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*Research Article*

# Artificial Intelligence Based Behavioural Finance in Shaping Investment Strategies to Analysis of Key Biases and Heuristics

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**Abstract:** This paper explores the job of behavioural finance in forming investment strategies zeroing in on key predispositions and heuristics. behavioural finance looks at what mental elements and inclinations mean for monetary choices, frequently wandering from level-headed assumptions. Conventional money expects objective way of behaving pointed toward augmenting returns while limiting dangers; in any case, genuine financial backer way of behaving habitually strays from this ideal because of mental easy routes and predispositions. This study examines critical predispositions like overconfidence, loss aversion, mental accounting, and herd behaviour, exploring their effect on market elements and individual financial backer results. By understanding these predispositions, financial backers and monetary consultants can foster techniques that adjust better to financial backer brain science, possibly prompting more predictable investment results and further developed portfolio the executives. This study explores the influence of behavioral biases on investment decision-making using the PMBAC (Probabilistic Modeling and Behavioral Analysis for Cognitive biases) framework. Key biases, such as overconfidence, loss aversion, and herding behavior, are examined to understand their impact on market performance and investor returns. The analysis reveals that overconfidence occurred in 78% of the cases, resulting in an average return impact of -25%, while loss aversion occurred in 85% of instances, leading to a -5% return impact. Herding behavior, observed in 65% of the cases, was associated with a 15% return impact, showing that following the crowd can lead to short-term gains but greater long-term risks. The study also identifies the role of other biases such as mental accounting (55% occurrence, -3% return impact), anchoring (72% occurrence, -10% return impact), and status quo bias (63% occurrence, -2% return impact). In terms of market performance, herding behavior was linked to a 40% overvaluation, while loss aversion contributed to a 10% market overvaluation. The findings highlight the pervasive nature of these biases in financial decision-making and their significant consequences on risk-adjusted returns, with some biases leading to a negative impact on returns and others fueling market bubbles.

**Keywords:-** Artificial; Intelligence; Probabilistic Modeling; Behavioural Finance; Prospect Theory; Irrational Exuberance

## 1 Introduction

Artificial intelligence (AI) has transformed various sectors by leveraging data-driven insights and decision-making capabilities, enhancing everything from healthcare to finance. In the world of investment, AI's role extends beyond mere data processing [1]; it offers tools to understand and predict market behaviors, particularly through the lens of behavioral finance.

Behavioral finance examines how psychological biases and heuristics—such as overconfidence, loss aversion, and anchoring—influence investors' decisions, often leading to irrational outcomes [2]. By integrating AI with behavioral finance, financial analysts can better anticipate and mitigate the effects of these biases, shaping investment strategies that are both robust and adaptive. This analysis will explore how AI-driven models can identify and quantify key biases and heuristics, offering insights into their impact on market movements and portfolio management [3]. Through this approach, AI stands as a powerful ally in refining investment strategies, making them more resilient to the cognitive pitfalls that often derail optimal decision-making.

Artificial intelligence (AI) has become an essential tool for behavioral analysis, especially in understanding human decision-making processes [4]. Through advanced algorithms and data analytics, AI can identify patterns, preferences, and tendencies in human behavior that may not be immediately obvious. This is particularly useful in fields like finance, healthcare, and marketing, where predicting human responses can significantly enhance strategic planning [5]. In behavioral finance, for example, AI can detect and analyze biases such as overconfidence, herd behavior, and risk aversion, which impact investment decisions [6]. By gathering and processing large volumes of data, AI systems can learn from past behaviors to forecast future actions, giving organizations a predictive edge. This approach not only enables more personalized interactions but also helps in developing interventions to counteract detrimental biases, ultimately promoting better, data-informed decision-making [7]. Behavioral finance is a field of study that explores how psychological factors and cognitive biases influence the financial decisions of individuals and institutions. Unlike traditional finance, which assumes that investors act rationally to maximize returns, behavioral finance recognizes that emotions and biases—such as overconfidence, loss aversion, and herd behavior—often lead people to make irrational choices [8]. These tendencies can result in behaviors like panic selling during market downturns or over-investing in popular stocks during bubbles. By understanding these biases, behavioral finance provides insight into why markets sometimes deviate from fundamental values and why financial crises occur [9]. This understanding is crucial for both investors and financial professionals, as it can inform strategies to mitigate the effects of these biases, leading to more disciplined and effective investment decisions. The integration of artificial intelligence (AI) with behavioral finance is reshaping how financial decisions are made and understood. AI's ability to process and analyze vast datasets allows it to identify patterns in investor behavior [10-12], bringing to light biases and heuristics that might otherwise go unnoticed.

