleasure of equivalent gains. Research shows that losses are often perceived as twice as impactful as gains, leading to risk-averse behaviours and asymmetrical decision-making (Nguyen & Slocum, 2024). This bias manifests in tendencies such as the disposition effect, where investors hold onto losing assets in hope of recovery while prematurely selling winners to secure gains (Mazilu, 2024).

2.1.6 Mental Accounting

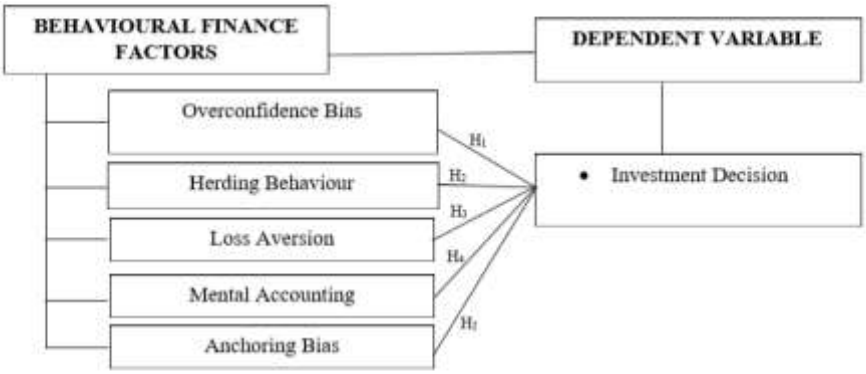
Mental accounting is a behavioural bias in which individuals categorize and treat money differently based on its source, purpose, or mental allocation, rather than viewing it as interchangeable, as assumed in standard economic theory (Javareshk, 2024). This cognitive framing leads to inconsistent financial decisions, such as treating investment gains as disposable house money while being more conservative with earned income (Nagina, 2025).

2.1.7 Anchoring Bias

Anchoring bias is a cognitive distortion in which individuals place undue emphasis on an initial piece of information such as a past stock price or analyst forecast when making investment decisions, even when that reference point is irrelevant to current market realities (Ali & Md, 2025). In financial contexts, this bias causes investors to fixate on arbitrary benchmarks like previous highs or round numbers, leading to distorted valuations and delayed responses to new information (Al Rahahleh, 2024; Eskinazi et al., 2024). Analysts and fund managers are also susceptible, often basing projections on outdated data or irrelevant historical performance (Nicholson & Al-Zoubi, 2024). Anchoring impairs rational belief updating, contributes to persistent mispricing, and often operates alongside other biases such as loss aversion and confirmation bias, compounding its effects (Qudrat-Ullah, 2025; Sathya & Gayathiri, 2024). Its impact is particularly detrimental in volatile or rapidly changing markets, where objective and adaptive decision-making is essential.

Following the review of the above behavioural finance components, the conceptual framework of this paper is presented in Figure 1 thus;

Figure 1 Conceptual Framework



Source: Researcher's conceptual framework (2025).

2.2 Theoretical Review

Behavioural finance draws upon several theoretical frameworks to explain deviations from rational decision-making in financial contexts. Prospect Theory, developed by Kahneman and Tversky (1979), challenges the assumptions of expected utility theory by demonstrating that individuals evaluate outcomes relative to reference points and display loss aversion, valuing losses more heavily than equivalent gains. Empirical studies have shown that investors often become risk-averse when facing potential gains and risk-seeking when dealing with losses, reflecting inconsistent behaviour not captured by classical models (Tversky & Kahneman, 1992; Barberis, 2013; Wakker, 2010). This framework has been instrumental in explaining anomalies such as the disposition effect, panic selling, and excessive caution during market downturns (Zhang & Zheng, 2015; Boda & Sun, 2018). In volatile markets like Nigeria's, where emotional and social reference points often shape investor expectations, Prospect Theory provides a crucial foundation for interpreting behaviour driven by fear, regret, or comparative judgement.

