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Research paper

Methodological Perspectives on Behavioral Biases in Individual Investors' Decision-Making: A Systematic Literature Review

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Abstract

This paper systematically reviews the literature on behavioral biases affecting individual investors' decision-making, with a particular focus on methodological approaches, including sampling techniques and data analysis methods. In accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines, this study analyzes 63 peer-reviewed studies published between 2015 and 2024, identifying key trends in research methodology, discussing their limitations, and exploring strategies to enhance methodological rigor. Findings indicate that most studies focus on emerging markets and predominantly employ survey-based research using non-probability sampling techniques, particularly convenience and snowball sampling. Additionally, there has been a notable shift from traditional regression analysis to Structural Equation Modeling (SEM) in recent years. However, survey-based research, such as a questionnaire with a cross-sectional design, raises concerns, for example, the inability to prove temporal relationships and self-report bias. Therefore, the paper highlights the need for future studies to address methodological shortcomings through advanced techniques such as AI, deep learning, and big data analytics. This paper will be useful in guiding potential researchers in selecting suitable methodologies for their studies on behavioral biases that affect individual investors' decision-making.

Keywords: *Behavioral Biases; Stock Markets; Decision-Making; Sampling Techniques; Data Analysis Methods.*

1. Introduction

Traditional finance theories, like the Expected Utility Theory (EUT) (Neumann & Morgenstern, 1947) and Efficient Market Hypothesis (EMH) (Fama, 1970), assume that investors make rational decisions according to fundamental and technical analysis. However, behavioral finance challenges this assumption, demonstrating that investors are often influenced by psychological factors, leading to systematic biases in decision-making (Kahneman & Tversky, 1979). Since the 2008 financial crisis, increasing attention has been given to behavioral biases, particularly in emerging markets where investors rely on heuristics due to market inefficiencies (Trifan, 2020). Behavioral biases, such as anchoring, herding, availability, and overconfidence, significantly impact investor behavior, leading to deviations from rational decision-making models.

The growing interest in behavioral finance has resulted in an expanding body of literature that analyzes the influence of these biases on stock market dynamics. Researchers have explored how investors' reliance on heuristics can lead to persistent market inefficiencies, speculative bubbles, and systemic risks. Despite this increasing body of work, there remains a lack of systematic reviews that analyze the methodological choices made in these studies. The selection of appropriate sampling techniques and data analysis methods is crucial in determining the applicability and reliability of research outcomes. This study aims to bridge this gap by systematically reviewing existing research and evaluating the methodologies employed in studying behavioral biases in financial decision-making.

Specifically, this review aims to:

1) Synthesize existing literature on behavioral biases in stock markets from a methodological perspective.
2) Identify the rationale behind the selection of different sampling techniques and data analysis methods.
3) Assess the limitations of current methodologies and propose ways to improve research validity.
4) Highlight gaps for future research to bridge using advanced analytical techniques.

2. Theoretical Background

Behavioral biases have been extensively studied in the field of finance, as they significantly affect investors' decision-making and lead to deviations from rational behavior. These biases arise from cognitive limitations, emotional influences, and social factors, often resulting in market inefficiencies. Various scholars, including Tversky and Kahneman (1974), have explored these biases in detail, demonstrating their pervasive influence on financial markets. This section reviews four commonly studied biases that play a vital role in shaping investor behavior.

Anchoring Bias is the tendency among investors to overweight prior data or specific reference points to make investment decisions, sometimes leading to inferior decisions. In stock markets, this is predominantly felt when valuing a stock, as investors tend to anchor their expectations based on past stock prices rather than intrinsic values (Jain et al., 2020). It has been shown empirically that anchoring frequently contributes to price inertia and lessens pricing effectiveness, especially in turbulent market conditions.

Availability Bias: Investors often examine the possibility of future events based on the ease with which past instances come to mind. This bias leads to distorted risk perceptions, as individuals tend to overweight information that is vivid, recent, or emotionally charged (Tversky & Kahneman, 1973). In financial markets, availability bias can cause investors to overreact to recent market news, amplifying market volatility and contributing to asset mispricing (Weixiang et al., 2022).