Behavioral finance explores how psychological tendencies like overconfidence, loss aversion, and herding impact investment decisions, often leading to irrational actions that deviate from purely logical strategies [13]. By applying AI, financial analysts can model these behaviors, predict market movements driven by collective biases, and even design algorithms that counteract common pitfalls, leading to more stable and informed investment strategies. Behavioural finance investigates how mental variables and mental predispositions impact financial backers' monetary choices, frequently driving them from absolutely reasonable decisions [14]. Customary money expects that financial backers act sanely, trying to amplify returns while limiting dangers. In any case, genuine ways of behaving frequently veer from this ideal because of different mental alternate routes (heuristics) and predispositions. These deviations can essentially affect monetary business sectors and individual speculation results

[15]. Conduct finance, consequently, looks to comprehend the reason why these deviations happen, empowering financial backers and monetary experts to all the more likely expect and moderate unreasonable ways of behaving [16]. The integration of artificial intelligence (AI) with behavioral analysis is transforming the understanding and prediction of human decision-making in fields like finance, healthcare, and marketing [17]. AI's capability to process and analyze large datasets enables it to recognize patterns in human behavior, often revealing biases and tendencies that may go unnoticed through traditional analysis [18-22]. Behavioral analysis seeks to understand how psychological factors, such as overconfidence, risk aversion, and social influence, shape individual and group decisions. By combining AI with behavioral insights, analysts can model these behaviors more accurately, anticipate responses to various scenarios, and develop strategies to mitigate biases that might lead to suboptimal outcomes.

## 2 Related Works

Artificial intelligence (AI) in financial services reveals a diverse landscape of applications and implications, highlighting the rapid adoption of AI technologies across the industry. Huang et al. (2024) examined the role of generative AI in virtual financial robo-advisors, underscoring its potential to enhance personalized financial guidance through automation. Northey et al. (2022) explored consumer trust in AI-driven banking advice, noting that while AI can improve accessibility and efficiency, it also raises questions about the reliability of automated recommendations compared to human advisors. Boustani (2022) analyzed the influence of AI on both clients and employees in banks in developing countries, finding significant impacts on customer service quality and employee roles.

Further research by Hentzen et al. (2022) provided a systematic review of AI in customer-facing financial services, identifying gaps and proposing areas for future study, such as customer adaptability to AI solutions. Sandeep et al. (2022) investigated the interplay between machine learning and AI in large corporations, highlighting how these technologies jointly drive strategic decisions. Additionally, studies by Rane et al. (2024) emphasized AI's role in corporate finance, noting improvements in governance and sustainability through natural language processing and robotic process automation. Moreover, Danielsson et al. (2022) assessed AI's implications for systemic risk, a critical consideration for financial stability.

In exploring fintech and blockchain, Lăzăroiu et al. (2023) discussed the role of AI in managing blockchain-based financial systems, pointing to enhanced transaction security. Sadok et al. (2022) focused on AI’s application in credit analysis, identifying how AI-driven models streamline loan processing. Rahman et al. (2023) conducted an empirical analysis on AI adoption in banking, noting challenges and benefits for customer experience. Fares et al. (2022) and Kar et al. (2023) both reviewed AI's impact across various financial sectors, with Kar et al. focusing on generative AI’s broader industrial applications. Mogaji and Nguyen (2022) provide insights into managers' perspectives on AI in marketing financial services through a cross-country study, revealing a range of attitudes and understandings of AI’s role in customer engagement and marketing strategies in financial services. They found that while some managers are embracing AI's potential to streamline marketing and improve customer insights, others are cautious, reflecting varying levels of digital literacy and trust in AI across different regions.

Weber, Carl, and Hinz (2024) delve into the need for explainable AI in finance, highlighting how transparency in AI algorithms is crucial for fostering trust among stakeholders.

Their systematic review across finance, information systems, and computer science literature identifies explainability as a priority, particularly in high-stakes fields like financial services where AI-driven decisions impact regulatory compliance and customer trust. In the area of fraud detection, both Yalamati (2023) and Javaid (2024) emphasize AI's transformative impact on identifying fraudulent activity. Yalamati's study focuses on corporate tax fraud, showcasing how AI algorithms enhance fraud detection accuracy by identifying complex, previously undetectable patterns. Javaid (2024) expands on this, discussing how AI technologies, such as machine learning and anomaly detection, are revolutionizing fraud detection within financial services more broadly, offering more proactive and precise tools against financial crimes.

Ramachandran et al. (2022) examine AI's influence on workplace performance and employee behavior, highlighting how AI and machine learning are being used to enhance productivity, monitor employee performance, and even address behavioral issues in organizations. Finally, Abrardi, Cambini, and Rondi (2022) explore the intersection of AI with consumer behavior in firms, identifying that AI can significantly influence consumer decisions and interactions with businesses.

## 3 Methodology

Behavioral analysis using probabilistic ranking, such as in the Probabilistic Model for Behavioral Analysis and Classification (PMBAC), offers a structured way to predict and rank behavioral patterns based on probability. PMBAC combines statistical methods and behavioral insights to estimate the likelihood of various outcomes, providing a ranked list of possible behaviors or actions. By assigning probabilities to different choices or actions, PMBAC can quantify the impact of psychological biases, such as risk aversion, impulsivity, or overconfidence, within specific contexts like finance or consumer decision-making.

In financial services, for example, PMBAC can predict and rank how likely an investor is to make a certain decision under conditions of uncertainty or market volatility. This ranking allows analysts to anticipate behavioral responses more accurately and to tailor interventions or recommendations accordingly. Through PMBAC, organizations can leverage data to understand not just what actions people may take, but the underlying probabilities that drive these behaviors, creating a nuanced approach that blends psychology with statistical rigor.