The Efficient Market Hypothesis (EMH), proposed by Fama (1970), serves as a contrasting paradigm by asserting that asset prices reflect all available information, leaving no room for consistent outperformance through active trading. While EMH underpins much of traditional finance, its empirical limitations are well-documented, particularly in light of market anomalies, behavioural patterns, and irrational investor sentiment (Lo, 2004; Shiller, 2013). Studies have demonstrated that factors such as overconfidence, herding, and selective attention often lead to mispricing and delayed corrections (Gao & Süss, 2015; Huang et al., 2019). These patterns contradict the core assumption of investor rationality and suggest that real-world financial markets are subject to inefficiencies that behavioural theories better explain. In this context, EMH remains useful as a theoretical benchmark, but its explanatory power is enhanced when integrated with psychological models that account for cognitive biases influencing investor decisions, particularly in markets characterized by low transparency and high uncertainty.

Complementing Prospect Theory and offering further behavioural insight are heuristic-driven bias theory, Regret Theory, and Mental Accounting. Heuristic-driven bias theory explains how investors use mental shortcuts such as representativeness, availability, and anchoring to simplify complex decisions, often resulting in systematic errors in judgement and risk evaluation (Tversky & Kahneman, 1974; Gigerenzer & Gaissmaier, 2015). These heuristics are especially prevalent during market volatility, where information overload prompts reliance on salient but often irrelevant cues (Choi & Lou, 2019). Regret Theory posits that investors anticipate the emotional discomfort of making poor choices and may avoid rational decisions to minimize future regret, while Mental Accounting illustrates how individuals categorize and treat money differently based on its origin or intended use, leading to fragmented and suboptimal financial strategies (Thaler, 1985; Benartzi & Thaler, 1995; Kim & Nofsinger, 2016).

These theories are particularly relevant in emerging markets like Nigeria, where cognitive constraints, emotional influences, and informal financial structures amplify non-rational investment behaviour. Collectively, these frameworks provide a robust theoretical basis for analysing how psychological and emotional factors shape investment decisions, offering an essential lens for understanding behavioural anomalies in capital market dynamics.

2.3 Empirical Review

Lam, Hasell, and Tipping (2024) explored the impact of behavioural finance biases on investment decisions among Australasian REIT managers. Utilizing a mixed-method approach that combined expert surveys with qualitative case studies, the study identified investor sentiment, anchoring, and overconfidence as significant behavioural influences, comparable in importance to traditional financial decision factors. However, the availability heuristic appeared negligible, suggesting that professional expertise may mitigate certain biases. These findings highlight the persistent role of behavioural influences, even in institutional investment contexts.

Vuković and Pivac (2024) examined the effects of behavioural biases and personality traits on investment outcomes among Croatian investors using partial least squares structural equation modeling. Their results revealed that overconfidence, emotional tendencies, and aspects of prospect theory had a significant positive influence on investment decisions, while herding behaviour negatively impacted decision-making. Additionally, a preference for long-term investment strategies was associated with higher satisfaction in investment performance, indicating that cognitive traits and psychological patterns significantly shape investor success.

Fateye, Peiser, and Ajayi (2024) studied behavioural influences in Nigeria’s real estate stock market by surveying registered brokers under the Nigeria Exchange Group. Applying Principal Component Factor Analysis and OLS regression, the research identified six behavioural dimensions, including herding and investor responsiveness. The study revealed that investor decisions were strongly shaped by market sentiment: bullish markets encouraged buying, while bearish conditions prompted selling. These patterns affirmed the importance of behavioural drivers in real estate investment strategies.

Benjamin (2024) investigated the effectiveness of behavioural finance education and structured investment guidelines in curbing behavioural biases in the Nigerian capital market. Using responses from 315 participants collected through Likert-scale surveys, the study found that financial literacy, targeted training, and clearly defined investment rules significantly reduced the influence of cognitive distortions. This underscores the practical benefits of behavioural finance interventions in improving decision quality and financial outcomes.