Herding Bias takes place when investors follow the moves of others without making significant independent analysis decisions. Herding Bias typically arises due to conformity, fear of losing out, and the assumption that others' decisions are informed due to superior knowledge (Kumar & Goyal, 2016). Herding Behavior is common in emerging markets, as uncertainty is not only perceived at times, but actual uncertainty directed by informational asymmetries creates the confidence to mirror the investment activities of others. Research evidence suggests that herding behavior can contribute to speculative pricing bubbles and even increase the risk of financial crises (Quaicoe & Eleke-Aboagye, 2021).

When investors overestimate their ability, skills, knowledge, and/or ability to predict the movement of the markets, this is known as 'Overconfident Bias', which can lead to disproportionately high trading activity and a tendency to take risks more than their risk exposure. Previous research has found a relationship between Overconfidence Bias and higher trading volume, lower portfolio diversification, and greater sensitivity to market risk (De Bondt & Thaler, 1995). This bias is often exacerbated by past successes, leading investors to develop an illusion of control over market results (Daniel et al., 1998).

3. Methodology

3.1. The review protocol (PRISMA)

This systematic literature review (SLR) followed the Preferred Reporting Items for Systematic Reviews and Meta-analysis guidelines (PRISMA) (Page et al., 2021) during the identification, screening, and eligibility stages. This approach carries several advantages, as Sierra-Correa and Kintz (2015) outline three benefits: (1) the identification stage establishes a clear, explicit query for systematic review on a topic; (2) establishing firm options for inclusion and exclusion; and (3) the ability to determine if the selection process is verified. The structured methodology works to ensure an objective and comprehensive review of the research landscape around behavioral biases in individual investing decisions. This review draws rich conclusions about the methodological strengths and limitations and will support the development of behavioral finance research into the future.

3.2 Systematic search strategies

3.2.1. Identification

The Scopus database was chosen due to its extensive collection of high-impact, peer-reviewed academic publications in finance and economics. Furthermore, the search keywords were divided into three groups: "behavioral biases," "stock markets," and "individual investors." As this review focuses on only four behavioral biases—anchoring, availability, herding, and overconfidence—the first keyword group included these four biases. In the second keyword group, "equity market" was used as a synonym for stock markets to refine the search. Lastly, in the third keyword group, "retail investors" was incorporated as a synonym for individual investors. Thus, the final search string was: "anchoring" OR "availability" OR "herding" OR "overconfidence" AND "stock market" OR "equity market" AND "individual investors" OR "retail investors." Boolean operators were applied to refine results and retrieve the most relevant articles.

3.2.2. Screening

Initially, 144 articles were identified within the scope of title, abstract, and keywords in Scopus by using the search keywords. Then, 100 articles were retained with restrictions by subject area (econometrics, economics, business, finance, accounting, and management), document type (article only), language (English only), and time horizon (from January 2015 to December 2024). Notice that no data was available before 2006 in the Scopus database based on the restrictions, and 85 of 100 articles were published from 2015 to 2024.

3.2.3. Eligibility

To maintain the rigor of the review, a manual review of the remaining articles was conducted in the eligibility stage. Studies lacking empirical analysis or methodological detail were excluded. Once the studies were selected, key methodological details such as sampling technique, sample size, analysis approach, and data collection method were extracted. The collected information was systematically synthesized to identify trends, strengths, and limitations in existing research. After applying the selection criteria, 63 studies were deemed relevant and included in the systematic review, forming the basis for subsequent analysis and discussion. Figure 1 shows the diagram to extract the final articles.

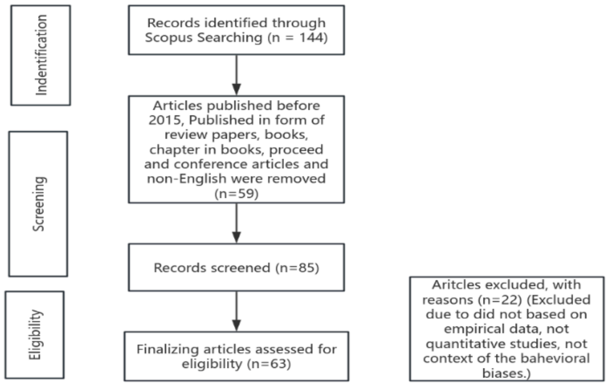

Fig. 1: PRISMA Flow Diagram for Study Selection Process. Source: Page et al. (2021)

4. Classification and Findings

This chapter systematically classifies and analyzes the selected 63 studies based on various factors, including publication year, study location, sampling techniques, and data analysis methods. By investigating these methodological choices, this chapter aims to provide deeper insights into the trends in behavioral bias research and highlight key areas for future investigation.