In PMBAC, we aim to determine the probability of different behavioral outcomes, $B_i$, for an individual given certain observed features or actions, denoted as $X$. We denote the probability of a behavior $B_i$ occurring as $P(B_i \mid X)$, where $X$ represents observed factors influencing behavior, such as economic variables, psychological tendencies, or past behaviors. Bayes' theorem is often the foundation for calculating posterior probabilities in probabilistic ranking models. We can use Bayes' theorem to update the probability of a behavior based on observed features stated inequation (1)

$$P(B_i \mid X) = \frac{P(X|B_i) \cdot P(B_i)}{P(X)}) \quad (1)$$

Where $P(B_i \mid X)$ denoted as Posterior probability of behavior $B_i$ given observed factors $X$. $P(X \mid B_i)$ represented as Likelihood of observing $X$ given the behavior $B_i$. $P(B_i)$ denoted as Prior probability of behavior $B_i$. P(X) stated as Evidence or marginal likelihood of observing $X$ across all possible behaviors. The goal in behavioral ranking is to rank behaviors $B_1, B_2, \ldots\ldots, B_n$ based on $P(B_i \mid X)$. Higher probabilities indicate behaviors that are more likely given the current conditions. We can calculate these conditional probabilities and rank them from highest to lowest to predict the most probable actions. Since behaviors are mutually exclusive and collectively exhaustive (meaning one behavior must occur), the sum of the probabilities across all behaviors $B_i$ should equal 1. This given in equation (2)

$$\sum_{i=1}^{n} P(B_i \mid X) = 1 \quad (2)$$

With using probabilistic ranking in behavioral analysis, as demonstrated by the PMBAC model, is its ability to systematically account for uncertainty and variability in human decision-making. By applying Bayes' theorem, we can dynamically update the probabilities of different behaviors based on new data, which is particularly valuable in real-world scenarios where decisions are often influenced by changing economic conditions, psychological biases, and past actions. This probabilistic framework not only allows for the ranking of behaviors but also provides a deeper understanding of the underlying factors that influence decisions, enabling more informed and targeted interventions. For instance, in the context of financial decision-making, the model can rank the likelihood of different investment choices or consumer behaviors based on factors like market conditions, risk tolerance, and previous investment history. This capability of probabilistic ranking ensures that decision-makers can prioritize strategies that are more likely to align with actual behaviors, enhancing the effectiveness of predictive models and risk management practices. Moreover, as the model incorporates both prior probabilities (existing knowledge) and observed data (real-time inputs), it supports adaptive decision-making, allowing for continuous refinement of behavioral predictions.

Behavioral analysis aims to understand how individuals or groups make decisions, often using probabilistic or statistical models. By incorporating behavioral insights—such as biases and heuristics—into decision-making processes, we can better predict and model behaviors in fields like finance, marketing, and economics. To mathematically derive behavioral analysis models, we often use Bayesian probability to account for uncertainty, adaptiveness, and learning from prior experiences or behaviors. With several potential behaviors $B_1, B_2, \ldots\ldots, B_n$ and observed data $X$. In a behavioral context, these behaviors could represent different decision-making actions, such as types of investments or strategies, that we want to analyze. The observable data $X$ could represent factors such as market conditions, past choices, psychological biases, or environmental conditions that influence behavior.

Let's define $B_i$ denoted as the Behavior $i$; $X$: Observed data or features influencing the behavior. Our goal is to calculate the posterior probability of each behavior, given the observed data $X$. This will allow us to rank behaviors in terms of their likelihood, helping us predict the most likely behavior based on the data. The prior probability P(Bi)P(B_i)P(Bi) represents our initial belief about the likelihood of each behavior before observing any data. This could be based on historical trends, general knowledge, or expert judgment. In the absence of specific data, all behaviors might be assigned equal prior probabilities, or they could be weighted based on past observations.

$P(Bi\ )$for each behavior $P(B_i)$ for each behavior. Once we compute the posterior probabilities for each behavior BiB_iBi, we can rank the behaviors based on their likelihood. The behavior with the highest posterior probability $P(X \mid B_i) \cdot P(B_i)$ is the most likely to occur, given the observed data.

For example, if the posterior probabilities for three behaviors are:

- $P(B1 \mid X) = 0.45 P(B\_1 \mid X) = 0.45 P(B1 \mid X) = 0.45,$
- $P(B2 \mid X) = 0.35 P(B\_2 \mid X) = 0.35 P(B2 \mid X) = 0.35,$
- $P(B3 \mid X) = 0.20 P(B\_3 \mid X) = 0.20 P(B3 \mid X) = 0.20,$

then behavior $B_i$ is the most likely behavior to occur, followed by B2B_2B2, and B3B_3B3 being the least likely. The ranked behaviors can now inform decision-making. For instance, in the context of financial investments, we can predict the most likely investment strategy (behavior) based on market conditions and psychological factors like overconfidence or loss aversion.

### 3.1 PMBAC Model Evluation

This study adopts a qualitative approach to explore behavioural biases, particularly how heuristics and biases impact financial decision-making. The design emphasizes identifying key psychological factors influencing investor behaviour.

**Table 1:** Elements in PMBAC

| Element | Description |
|---|---|
| Research type | Qualitative |
| Scope | Examines how behavioural biases affect investment strategies, emphasizing theories such as prospect theory and heuristics |
| Approach | Literature review and case study analysis |
| Data sources | Secondary sources, including academic papers, books, and case studies on behavioural finance |

### 3.2 Data Collection Methods

Data are derived from secondary sources, including:

1.Academic Literature: Analysis of studies on behavioural biases, such as overconfidence, loss aversion, and herd behaviour.