Michael (2023) analyzed the impact of overconfidence, anchoring, disposition, and herding on investment decisions among 340 active investors on the Nigerian Stock Exchange. Regression analysis revealed that all four biases significantly shaped investment decisions, with overconfidence and the disposition effect showing the strongest influence. These findings emphasized how psychological tendencies such as excessive self-belief and attachment to underperforming assets disrupt rational investment behaviour and highlight the need for behavioural awareness in improving market efficiency.

Elessa and Yassin (2023) focused on investment companies in Jordan to assess how behavioural finance variables affect investment decision quality, introducing rationality as a mediating factor. Using AMOS and SPSS for data analysis, the study found that behavioural factors significantly influenced decision-making, with expectation bias exerting the strongest effect. The mediating role of rationality was crucial, suggesting that cognitive structure can shape how behavioural tendencies translate into investment outcomes.

Almansour, Elkrghli, and Almansour (2023) examined how behavioural biases affect investment decisions in the Saudi equity market, emphasizing the mediating role of risk perception. Using structural equation modeling, they found that herding, the disposition effect, and blue-chip bias increased perceived risk, which in turn positively affected investment decisions. Interestingly, overconfidence influenced decisions directly without altering risk perception, demonstrating that behavioural factors operate through both direct and indirect psychological mechanisms.

Sorongan (2022) explored the relationship between financial behaviour, attitudes, and literacy among university students in South Jakarta and their investment decisions. Employing Partial Least Squares analysis on 110 responses, the study showed that financial behaviour and attitudes significantly influenced investment actions, while financial literacy had no moderating effect. This suggests that while knowledge is valuable, behavioural conditioning and attitude formation play a more decisive role in shaping investment practices among young investors.

Edeh, Ibrahim, Maitala, and Daniel (2022) analyzed the relationship between behavioural biases and investment performance in the Nigerian capital market using structural equation modeling. Drawing from 384 investor responses, the study identified significant positive effects of heuristics, prospect theory elements, herding, and market-driven factors on investment outcomes. These results suggest that, under certain conditions, behavioural tendencies may not hinder but instead enhance investment performance when aligned with market opportunities.

Ogunlusi and Obademi (2021) investigated the role of behavioural finance in shaping investment decisions within selected Nigerian investment banks. Based on responses from 180 participants and using regression and correlation techniques, the study revealed a significant relationship between behavioural variables and investment decisions. Interestingly, both heuristics and elements of prospect theory were negatively associated with investment outcomes, suggesting that even within structured institutions, cognitive biases can undermine rational decision-making.

Bogunjoko (2021) examined the behavioural tendencies of millennial investors in Nigeria, focusing on generational differences in investment behaviour. The study found that price overreaction had the most significant effect on decision-making, while biases like heuristics, framing, emotions, and herding had moderate to limited influence. Notably, younger and less experienced investors were more vulnerable to overconfidence, indicating the importance of generational factors in the expression of behavioural biases.

Kartini and Nahda (2021) studied Indonesian individual investors and found that a range of cognitive and emotional biases, including anchoring, representativeness, overconfidence, optimism, loss aversion, and herding, significantly influenced investment decisions. Using a one-sample t-test approach with 165 respondents, the research confirmed that behavioural biases are pervasive and impactful, highlighting the importance of incorporating behavioural insights into investor education and policy frameworks.

2.5 Research Gaps

Despite substantial empirical evidence confirming the influence of behavioural finance biases such as overconfidence, herding, anchoring, and loss aversion on investment decisions, existing studies remain limited in their contextual and methodological focus regarding the Nigerian capital market. Most prior research, including that by Ogunlusi and Obademi (2021), Michael (2023), and Benjamin (2024), either generalizes behavioural influences or concentrates on specific investor categories such as institutions or millennials, without disaggregating the distinct impact of individual biases. Key constructs like mental accounting and anchoring, though acknowledged in global studies (e.g., Lam et al., 2024), have not been robustly examined within the Nigerian retail investment landscape. Additionally, earlier studies (e.g., Edeh, 2020; Edeh et al., 2022) largely excluded these variables and often lacked a model that systematically tests multiple behavioural biases within Nigeria's market-specific structure. This study addresses these gaps by empirically testing a behavioural finance model tailored to the Nigerian capital market, focusing on the individual and comparative effects of overconfidence, herding, loss aversion, anchoring, and mental accounting on investment decision-making.