4.1. Year of publication

Figure 2 shows the number of articles published over the past 10 years, indicating a clear incline in research on the behavioral biases affecting decision-making in individual investors. There is a significant increase in publication volume since 2018, with a peak occurring between 2020 and 2023. This coincides with the findings of Dhingra et al. (2023), who found an increase in behavioral finance articles during the COVID-19 pandemic because the uncertainty created by the pandemic increased interest in how behavioral biases affect investment decisions.

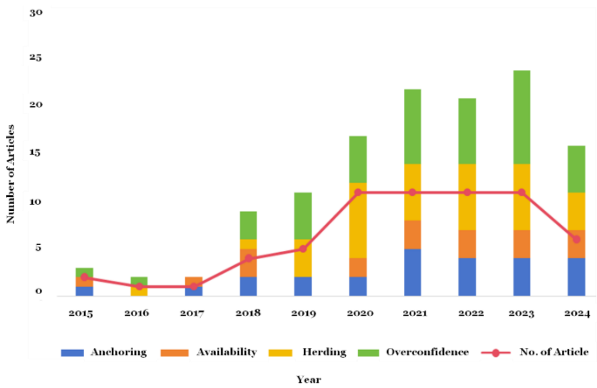

Fig. 2: Trends in Behavioral Biases Studied in Individual Investor Research from 2015 to 2024.

4.2. Distribution of countries from selected articles

Table 1 describes the count of studies in the varying countries, with most of the studies being conducted in emerging markets, specifically Pakistan and India, where individual investors play a strong role in stock market activity. The research conducted in developed markets is comparatively limited, which suggests an opportunity for future research.

Table 1: Distribution of Behavioral Biases and Number of Articles by Country

Country	Anchoring	Availability	Herding	Overconfidence	No. of article
Bangladesh	1		3	2	3
China	3	3	3	4	4
Egypt			2	2	2
Ghana	1		1	1	1
Indonesia	2	1	2	2	3
India	11	7	17	18	26
Jordan	1	1	1	2	2
Pakistan	2	4	6	9	15
Saudi			1	1	1
Tunisia	1	1		1	2
United Arab Emirates	1	1		1	1
Vietnam	1		2	2	2
Multiple countries	1	1			1
Total	25	19	38	45	63

4.3. Sampling techniques in primary data collection

Table 2 demonstrates the frequency of sampling techniques applied by selected articles. A key methodological choice in these studies is the utilization of non-probability sampling techniques, particularly convenience and snowball sampling. Conversely, few studies employed probability sampling for their questionnaire-based surveys. Additionally, it is noticeable that a few studies applied mixed samplings, especially the mixed samplings combining convenience and purposive samplings to examine how behavioral biases impact investors' decision-making.

Table 2: Frequency of Sampling Techniques in Behavioral Bias Studies

Sampling classification	Sampling technique	No. of article
Probability samplings	Cluster	1
	Random	6
Non-probability samplings	Convenience	13
	Purposive	5
	Snowball	11
Mixed samplings	Random & purposive	2
	Convenient & purposive	4
	Convenient & snowball	2
	Snowball & purposive	1
	Unknown	18
	Total	63

4.4. Data analysis methods in behavioral bias studies

Table 3 gives the frequency of data analysis methods employed by selected articles. To evaluate the relationships between investor decision-making and behavioral biases, various statistical techniques have been employed across the selected studies. These methods generally fall into three main categories: traditional statistical tests, regression models, and structural equation modeling (SEM). Most selected studies utilized structural equation modeling (SEM), including covariance-based SEM and partial least squares SEM, to examine complex relationships between decision-making and behavioral biases. Then, a few studies employed regression analysis, including multiple regression, ordinary least squares (OLS) regression, and hierarchical regression, to deal with direct effects related to behavioral finance. Noticeably, a few studies employed traditional statistical tests, including chi-square, analysis of variance (ANOVA), and t-test to verify whether there exist differences in the impacts of behavioral biases among groups of demographics, such as gender, educational levels, investment experience, and age.