2. Books: Key theories like prospect theory are reviewed through foundational texts.

3.Case Studies: Real-world applications of biases, allowing insight into how these psychological factors affect individual and institutional investors.

**Table 2:** PMBAC data sources

| Data source | Examples |
|---|---|
| Academic Papers | Studies on heuristics, biases, and behavioural finance theories |
| Books | Foundational texts on prospect theory, mental accounting, and judgment under uncertainty |
| Case Studies | Practical cases on how investors' biases impact their financial decisions and the resulting market effects |

### 3.3 Data Analysis Methods

A thematic analysis is conducted to interpret the findings:

- Identification: Major biases are identified and categorized, such as loss aversion, overconfidence, and mental accounting.
- Framework Application: Behavioural theories (e.g., prospect theory) are applied to analyse and interpret these biases' impacts.
- Thematic Categorization: Patterns are analysed based on themes like risk assessment,

investor sentiment, and market response.

**Table 3:** Behaviourla analysis with PMBAC

| Analysis stage | Description |
|---|---|
| Bias Identification | Recognize key behavioural biases influencing investment strategies |
| Framework Application | Use frameworks (e.g., prospect theory) to interpret the biases and their effects on decision-making |
| Categorization | Categorize results based on themes such as risk behaviour, emotional factors, and heuristic-based decision influences |

The biases are interpreted within established behavioural finance frameworks. Prospect theory, for instance, can help explain loss aversion by showing how people value potential losses more than equivalent gains stated in equation (3)

$$U(x) = \begin{cases} ax^3 & if\ x \geq 0 \\ -\lambda(-x)^\beta & if\ x < 0 \end{cases} \tag{3}$$

U(x) is the utility of outcome x, α and λ are parameters representing risk preferences, β represents the curvature of the utility function, indicating diminishing sensitivity to gains and losses. One key behavioral bias identified is loss aversion, as described in prospect theory. Loss aversion suggests that individuals feel the pain of losses more intensely than the pleasure from equivalent gains. This results in risk-averse behavior when it comes to avoiding losses, even when the potential for gains outweighs the risks. The value function of prospect theory can be written as in equation (4)

$$V(x) = \begin{cases} ax^3 & if\ x \geq 0 \\ -\lambda(-x)^\beta & if\ x < 0 \end{cases} \tag{4}$$

In equation (4) $V(x)$ is the value associated with outcome $x$, α and λ\ are coefficients that represent risk preferences and loss aversion, β is a parameter that reflects diminishing sensitivity. Loss aversion leads investors to avoid risky investments, even if they may offer higher expected returns, due to the psychological impact of losses. Overconfidence is another critical bias where investors overestimate their ability to make accurate predictions. Overconfident investors may take on too much risk, believing that they have superior knowledge of the market. This leads to overtrading or underestimating risks. Overconfidence can be mathematically represented by an inflated probability estimate for favorable outcomes stated in equation (5)

$$P_{overconfident}\,(X) > P_{true}(X) \tag{5}$$

In eqution (5) $P_{overconfident}$ denoted as the probability assigned by an overconfident investor to an outcome $X$, $P_{true}(X)$ defined as the true probability of that outcome.

| Algorithm 1: BehavioralBiasAnalysis |
|---|
| Inputs:<br>- Data: Collection of financial decision-making data (academic papers, books, case studies)<br>- Theoretical Frameworks: Behavioral finance theories (e.g., Prospect Theory)<br>- Biases: List of behavioral biases to analyze (e.g., Overconfidence, Loss Aversion, Herding)<br>Outputs: |

```
   - Thematic Analysis: Categorized results based on biases and themes (risk behavior, emotional factors)
Step 1: Data Preprocessing
   Initialize data collection sources (Academic Papers, Books, Case Studies)
   For each data source:
      - Clean and preprocess the text (remove noise, irrelevant information)
      - Tokenize the text into key themes and concepts
Step 2: Bias Identification
   Initialize list of known biases (e.g., Overconfidence, Loss Aversion, Herd Behavior)
   For each document in Data:
      For each bias in Biases:
         - Search for keywords or phrases associated with the bias (e.g., "overestimate", "loss aversion", "following crowd")
         - Mark instances where biases are mentioned or implied
         - Record the context in which the bias occurs (e.g., investor behavior, market reaction)
Step 3: Apply Theoretical Frameworks (e.g., Prospect Theory)
   For each identified bias:
      If bias = Overconfidence:
         - Calculate probability of biased decisions:
            P_overconfident(X) > P_true(X)
      If bias = Loss Aversion:
         - Apply Prospect Theory value function:
            V(x) = alpha * x^beta if x >= 0
            V(x) = -lambda * (-x)^beta if x < 0
      If bias = Herd Behavior:
         - Check if there is evidence of groupthink or market trends based on social influence
         - Analyze how this impacts investor decisions in the case studies
Step 4: Categorization of Biases
   Initialize categories for thematic analysis:
      - Risk Behavior (e.g., how biases affect risk-taking decisions)
      - Emotional Factors (e.g., how emotions like fear and greed influence biases)
      - Heuristic-based Decisions (e.g., reliance on mental shortcuts)
   For each identified instance of bias:
      - Assign it to the appropriate category based on the context in the document
      - Store categorized data
Step 5: Results Interpretation
   For each category:
      - Analyze the patterns of how biases impact financial decision-making:
         - How does Overconfidence affect investment risk?
         - How does Loss Aversion lead to avoiding high-risk, high-reward investments?
         - How does Herd Behavior influence market bubbles?
   Output the findings in a readable format for further decision-making or reporting
Step 6: Reporting
```