3. Methodology

This study adopts a descriptive survey research design, which is suitable for examining behavioural patterns across a defined population. It allows for the collection of structured, quantifiable data, facilitating the empirical analysis of relationships among key behavioural biases (namely overconfidence, loss aversion, herding, mental accounting, and anchoring) and their influence on investment decision-making. As supported by Creswell and Creswell (2018), this design is appropriate for studies seeking to observe behavioural phenomena in real-world contexts, especially when large-scale generalisations are intended (Saunders, Lewis, & Thornhill, 2019).

The population targeted comprises individual investors, stockbrokers, and portfolio managers actively involved in Nigeria's capital market. This group was selected due to their routine exposure to market uncertainty and susceptibility to behavioural biases (Michael, 2023). A stratified random sampling technique was adopted to ensure representative coverage across investor categories. As the population size is unknown, Cochran's formula was used to determine the minimum sample size required for the study.

The formula is expressed as:

$$n_0 = \frac{Z^2 \cdot p \cdot (1-p)}{e^2}$$

Where:

n_0 = required sample size

Z = z-value corresponding to a 95% confidence level (1.96)

p = estimated proportion of the population with the attribute of interest (0.5 for maximum variability)

e = desired level of precision or margin of error (0.05)

Substituting into the formula:

$$n_0 = \frac{(1.96)^2 \cdot 0.5 \cdot (1-0.5)}{(0.05)^2} = \frac{3.8416 \cdot 0.25}{0.0025} = \frac{0.9604}{0.0025} = 384.16$$

Thus, based on a 95% confidence level and 5% margin of error, the calculated minimum sample size was 384 respondents (Bartlett, Kotrlik, & Higgins, 2001).

Data for this study were obtained through a structured questionnaire, designed with closed-ended items measured on a five-point Likert scale ranging from "Strongly Disagree" (1) to "Strongly Agree" (5). This format is particularly appropriate for capturing subjective behavioural attributes, as recommended in behavioural finance research (Bryman & Bell, 2015). The questionnaire was subjected to expert review to ensure content validity and was pre-tested on a pilot group to confirm clarity and appropriateness. Each section of the instrument was designed to operationalise the behavioural constructs under investigation.

3.1 Model Specification

To evaluate the influence of behavioural biases on investment decision-making, this study modifies the structural equation model (SEM) proposed by Edeh et al. (2022). The revised model replaces the original dependent variable (investment performance) with investment decision-making (ID) and introduces mental accounting and anchoring as separate predictors, excluding market variables and demographic controls to maintain a clear behavioural focus. The model is specified as:

$$ID = \beta_0 + \beta_1 OCF + \beta_2 LAV + \beta_3 HRB + \beta_4 MAC + \beta_5 ANB + \varepsilon \text{--------------}(1)$$

Where:

ID = Investment Decision-Making

OCF = Overconfidence

LAV = Loss Aversion

HRB = Herd Behaviour

MAC = Mental Accounting

ANB = Anchoring Bias

β_0–β_5 = Regression Coefficients

ε = Error Term

3.2 Operationalisation of Variables

All constructs were measured using Likert-scale indicators, with each behavioural bias defined according to its psychological attributes and decision-making implications.

Table 1: Operational Definitions of Variables

Variable	Code	Description	Scale
Investment Decision	ID	Self-assessed decision quality and portfolio behaviour	5-point Likert Scale
Overconfidence	OCF	Perceived judgement accuracy and forecast confidence	5-point Likert Scale
Loss Aversion	LAV	Tendency to avoid losses relative to equivalent gains	5-point Likert Scale
Herd Behaviour	HRB	Inclination to follow market consensus or peer action	5-point Likert Scale
Mental Accounting	MAC	Segregation of financial decisions into mental categories	5-point Likert Scale
Anchoring Bias	ANB	Reliance on past values or reference points in decision-making	5-point Likert Scale

Source: Author's Compilation (2025)

3.3 Validity and Reliability

Instrument validity was established through face and content validation, involving expert assessment of item clarity and construct alignment. Reliability was assessed through Cronbach's Alpha, with all variables meeting the recommended threshold of 0.70 for internal consistency (Nunnally & Bernstein, 1994). A pilot test with 20 participants confirmed the reliability of the instrument, supporting its use in the main data collection phase.