Table 3: Distribution of Data Analysis Methods Used in Reviewed Studies

Data analysis method	Frequency
ANOVA	6
Chi-square	2
T-test	5
Multiple regression	12
Hierarchical regression	5
OLS regression	2
Regression (unspecified)	4
PLS-SEM	17
CB-SEM	15
SEM (unspecified)	5
Others	6

4.5. Data analysis methods specified in relationships among variables

Figure 3 displays the distribution of utilization in regression analysis and SEM across selected studies within the past decade. A key observation from the figure is the progressive movement away from conventional regression models toward SEM as an advanced analytical tool for examining complex relationships.

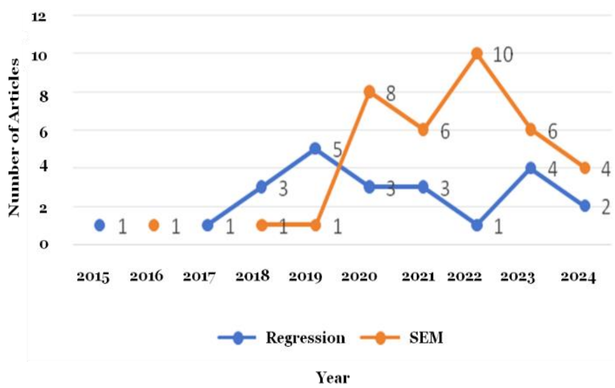

Fig. 3: Trends in Data Analysis Techniques: Regression vs. SEM.

5. Analysis

5.1. Reasons for the growing research focus on emerging markets

There has been a growing interest in studying how behavioral biases affect individual stock investors' decision-making, particularly in emerging markets. This trend can be explained using heuristic theory, which suggests that investors rely on mental shortcuts when making decisions under uncertain and complex market conditions (Tversky & Kahneman, 1974). Scholars have increasingly turned their attention to emerging markets due to the greater susceptibility of individual investors to behavioral biases, largely influenced by market inefficiencies and limited access to information.

One major reason for this research focus is the restricted availability of information in emerging markets. These markets often have low transparency and inefficient information dissemination, making it complex for investors to make rational decisions. Studies by Raut et al. (2020) and Xia and Madni (2024) highlight that the occurrence of behavioral biases, such as herding, is more common in emerging markets than in developed economies because of poor information disclosure, which is often worsened by government intervention. Similarly, Hossain and Siddiqua (2022) found that in Bangladesh, external market fluctuations create a weak correlation between stock prices and company fundamentals, limiting the usefulness of historical data for investment decision-making.

Another critical factor is the lower financial literacy levels in emerging markets, which affect investors' ability to process and interpret financial information. Financial literacy plays a vital role in reducing the negative effects of behavioral biases, as it helps investors make more informed decisions and lowers the chances of market anomalies (Rasool & Ullah, 2020; Abideen et al., 2023). However, Chowdhury et al. (2024) argue that the slow growth of stock markets in developing economies is linked to investors' inadequate financial knowledge and skills. Many empirical studies suggest that financial literacy acts as a moderating variable in the relationship between investment decisions and behavioral biases. For instance, Ahmad and Shah (2020) found that financial literacy mitigates the impact of overconfidence bias among Pakistani investors, leading to better decision-making. Mahmood et al. (2024) observed similar findings, where financial literacy significantly moderated the influence of overconfidence, herding, and anchoring biases on investors in Pakistan.

Additionally, cultural factors contribute to behavioral biases in emerging markets. Ahmed et al. (2022) demonstrated that collectivist cultures, such as those of Pakistan, promote peer-influenced decision-making, increasing the likelihood of herding behavior among investors. These results suggest that behavioral biases are not only driven by market inefficiencies but also by socio-cultural factors, reinforcing the need for further cross-cultural behavioral finance research.

The research focuses on the impact of liquidity constraints, higher volatility, and weaker regulatory enforcement on behavioral finance in emerging markets like India and Pakistan. However, this concentration can limit the global suitability of the result. Expanding the discussion to other underrepresented emerging markets, such as Africa and Latin America, could help contextualize the results. African markets often face liquidity constraints, higher volatility, and weaker regulatory enforcement, which can amplify herding and loss-aversion biases. Including these perspectives would highlight regional variations in bias drivers and the need for cross-regional comparative studies.