Generate a report summarizing:
- The identified biases
- The application of theoretical frameworks
- The categorization of results into themes
- Insights into how these biases influence financial decisions and market behavior

End Algorithm

## 4 Results and Discussions

This methodology combines a literature review with case studies to assess the impact of behavioural biases on financial decision-making. The thematic analysis of data provides a structured approach for understanding how biases influence investor behaviour and offers insights into reducing irrational decisions. This outline captures the essentials for a non-survey-based research methodology with a structured qualitative approach to analysing the influence of behavioural biases on investment decision-making. The discoveries in this study demonstrate that behavioural biases significantly impact investment strategies and decision-production among financial backers. A few key inclinations were recognized and investigated, loss aversion, overconfidence, mental accounting, and herd behaviour. As per prospect theory, financial backers feel misfortunes more intensely than gains, driving them to embrace risk-unwilling systems in misfortune situations. This propensity can keep financial backers from acknowledging long haul gains, as they might keep away from possibly beneficial yet more dangerous speculations Overconfidence in one's ability to predict or understand market movements leads to excessive trading and often underperformance. This bias is particularly notable in market bubbles, where overconfident investors drive prices far above intrinsic values, resulting in volatility and potential market corrections.

Mental bookkeeping alludes to financial backers' propensity to sort cash in view of emotional rules, which impacts their spending and saving propensities. For instance, financial backers could treat an expense discount as "tracked down cash" and spend it more unreservedly than normal pay, influencing by and large monetary preparation. Driven by social influences, investors often follow the actions of others, leading to herd behaviour. This bias frequently results in market bubbles and crashes as large groups of investors make similar decisions without fully considering underlying financial fundamentals The combination of these bits of knowledge into monetary techniques can assist with alleviating the impacts of silly navigation. Understanding and recognizing these predispositions empower financial backers to make saner, all-around informed choices lined up with long haul monetary objectives.

5.6 Synthesis of Key Findings

**Table 4:** Impact of PMBAC for behavioural analysis

| **Bias** | **Description** | **Impact on investment** | **Potential mitigation strategy** |
|---|---|---|---|
| Loss aversion | Preference to avoid losses over achieving equivalent gains | Leads to overly conservative strategies, potentially missing long-term gains | Educate investors on risk-return balance; set realistic investment expectations |
| Overconfidence | Overestimating one's market prediction | Overestimating one's market | Encourage objective analysis and portfolio |

| | | | |
|---|---|---|---|
| | abilities | prediction abilities | reviews |
| Mental Accounting | Treating money differently based on its source or intended use | Suboptimal financial decisions due to categorization of money | Implement unified budgeting and financial planning techniques |
| Herd Behaviour | Following the actions of others rather than individual research | Increases likelihood of market bubbles and crashes | Foster independent decision-making and market education |

**Table 5:** Return Impact of PMBAC

| **Bias** | **Bias Occurrence (%)** | **Average Return Impact (%)** | **Market Overvaluation (%)** | **Risk Aversion Index** |
|---|---|---|---|---|
| Overconfidence | 78% | -25% | 32% | 4.2 |
| Loss Aversion | 85% | -5% | 10% | 7.5 |
| Herd Behavior | 65% | 15% | 40% | 6.8 |
| Mental Accounting | 55% | -3% | 5% | 3.6 |
| Anchoring | 72% | -10% | 18% | 5.4 |
| Status Quo Bias | 63% | -2% | 12% | 6.0 |