3.4 Analytical Techniques

Data analysis involved both descriptive and inferential statistical techniques. Descriptive statistics, including means, standard deviations, and frequency distributions, were employed to summarise respondent demographics and behavioural response patterns. For inferential analysis, the study utilised the Generalized Linear Model (GLM) to assess the predictive influence of each behavioural bias (overconfidence, loss aversion, herding behaviour, mental accounting, and anchoring bias) on investment decision-making. This approach was selected based on the presence of serial correlation, as revealed by diagnostic tests, which rendered Ordinary Least Squares (OLS) regression unsuitable. To ensure the robustness of the GLM estimation, diagnostic procedures were conducted, including the Durbin-Watson test for autocorrelation, the Breusch-Pagan test for heteroskedasticity, and the Ramsey RESET test for functional specification. A significance threshold of $p < 0.05$ was used to determine statistical relevance. All data analyses were performed using EViews 12 and SPSS version 25, consistent with established practices in behavioural finance and econometric research (Gujarati & Porter, 2009; Wooldridge, 2016).

4. Results and Discussion

This section presents the empirical findings in alignment with testing behavioural finance model in Nigeria capital market. Before analysing the core variables, the internal consistency of the measurement constructs is reported. Subsequent analyses include descriptive statistics, correlation analysis, diagnostic evaluations, and multiple regression results. Of the 384 questionnaires administered, 361 were duly completed and returned, resulting in a valid response rate of 94.01%.

4.1 Reliability Statistics

Before administering the main survey, a pilot study was conducted to assess the internal consistency of the research instrument and to confirm the reliability of the measurement constructs. The analysis was carried out using IBM SPSS (Version 25), and the results of the reliability evaluation are presented in Table 2.

Table 2: Reliability Analysis of Measurement Constructs

Construct	Item Code Range	Cronbach's Alpha
Overconfidence	OCF1–OCF5	0.874
Loss Aversion	LAV1–LAV5	0.861
Herding Behaviour	HRB1–HRB5	0.849
Mental Accounting	MAC1–MAC5	0.843
Anchoring Bias	ANB1–ANB5	0.858
Investment Decision-Making	ID1–ID5	0.832
Overall Instrument Reliability	All items	0.928

Source: Author's Fieldwork Analysis using SPSS v.25 (2025)

Table 2 presents the internal consistency values for all behavioural constructs using Cronbach's Alpha. Each construct exceeded the commonly accepted threshold of 0.70, indicating that the scale items are highly consistent and suitable for further statistical procedures (Tavakol & Dennick, 2011; Gliem & Gliem, 2003). The alpha coefficients ranged from 0.832 for investment decision-making to 0.874 for overconfidence, reflecting the sound psychometric quality of the instrument. The overall instrument reliability stood at 0.928, signifying a robust and cohesive measurement framework. These results validate the reliability of the scale for analysing the behavioural determinants of investment decisions in the Nigerian capital market.

4.2 Preliminary Analyses

This section provides a preliminary analysis of the study variables, comprising a descriptive statistical summary and an exploration of the interrelationships among the variables through correlation analysis.