5.2. Selection of sampling techniques

Most selected studies that focus on emerging markets rely on questionnaire-based surveys to examine how behavioral biases affect individual stock investors' decision-making. The preference for surveys stems from the lack of reliable secondary data in these markets (Chowdhury et al., 2024). As a result, researchers frequently employ non-probability sampling techniques, including convenience, snowball, and purposive sampling, either independently or in combination.

Among these methods, convenience sampling is the most widely used due to its cost-effectiveness and high response rates. This technique is particularly useful in markets such as Pakistan, where standardized investor databases are unavailable (Ahmad, 2020). Mahmood et al. (2024) highlighted that convenience sampling enables researchers to efficiently reach respondents who meet specific research criteria in Pakistan's stock market. Similarly, Xia and Madni (2024) employed convenience sampling to optimize cost and maximize survey responses in China.

Snowball sampling is another commonly used method, particularly when access to investors is restricted. This technique is advantageous for identifying investors in remote areas or within tightly connected social networks. Das and Panja (2022) applied snowball sampling in India due to restrictions on brokerage data access. Sharma and Firoz (2020) also adopted this method to navigate legal, social, and ethical barriers to reaching investors in underdeveloped regions. However, while snowball sampling is effective for reaching hidden populations, it carries the risk of sample bias, as respondents are likely to refer individuals with similar characteristics. This limitation raises concerns about the validity of findings related to herding bias, as noted by Kumar and Goyal (2016) and Jain et al. (2022), who caution against the over-reliance on non-independent sample units.

Purposive sampling is another non-probability technique often used to enhance data accuracy. This method allows researchers to target respondents who best match their studies' objectives (Campbell et al., 2020). Gupta and Shrivastava (2022) argue that purposive sampling improves research precision in India's stock market. Almansour et al. (2023) reached a similar conclusion in Saudi Arabia, as did Ahmed et al. (2022) in Pakistan.

Probability sampling techniques, such as random and cluster sampling, are less frequently applied due to practical limitations. Random sampling assumes that all investors have an equal chance of selection, which is often unrealistic in emerging markets where the investor population is uncertain. Ahmad and Shah (2020) noted that random sampling was unsuitable for studying overconfidence bias in Pakistan due to difficulties in defining the total investor pool.

Overall, in term of investigating how behavioral bias impact individual stock investors' decision-making in emerging markets by employing questionnaire-based surveys, non-probability samplings are widely employed due to their merits, such as cost-effectiveness and ease of accessing respondents in markets where comprehensive investor databases are often unavailable, and practical limitations of probability sampling, such as the individual investors' unequal chances to be selected. However, they come with limitations, like potential sampling bias and lack of generalizability.

To address these limitations, some studies have adopted mixed-sampling techniques, combining convenience, purposive, or snowball sampling. Adil et al. (2022) combined snowball and purposive sampling to study herding and overconfidence biases in India, while Yasmin and Ferdaous (2023) integrated snowball and convenience sampling to investigate investor biases in Bangladesh. Although this way enhances representativeness to some extent, it does not fully resolve the issue of sample bias. Future research should explore the feasibility of incorporating probability sampling methods to improve the robustness of findings or the implementation of multi-stage sampling approaches, such as those used by P.H. and Uchil (2020b), further enhancing research validity by incorporating different sampling techniques at various study phases.

5.3. Comparison of data analysis methods

The selected studies employ various data analysis methods, which can be categorized into three primary groups: traditional statistical tests (chi-square tests, t-tests, ANOVA), regression models, and Structural Equation Modeling (SEM).

Commonly used traditional statistics techniques, such as ANOVA, t-tests, and chi-square tests, are prevalent for approaching a difference in demographics regarding the relationship between behavioral biases and investment decisions. For example, Kumar and Goyal (2016) found that male investors showed more overconfidence and herd bias than female investors, and Baker et al. (2019) found a significant variation in consumer behavior depending on gender for investors in the Indian stock market. While these methods are useful for identifying statistically significant group differences, they do not indicate causality nor measure relationship strength between variables; however, this gap can be filled by regression models and/or Structural Equation Modeling (SEM).

Regression models, including OLS regression, multiple regressions, and hierarchical regression, are widely utilized to quantify the impact of behavioral biases on investment decisions, especially in assessing the direct effects. It is worth mentioning that hierarchical regression is particularly useful for controlling demographic factors before introducing behavioral biases into the analysis, providing a more refined understanding of their influence. Shah et al. (2018) and Ahmad and Shah (2020) applied this method to examine how factors such as education, investment experience, and age influence investor decision-making in Pakistan.