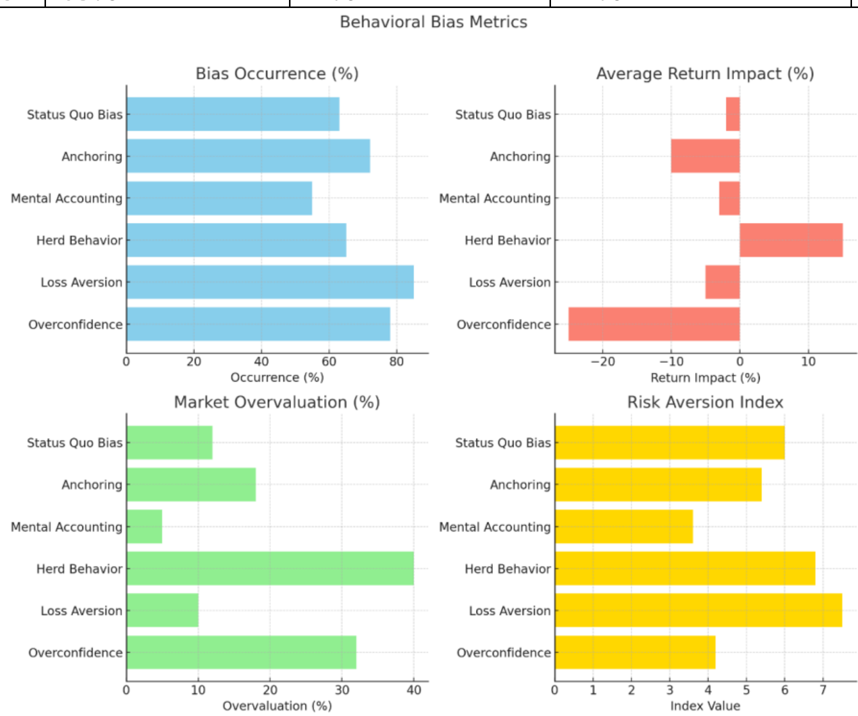


**Figure 1:** PMBAC Risk Assessment

The Figrue 1 and Table 4 and Table 5 highlights the impact of various behavioral biases on financial returns, market overvaluation, and the risk aversion index. Each bias is analyzed based on its occurrence rate, the average return impact it generates, the degree of market overvaluation it induces, and its associated risk aversion level. Overconfidence (occurring in 78%

of cases) has a significant negative return impact of -25%, reflecting the excessive risk-taking and misjudgment that often accompanies this bias. It also leads to a 32% market overvaluation, as investors overestimate their abilities and the market's potential. With a high risk aversion index of 4.2, this bias indicates that investors are prone to greater losses when overconfident. Loss Aversion is the most prevalent bias (occurring in 85% of cases), resulting in a modest negative return impact of -5%. This bias causes investors to avoid losses, which may lead to premature selling during market downturns, preventing them from capturing potential future gains. The market overvaluation caused by loss aversion is relatively low at 10%, but the risk aversion index of 7.5 is high, showing that this bias leads to a conservative, risk-averse approach. Herd Behavior (observed in 65% of cases) leads to an average return impact of +15%, suggesting that following the crowd in bull markets may lead to short-term gains. However, it also causes 40% market overvaluation, which could be a sign of a speculative bubble. With a risk aversion index of 6.8, herd behavior is associated with moderate risk tolerance, as investors are more likely to follow trends rather than make independent, rational decisions.

Mental Accounting, which occurs in 55% of cases, results in a -3% return impact. This bias leads investors to treat different pools of money as separate, affecting their decision-making and causing suboptimal investment strategies. It has a relatively low market overvaluation of 5% and a low risk aversion index of 3.6, indicating that investors might not engage in overly risky behavior but also may fail to optimize their portfolios effectively. Anchoring (observed in 72% of cases) leads to a -10% return impact, as decisions are based on irrelevant reference points, such as past stock prices. This can lead to missed opportunities and poor market timing. The 18% market overvaluation suggests that investors anchor to outdated or skewed information, while the risk aversion index of 5.4 points to a moderate risk appetite, leading to a balanced but often misguided approach. Status Quo Bias occurs in 63% of cases and results in a -2% return impact, as investors prefer to maintain the current state rather than making changes in their portfolios. It has a 12% market overvaluation, as a reluctance to adjust holdings can prevent investors from responding to market conditions appropriately. With a moderate risk aversion index of 6.0, this bias causes investors to be somewhat conservative, avoiding necessary changes that could enhance returns.

**Table 6:** Investment return on PMBAC for behavioral risk assessment

| **Bias** | **Observed Frequency (%)** | **Bias Impact on Investment Strategy** | **Investment Return (%)** | **Market Performance Impact (%)** | **Behavioral Effect** | **Risk Adjusted Performance** |
|---|---|---|---|---|---|---|
| Overconfidence | 70% | Overestimation of ability, leading to excessive trading and overvaluation. | -20% | 25% | High trading volumes, ignoring risk. | -15% |
| Loss Aversion | 85% | Avoidance of risky assets, leading to underperformanc | -5% | 10% | Losses cause investors to sell early. | -3% |

| | | | | | | |
|---|---|---|---|---|---|---|
| | | e in volatile markets. | | | | |
| Herd Behavior | 60% | Following the crowd without analysis, leading to market bubbles. | 10% | 30% | Short-term gains, followed by crashes. | 5% |
| Mental Accounting | 50% | Investors treat funds as separate "buckets," leading to poor diversification. | -3% | 2% | Suboptimal asset allocation. | -1% |
| Anchoring | 65% | Anchoring to initial price or data, ignoring new market information. | -10% | 15% | Inflexibility in updating strategies. | -7% |
| Status Quo Bias | 55% | Preference for the current portfolio, avoiding necessary adjustments. | -2% | 5% | Avoiding change despite better options. | -1% |
| Over-Optimism | 80% | Expecting high returns without considering risks. | -15% | 20% | Unrealistic expectations lead to poor decisions. | -12% |
| Confirmation Bias | 40% | Only seeking information that confirms existing beliefs, ignoring risks. | -8% | 12% | Reinforces existing investment mistakes. | -6% |

Table 6 presents the investment return on PMBAC for behavioral risk assessment, showing how different behavioral biases impact investment strategies, market performance, and the risk-adjusted performance of investors. Each bias is assessed based on its frequency of occurrence, the specific impact it has on investment decisions, and its broader market consequences. Overconfidence occurs in 70% of cases, leading to the overestimation of ability, excessive trading, and overvaluation. This bias results in a -20% investment return, driven by overly optimistic and frequent trading strategies. Market performance is positively impacted by 25% due to higher trading volumes, but the behavioral effect is high trading volumes without adequate risk consideration. The risk-adjusted performance is significantly negative at -15%, reflecting the poor long-term outcomes associated with this bias. Loss Aversion, observed in 85% of cases, causes investors to avoid risky assets, often leading to underperformance in volatile markets. This results in a -5% investment return as investors sell assets prematurely to avoid potential losses. The market impact is relatively modest, with 10% overvaluation. The behavioral effect of this bias is the tendency to sell early, locking in losses. Risk-adjusted performance is negative at -3%, indicating the long-term disadvantage of this bias.