Table 3: Descriptive statistics

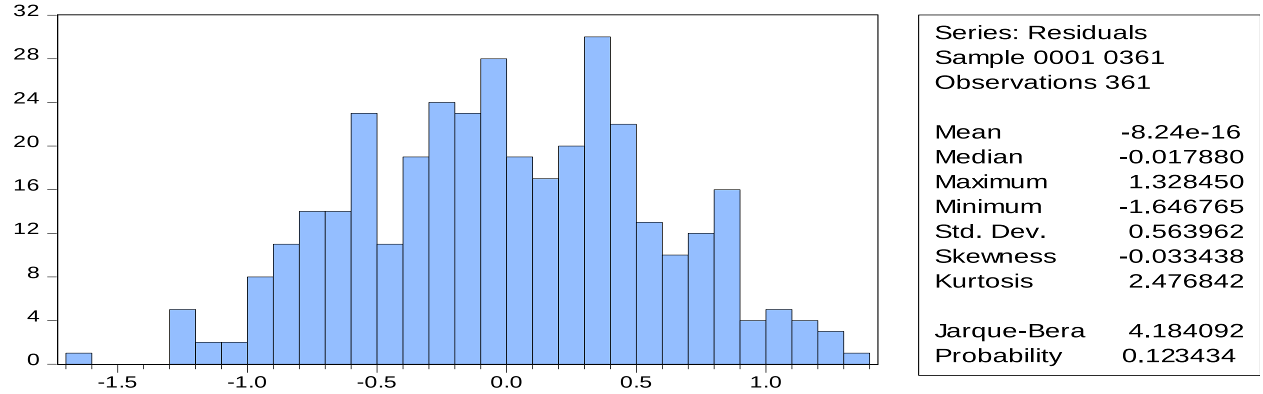
	ID	OCF	LAV	HRB	MAC	ANB
Mean	3.118560	3.400000	3.264820	3.341828	3.126870	3.611357
Maximum	4.800000	5.000000	5.000000	5.000000	5.000000	4.800000
Minimum	1.600000	1.600000	1.400000	1.200000	1.200000	1.000000
Std. Dev.	0.616544	0.615720	0.607461	0.628973	0.654704	0.594240
Skewness	0.053615	-0.115543	0.206849	-0.245344	-0.089811	-0.883821
Kurtosis	2.454756	3.179425	2.958308	3.404074	2.919035	4.587656
Jarque-Bera	4.644713	1.287474	2.600479	6.077584	0.583912	84.91340
Probability	0.098042	0.525326	0.272467	0.047893	0.746801	0.000000

ID = Investment Decision in Nigeria Capital Market (dependent variable); OCF = Overconfidence; LAV = Loss Aversion; HRB = Herding Behaviour; MAC = Mental Accounting; ANB = Anchoring Bias (All in Five-Point Likert Scales)

Source: Researcher's compilation (2025)

Table 3 presents the descriptive statistics for the study variables measured on a five-point Likert scale. The mean scores for all variables range between 3.12 and 3.61, indicating moderate agreement among respondents, with anchoring bias (ANB) recording the highest average (3.61) and investment decision (ID) the lowest (3.12). Standard deviations are relatively low across all constructs (ranging from 0.59 to 0.65), suggesting limited variability in responses. Skewness values are generally close to zero, indicating approximate symmetry in distribution, although anchoring shows moderate negative skewness (–0.88). Kurtosis values range from 2.45 to 4.59, with anchoring exhibiting a leptokurtic distribution, indicating a more peaked data pattern. The Jarque-Bera test confirms normality for most variables ($p > 0.05$), except for herding behaviour (HRB) and anchoring bias (ANB), which deviate significantly ($p = 0.048$ and $p = 0.000$, respectively), suggesting that these two variables may not follow a normal distribution and may require careful interpretation in subsequent analyses.

Figure 2: Normality Test



Source: EViews 12

Figure 2 verifies the normal distribution of the study variables, as evidenced by a p-value of 0.12, which exceeds the threshold of 0.05.