Previously, multiple regression and hierarchical regression were widely employed to analyze the influence of behavioral biases on investment decisions. These methods remain valuable for assessing direct relationships between variables. However, in recent years, SEM has become the preferred approach for analyzing complex relationships among variables. Unlike regression models, SEM allows for the simultaneous examination of direct and indirect effects, such as mediating and moderating effects, within a single framework, offering a more comprehensive analysis of the mechanisms underlying investor decision-making. Notably, PLS-SEM has gained popularity due to its robustness in handling non-normal data distributions, which is a frequent concern in behavioral finance research, and generates robust path estimates. This transition reflects an increasing preference for more sophisticated techniques that provide deeper insights into investor behaviors. Studies such as Gupta and Shrivastava (2022) and Jain et al. (2023b) employed PLS-SEM to explore mediating factors like fear of missing out (FOMO) and risk perception in investment decision-making. CB-SEM, on the other hand, is preferred when data meet normality assumptions (Rasheed et al., 2018).

6. Discussion

Most of the selected studies concentrate on emerging markets, which are characterized by information asymmetry and limited investor ability to process complex financial data. These constraints often lead individual investors to rely on heuristics and cognitive biases when making investment decisions. Given these market conditions, scholars have predominantly employed primary data collection methods to examine the relationship between stock investment decisions and behavioral biases, particularly in emerging economies.

The research focuses on emerging markets due to their unique characteristics, such as information asymmetry, limited financial literacy, and cultural influences. It acknowledges that developed markets have higher transparency, better regulatory oversight, and more sophisticated investor profiles. The research highlights how behavioral biases manifest differently in developed and emerging markets. Overconfidence in developed markets can stem from abundant information and advanced trading platforms, while herding in emerging markets can be driven by information scarcity and social influence. Including developed market studies can help position emerging market findings within a global context.

Due to the inadequacy of secondary data, which aggregates the effects of all market participants—including institutional and retail investors—it is challenging to isolate the specific contributions of individual investors to stock price movements. Consequently, primary data collection remains the most suitable approach for exploring behavioral finance in this context. Questionnaires are widely utilized as they offer a time-efficient and cost-effective means of gathering insights from large and diverse investor populations, particularly in volatile and uncertain market environments.

Given the challenges associated with probability sampling in emerging markets, non-probability sampling techniques have been widely adopted in behavioral finance studies. These techniques enable researchers to reach target respondents more effectively, even in cases where comprehensive investor databases are unavailable. To enhance the credibility and generalizability of findings, mixed-sampling techniques are often employed, combining multiple non-probability approaches.

Despite efforts to improve the representativeness of findings, non-probability sampling methods inherently limit the generalizability of results. As Stratton (2023) argues, findings based on non-probability samples should be interpreted cautiously due to potential selection biases. Furthermore, cross-sectional survey designs, which are commonly used in behavioral finance studies, present another limitation. Since cross-sectional studies capture exposure and outcome variables at a single point in time, they do not provide evidence of causality (Solem, 2015). Thus, while these studies establish correlations between investment decisions and behavioral biases, they cannot definitively prove temporal relationships.

In addition, the heavy reliance on questionnaire-based surveys raises concerns about self-report bias. Future studies could incorporate alternative data sources, such as transaction-level data, to validate self-reported investor behaviors.

To overcome these methodological limitations, future research should consider leveraging technological advancements like deep learning, artificial intelligence (AI), and big data analytics. These tools can enhance the accuracy and depth of behavioral finance research by processing large-scale, real-time investor data (Annu & Tripathi, 2024). For instance, AI-driven models can assess and predict behavioral biases by continuously analyzing investor decision-making patterns. Deep learning algorithms can track longitudinal data on investor behavior, offering a more comprehensive understanding of how biases evolve. Similarly, big data analytics can help researchers extract insights from vast and diverse financial datasets, mitigating some of the limitations associated with survey-based studies.

Another promising approach is the integration of experimental designs, such as randomized controlled trials (RCTs), into behavioral finance research. Unlike cross-sectional studies, experimental research allows for the manipulation of specific variables, helping to establish causal relationships between investment decisions and behavioral biases (Heim & Huber, 2022). While these experiments require more resources and careful planning, they offer a more robust framework for understanding how investors react to different financial scenarios.