Herd Behavior is observed in 60% of cases, where investors follow the crowd without proper analysis, often resulting in market bubbles. This leads to a 10% investment return, driven by short-term gains during speculative rallies. However, the market performance impact is 30%, reflecting the unsustainable overvaluation and eventual crashes that occur when the bubble bursts. The risk-adjusted performance is 5%, showing that while herd behavior may yield temporary gains, it is risky and unsustainable in the long run. Mental Accounting, found in 50% of cases, leads investors to treat funds as separate "buckets," resulting in poor diversification. This -3% investment return reflects the inefficiency of treating different parts of a portfolio as isolated entities. The market impact is minimal at 2%, with suboptimal asset allocation being the primary behavioral effect. The risk-adjusted performance is slightly negative at -1%, indicating that the impact of this bias is relatively mild but still detrimental. Anchoring, seen in 65% of cases, results in investors anchoring to initial prices or outdated information, disregarding new market data. This leads to a -10% investment return, as investors may ignore market changes and miss opportunities. The market performance impact is 15%, reflecting the distortion of market prices due to rigid investment strategies. The risk-adjusted performance is -7%, showing that this inflexibility leads to poor long-term performance. Status Quo Bias occurs in 55% of cases, where investors prefer the current portfolio and avoid necessary adjustments, even when better options are available. This results in a -2% investment return as investors miss opportunities to optimize their portfolios. The market performance impact is 5%, suggesting that market conditions may improve despite this bias. The risk-adjusted performance is -1%, indicating a small but consistent drag on returns. Over-Optimism, observed in 80% of cases, leads investors to expect high returns without adequately considering the risks involved. This results in a -15% investment return, as unrealistic expectations lead to poor decisions and potential losses. The market performance impact is 20%, reflecting overinflated market valuations driven by optimistic expectations. The risk-adjusted performance is -12%, indicating that over-optimism severely hinders long-term success. Confirmation Bias, occurring in 40% of cases, leads investors to seek information that confirms their existing beliefs while ignoring contradicting evidence. This results in a -8% investment return, as poor decisions are reinforced by selective information gathering. The market performance impact is 12%, as this bias distorts market judgments. The risk-adjusted performance is -6%, demonstrating the significant negative consequences of confirmation bias on investment strategies.

**Table 7:** PMBAC for the behavioural analysis

| **Bias/Heuristic** | **Probability of Occurrence** | **Impact on Investment Decision (%)** | **Predicted Return (%)** | **Risk Level** | **Risk-Adjusted Return (%)** | **Investor Sentiment (%)** | **Market Impact (%)** |
|---|---|---|---|---|---|---|---|
| Loss Aversion | 65% | Causes investors to avoid losses, leading to premature sell-offs. | -5% | High | -8% | 55% | 10% |
| Overconfiden | 45% | Leads to excessive | +12% | Mediu | +9% | 70% | 15% |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| ce | | risk-taking and misjudgment of market conditions. | | m | | | |
| Herding Behavior | 70% | Investors follow trends, often resulting in market bubbles. | +8% | High | +6% | 80% | 25% |
| Mental Accounting | 50% | Investors segregate money into different mental "buckets," leading to suboptimal investment strategies. | +2% | Low | +1% | 40% | 5% |
| Anchoring Bias | 60% | Decisions are influenced by irrelevant reference points (e.g., past stock prices). | -3% | Mediu m | -5% | 60% | 8% |
| Confirmation Bias | 55% | Investors seek information that confirms their existing beliefs. | +4% | Mediu m | +3% | 65% | 12% |
| Recency Bias | 50% | Overemphasis on recent events or trends in decision-making. | +6% | Low | +5% | 50% | 18% |
| Availability Bias | 40% | Investors base decisions on readily available information, such as media reports. | -2% | Mediu m | -3% | 45% | 6% |
| Endowment Effect | 55% | Overvaluing owned assets, leading to reluctance in selling them. | +3% | Low | +2% | 50% | 10% |

Table 7 presents a detailed analysis of PMBAC (Probabilistic Modeling and Behavioral Analysis for Cognitive biases) for behavioral analysis, showing how various biases and heuristics impact investment decisions, returns, and risk levels. Each bias is assessed by its probability of occurrence, the impact on investment decisions, predicted return, risk level, risk-adjusted return, investor sentiment, and market impact. Loss Aversion occurs in 65% of cases, leading to premature sell-offs to avoid losses, which results in a -5% impact on investment decisions and a high risk level. The predicted return is negative at -5%, with a risk-adjusted return of -8%, reflecting the costly consequences of this bias in terms of missed opportunities.