Table 4: Correlation Matrix and Test for Multicolinearity (VIF)

	ID	**OCF**	**LAV**	**HRB**	**MAC**	**ANB**	VIF
ID	1.000000						
OCF	0.374352*	1.000000					1.825521
LAV	0.345515*	0.612554*	1.000000				1.848105
HRB	0.267110*	0.554306*	0.522301*	1.000000			2.147525
MAC	0.232666*	0.461132*	0.507571*	0.657185*	1.000000		1.892648
ANB	0.012691	0.094596	0.008728	0.217300*	0.158504*	1.000000	1.070532

* Sig @ 1%; * * Sig @ 5%

Source: Researcher's compilation (2025)

Table 4 presents the correlation coefficients among the study variables and the Variance Inflation Factor (VIF) values used to assess multicollinearity. All behavioural variables, except anchoring bias (ANB), show statistically significant positive correlations with investment decision (ID) at the 1% level, with overconfidence (r = 0.374) and loss aversion (r = 0.346) exhibiting the strongest associations. Anchoring bias, however, shows a negligible and non-significant correlation with investment decision (r = 0.013), suggesting its limited direct influence in this context. Inter-variable correlations are generally moderate, and while herding and mental accounting display relatively strong associations (r = 0.657), no pair exceeds the threshold indicative of multicollinearity. This is further confirmed by the VIF values, all of which range between 1.07 and 2.15 well below the conventional cut-off of 10 indicating the absence of multicollinearity and justifying the inclusion of all independent variables in the regression model.

4.3 Diagnostic Tests

Table 5 :Serial, Heteroskedasticity, and Specification Tests

Breusch-Godfrey Serial Correlation LM Test:			
F-statistic	11.25974	Prob. F(2,353)	0.0000
Obs*R-squared	21.64876	Prob. Chi-Square(2)	0.0000
Heteroskedasticity Test: Breusch-Pagan-Godfrey			
F-statistic	0.327954	Prob. F(5,355)	0.8960
Obs*R-squared	1.659817	Prob. Chi-Square(5)	0.8939
Ramsey RESET Test: Specification: FC RQ CG TP RL BO IA C			
t-statistic	0.664499	354	0.5068
F-statistic	0.441559	(1, 354)	0.5068
Likelihood ratio	0.450010	1	0.5023

Source: Researcher's compilation (2025)

Table 5 presents the results of key diagnostic tests assessing the assumptions of the regression model. The Breusch-Godfrey test indicates the presence of serial correlation, with both the F-statistic (11.26, $p < 0.01$) and the Chi-square statistic (21.65, $p < 0.01$) confirming significant autocorrelation in the residuals. In contrast, the Breusch-Pagan-Godfrey test for heteroskedasticity yields non-significant results ($F = 0.33$, $p = 0.896$), suggesting that the error terms exhibit constant variance. Similarly, the Ramsey RESET test indicates no evidence of model misspecification, as all test statistics are insignificant ($p > 0.50$). Given the presence of serial correlation but no heteroskedasticity or specification error, the adoption of a generalised linear model (GLM) is justified to correct for autocorrelation and produce consistent, efficient estimates.

4.4 Multivariate Analysis for Testing Behavioural Finance Model in Nigeria Capital Market

Table 6: Generalized Linear Model

Dependent Variable: ID

Method: Generalized Linear Model (Newton-Raphson / Marquardt steps)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
OCF	0.246113	0.065682	3.747049	0.0002
LAV	0.170982	0.066985	2.552518	0.0107
HRB	0.040049	0.069739	0.574273	0.5658
MAC	0.009934	0.062896	0.157947	0.8745
ANB	-0.023427	0.052116	-0.449512	0.6531
C	1.643253	0.253774	6.475261	0.0000

LR statistic: 69.28456

Prob(LR statistic): 0.000000

Source: Researcher's compilation (2025)