7. Conclusion and Implications

This study, through a systematic literature review of 63 studies published between 2015 and 2024, has aimed to analyze the different methodologies applied in research on behavioral biases affecting individual investors' decision-making in stock markets. It has further explored the conditions that influence methodological choices and proposed solutions to address limitations associated with these methodologies.

7.1. Summary of key findings

The outcomes point to that the majority of relevant studies focus on emerging markets, which are characterized by factors such as low-quality information disclosure due to government interventions, low reference value of stock prices caused by external fluctuations, limited financial literacy among investors, and cultural factors that shape investor behaviors. These unique market conditions contribute to the higher susceptibility of investors to behavioral biases, leading researchers to predominantly utilize questionnaire surveys to examine investor decision-making.

Non-probability sampling techniques, including convenience, snowball, and purposive sampling, are widely adopted in these studies due to the practical challenges of accessing well-defined investor populations in emerging markets. However, non-probability sampling introduces concerns regarding the representativeness of findings. To mitigate these concerns, mixed sampling techniques have been increasingly used to enhance data reliability and validity.

Among the statistical methods employed, Structural Equation Modeling (SEM) has emerged as a preferred choice over traditional regression analysis because of its ability to process complex relationships among behavioral biases, mediators, or moderators, and investment decisions. The findings suggest that SEM offers greater flexibility and robustness, particularly in handling latent variables and indirect effects.

7.2. Methodological considerations and limitations

While the cross-sectional survey design is the most employed approach in behavioral finance research related to individual investors, it presents inherent limitations, particularly regarding causality. Since cross-sectional studies capture data at a single point in time, they cannot establish temporal relationships between investment decisions and behavioral biases. This limitation suggests a need for future research to incorporate longitudinal studies or experimental approaches to better understand how behavioral biases evolve and influence decision-making processes.

Another key limitation is the reliance on self-reported data, which is subject to response biases like recall inaccuracies and social desirability. Future studies could find this issue by integrating alternative data sources, such as transactional data, to validate self-reported behavioral patterns. Additionally, experimental methods, such as randomized controlled trials (RCTs), could provide stronger causal inferences regarding the impact of behavioral biases on investment decisions.

The research explores the limitations of non-probability sampling and cross-sectional designs in behavioral finance surveys. It suggests that these limitations can be addressed by addressing methodological biases and offering targeted solutions. Common method bias (CMB) is a concern, where the measurement method artificially inflates or deflates observed relationships between variables. Remedies include procedural controls, such as separating predictor and criterion variables over time, ensuring respondent anonymity, and varying scale formats, and statistical controls like Harman's single-factor test or the marker variable technique. The review also references AI and big data, suggesting that greater specificity would improve the practical value of these recommendations. Experimental approaches like Randomized Controlled Trials and field experiments with live financial platforms could also be used to isolate behavioral effects from methodological artifacts.

7.3. Future directions and technological integration

As financial markets continue to evolve, integrating advanced technologies like machine learning, big data analytics, and artificial intelligence (AI) can facilitate the identification of new behavioral finance patterns that traditional methods might overlook. For example, by incorporating machine learning techniques, researchers can analyze vast amounts of investor transactions, sentiment analysis from financial news, and even social media interactions to gauge investor sentiment in real-time (Cao & Zhai, 2022). These methods can provide deeper insights into how biases interact with external factors such as macroeconomic events, political instability, and sudden market shocks. Moreover, Machine learning algorithms can improve predictive models by analyzing historical market behavior and detecting patterns of irrational investment decisions.

AI and big data analytics are promising tools for behavioral finance research. Machine learning platforms like TensorFlow, PyTorch, and Scikit-learn can train predictive models on historical trading data, detecting anomalies like panic selling or excessive trading activity. Natural Language Processing (NLP) frameworks like BERT, spaCy, and Gensim can process large volumes of financial news, social media posts, and earnings call transcripts to quantify investor sentiment and link these shifts to trading patterns. Big data tools like Apache Spark and Hadoop can efficiently manage transactional and market data, facilitating near-real-time detection of bias-driven behaviors. For example, XGBoost models were used in China's A-share market to classify investors based on overconfidence levels. Practical integration can involve hybrid approaches, such as pairing Long Short-Term Memory (LSTM) networks for modeling sequential trading behaviors with experimental designs on simulated trading platforms.