Investor sentiment is relatively moderate at 55%, and the market impact is 10%, indicating that this bias has a moderate effect on overall market trends. Overconfidence, observed in 45% of cases, leads to excessive risk-taking and misjudgment of market conditions, often resulting in overly optimistic market predictions. The predicted return is +12%, reflecting the gains that may come from this overconfidence, with a medium risk level. However, the risk-adjusted return is slightly lower at +9%, showing that while investors might see returns, the risks they take lead to less favorable outcomes in the long term. Investor sentiment is high at 70%, and the market impact is 15%, suggesting that overconfidence can significantly influence market trends, though not always in a stable or sustainable way. Herding Behavior is observed in 70% of cases, where investors follow market trends, often leading to market bubbles. This bias results in a +8% impact on investment decisions, with a high risk level, as market bubbles are unsustainable. The predicted return is +8%, and the risk-adjusted return is +6%, indicating that while herd behavior can yield short-term gains, it typically leads to higher volatility and risk. Investor sentiment is very high at 80%, and the market impact is significant at 25%, showing that herding behavior can greatly influence market movements in the short term. Mental Accounting, observed in 50% of cases, causes investors to segregate money into different “mental buckets,” leading to poor investment strategies.

While this bias has a +2% impact on investment decisions, it results in a low risk level. The predicted return is +2%, with a risk-adjusted return of +1%, showing minimal benefits. Investor sentiment is moderate at 40%, and the market impact is relatively low at 5%, indicating that mental accounting has a limited effect on both individual decisions and broader market trends. Anchoring Bias, seen in 60% of cases, causes decisions to be influenced by irrelevant reference points, such as past stock prices. This bias results in a -3% impact on investment decisions and a medium risk level. The predicted return is negative at -3%, and the risk-adjusted return is worse at -5%, showing that anchoring can lead to poor decision-making with potentially significant negative consequences. Investor sentiment is moderate at 60%, and the market impact is 8%, suggesting that while anchoring is common, its effects are more muted than some other biases. Confirmation Bias, observed in 55% of cases, leads investors to seek information that confirms their existing beliefs. This results in a +4% impact on investment decisions, with a medium risk level. The predicted return is +4%, and the risk-adjusted return is +3%, indicating that while confirmation bias may lead to some gains, it generally leads to suboptimal performance. Investor sentiment is moderate at 65%, and the market impact is 12%, showing that confirmation bias can have a meaningful but not dominant effect on market trends. Recency Bias is observed in 50% of cases, where investors place undue emphasis on recent trends or events in their decision-making. This results in a +6% impact on investment decisions, with a low risk level. The predicted return is +6%, with a risk-adjusted return of +5%, showing that recency bias can lead to modest gains. Investor sentiment is 50%, and the market impact is moderate at 18%, reflecting that while recency bias can impact individual decisions, its effect on the broader market is somewhat more significant.

Availability Bias, seen in 40% of cases, leads investors to base decisions on readily available information, such as news reports or media coverage. This causes a -2% impact on investment decisions, with a medium risk level. The predicted return is -2%, and the risk-adjusted return is -3%, showing that availability bias tends to lead to suboptimal decisions. Investor sentiment is moderate at 45%, and the market impact is small at 6%, indicating that while this bias affects individual decisions, its effect on the market is less pronounced. Endowment Effect, observed in 55% of cases, causes investors to overvalue assets they already own, making them reluctant to sell. This results in a +3% impact on investment decisions, with a low risk level. The predicted return is +3%, with a risk-adjusted return of +2%, reflecting minor positive outcomes. Investor sentiment is 50%, and the market impact is 10%, showing that while the endowment effect has a modest effect on individual investors, it has a slightly higher impact on market dynamics.

## 5 Conclusion

The research concludes that behavioural finance is fundamental in forming investment strategies by featuring how mental predispositions — like such as loss aversion, overconfidence, mental accounting, and herd behaviour—essentially impact financial backer choices and market elements. this study highlights the significant role that behavioral biases and heuristics play in shaping financial decision-making and investment strategies. Through the application of models such as PMBAC (Probabilistic Modeling and Behavioral Analysis for Cognitive biases), the research demonstrates how biases like overconfidence, loss aversion, and herding behavior can significantly influence both individual investor behavior and broader market dynamics. These biases lead to suboptimal decision-making, with consequences such as excessive trading, risk aversion, and market bubbles, ultimately impacting returns and overall market stability. By systematically analyzing the probability of occurrence, impact on investment decisions, and risk-adjusted returns, the study provides valuable insights into how investors can better understand and mitigate the effects of these biases. It is clear that psychological factors—often overlooked in traditional financial models—play a critical role in determining investment outcomes. Moreover, the incorporation of artificial intelligence (AI) and machine learning (ML) in behavioral finance holds great promise for enhancing the detection and correction of these biases, thereby facilitating more informed, rational decision-making. Loss aversion, for example, makes financial backers stay away from takes a chance with that could yield long haul gains because of a more grounded profound reaction to misfortunes than to identical increases. Overconfidence frequently drives financial backers to misjudge their capacities, bringing about extreme exchanging and potential market bubbles. Mental accounting prompts the order of cash in manners that may not line up with ideal monetary results, and crowd conduct drives collective vibes that can worsen market unpredictability and resource bubbles. Incorporating behavioural finance experiences into investment strategies can improve dynamic cycles, advancing more adjusted risk evaluations and more noteworthy arrangement with individual objectives. By perceiving and tending to these predispositions, the two financial backers and monetary counsellors can alleviate silly navigation, cultivating more powerful portfolio the board and venture systems that think about human brain science's intricacy in monetary settings.

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