The results of the Generalized Linear Model in Table 6 provide empirical insights into the behavioural finance model within the Nigerian capital market. Among the five behavioural variables examined, overconfidence ($\beta = 0.246$, $p < 0.01$) and loss aversion ($\beta = 0.171$, $p < 0.05$) significantly and positively influenced investment decisions, suggesting that investors who display excessive confidence in their judgments or exhibit a strong aversion to losses are more likely to make active investment choices. This finding aligns with studies by Vuković and Pivac (2024), who reported a similar positive relationship between overconfidence and investment behaviour among Croatian investors, and Alquraan et al. (2016), who confirmed the relevance of loss aversion among Saudi investors. The significant role of overconfidence is also consistent with Michael (2023), who found it to be one of the strongest behavioural predictors among Nigerian investors. Conversely, herding behaviour, mental accounting, and anchoring bias were statistically insignificant, indicating that these biases did not meaningfully influence investment decision-making in this context. This contrasts with findings by Fateye et al. (2024), who observed strong herding behaviour in Nigeria's real estate market, and Kartini and Nahda (2021), who reported a significant anchoring effect among Indonesian investors. The results imply that the influence of these biases may be context-specific or moderated by investor characteristics, such as experience and market familiarity.

Furthermore, the insignificance of anchoring and mental accounting resonates with findings by Pokharel (2020), who reported a limited role for these biases in Nepal's emerging capital market. Additionally, the positive but insignificant coefficient for herding supports Edeh (2020), who also found no notable impact of herding behaviour among Nigerian retail investors. This suggests that collective sentiment may be less influential in broader market contexts compared to niche sectors like real estate. Overall, the Likelihood Ratio statistic ($LR = 69.28$, $p < 0.001$) confirms the joint explanatory power of the behavioural model. Thus, the overarching conclusion is that the behavioural finance model holds partial empirical validity in Nigeria's capital market, with overconfidence and loss aversion emerging as key behavioural determinants, while other biases appear to exert more limited or context-dependent effects. These findings support the need for targeted behavioural interventions in financial education and portfolio management, particularly addressing cognitive distortions that drive active but potentially flawed investment decisions.

5. Conclusion and Recommendations

This study empirically tested a behavioural finance model to examine the influence of key psychological biases such as overconfidence, loss aversion, herding behaviour, mental accounting, and anchoring on investment decision-making in the Nigerian capital market. Using a Generalized Linear Model, the findings revealed that overconfidence and loss aversion exert statistically significant and positive effects on investment decisions, indicating that Nigerian investors are more likely to act when they are excessively confident in their judgment or strongly motivated to avoid potential losses. In contrast, herding behaviour, mental accounting, and anchoring bias were found to have no significant impact on investment actions, suggesting that collective sentiment, mental compartmentalisation of funds, and reliance on reference points are less influential under current market conditions. These results highlight a partially validated behavioural finance model, where not all biases uniformly shape decision-making. The findings align with those of Michael (2023) and Vuković and Pivac (2024), who also identified overconfidence and loss aversion as dominant psychological drivers, while contrasting with studies such as Fateye et al. (2024) and Kartini and Nahda (2021), which emphasised the role of herding and anchoring in other markets.

In light of these outcomes, several policy recommendations are proposed. First, regulatory bodies such as the Nigerian Securities and Exchange Commission (SEC) and the Nigerian Exchange Group (NGX) should strengthen investor education programmes, with a focus on mitigating overconfidence and promoting realistic expectations about market returns. Such interventions should emphasise behavioural risk awareness and provide practical decision-making tools tailored to retail investors. Financial literacy curricula should incorporate behavioural content, especially regarding the psychological costs of loss aversion and overconfidence-driven trading errors. Second, investment advisors and portfolio managers must be trained to recognise and address client biases that may distort asset allocation strategies. Behavioural finance insights should be integrated into professional certification schemes and advisory protocols. Third, digital platforms and trading applications can be redesigned to include nudges, such as warnings about excessive trading frequency or portfolio concentration, to counteract bias-driven actions in real-time.

Additionally, data-driven policymaking is critical. Regulators should support the development of behavioural data repositories and periodic surveys to track investor sentiment and decision patterns. Collaboration between academics, market practitioners, and policymakers is essential for designing and testing targeted behavioural interventions. Finally, by focusing on psychological determinants of market participation, the Nigerian capital market can evolve beyond the classical rational agent framework, enabling more inclusive and responsive regulatory strategies. Such an evidence-based approach will contribute not only to improving individual investment outcomes but also to fostering a more stable and efficient market environment in line with global best practices in behavioural finance regulation.

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