The discussion highlights the need for AI models and analytical tools that align with behavioral finance research objectives. Neural Networks (ANN, CNN, RNN) can uncover hidden patterns in investor transaction sequences, with LSTM models being particularly useful for capturing temporal dependencies in trading behavior. Sentiment analysis tools like VADER, TextBlob, and FinBERT can process vast amounts of financial news, analyst reports, and social media content to quantify market sentiment and link it to bias-driven trading patterns. Graph Neural Networks (GNNs) can map and analyze herding behavior by modeling complex networks of investor transactions. Reinforcement learning frameworks like OpenAI Gym and Stable Baselines can simulate adaptive investment strategies, enabling researchers to test interventions that counteract biases under dynamic market conditions.

Furthermore, the use of big data analytics can help mitigate issues associated with traditional survey-based studies. By collecting and analyzing large-scale transactional data, researchers can gain a more accurate understanding of how biases manifest in real trading environments. Longitudinal data tracking investor behavior over time could provide insights into how biases fluctuate across different market conditions and economic cycles.

The integration of interdisciplinary approaches could further advance research in this field. Combining psychology, neuroscience, and behavioral economics with financial studies can offer new perspectives on investor behavior. For example, neurofinance, which examines how brain activity influences financial decision-making (Srivastava et al., 2019), can provide deeper insights into why investors make irrational choices under certain conditions. By exploring these intersections, future research can uncover novel ways to address the challenges posed by behavioral biases in investment decisions.

The integration of these advanced methodologies could significantly improve the robustness of research on behavioral biases in stock markets, particularly in emerging economies. By moving beyond traditional survey methods and incorporating real-time investor data, scholars can develop more predictive and explanatory models of investor behavior, ultimately contributing to a deeper understanding of market dynamics. Expanding the scope of behavioral finance research to include these new technological and methodological advancements will not only enhance academic knowledge but also provide practical benefits for investors, financial institutions, and policymakers alike~~.~~

7.4. Practical implications for investors and policymakers

The outcomes of this study carry major implications for individual financial institutions, investors, and policymakers. Investors can benefit from greater awareness of their own cognitive biases and take proactive steps to mitigate their influence on investment decisions. Financial literacy programs should be designed to educate investors on common biases such as herding, overconfidence, and anchoring, with an emphasis on strategies to counteract their effects.

For financial institutions, integrating behavioral finance insights into investment advisory services can improve client decision-making. Robo-advisors, enhanced with AI-driven behavioral analytics, could provide personalized recommendations that account for an investor's susceptibility to specific biases (Bhatia et al., 2022). Furthermore, financial firms could implement nudges—subtle interventions designed to guide investors toward more rational decisions—based on behavioral finance principles.

Regulators and policymakers can leverage these findings to design more effective investor protection policies. Given the prevalence of biased decision-making, regulatory frameworks should incorporate behavioral insights to promote market stability. For instance, disclosures and warnings about potential biases could be included in investment platforms to encourage more deliberate decision-making. Additionally, policies promoting financial literacy, particularly in emerging markets, could help mitigate the negative impacts of biases on investment behavior.

7.5. Conclusion

This study has provided a comprehensive analysis of methodologies used in behavioral finance research, highlighting their strengths, limitations, and potential areas for improvement. The dominance of non-probability sampling and cross-sectional survey designs underscores the challenges of studying investor behavior in emerging markets, but also reveals opportunities for methodological advancements through technology-driven approaches.

By integrating AI, big data analytics, and neuroscientific methods, future research can offer deeper insights into behavioral biases and their impact on investment decisions. Such advancements will not only enhance academic understanding but also provide practical benefits for investors, financial institutions, and regulators seeking to create more efficient and stable financial markets.

Ultimately, this study serves as a foundation for future research in behavioral finance, encouraging scholars to explore new methodological approaches, expand the scope of analysis, and contribute to a more comprehensive understanding of investor behavior in a rapidly evolving financial landscape.

The conclusion suggests that integrating behavioral finance principles into policy and technology can lead to measurable outcomes. Examples of successful interventions were implemented in-person workshops and digital modules to improve investment risk understanding, reduce overconfidence bias, and offer interactive budgeting and investment simulators. These examples demonstrate the feasibility and effectiveness of integrating behavioral finance principles into policy and technology.

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