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Integrating Behavioural Biases into Portfolio Optimisation: A Systematic Literature Review and Bibliometric Analysis

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Abstract

Behavioural finance has evolved into a significant field of study that challenges traditional financial theories, which are based on fully rational investors and efficient markets. This research conducts a systematic literature review and bibliometric analysis of 72 peer-reviewed studies published between 2014 and 2024, examining the convergence of behavioural finance and portfolio optimisation. The literature selection followed the PRISMA framework, while Biblioshiny and VOS viewer were used to perform bibliometric mapping and thematic analysis. A Theory Construct Methodology (TCM) approach was adopted to identify prevailing theoretical foundations, behavioural constructs, and methodological patterns in existing research. The results indicate a steady rise in scholarly interest, highlighting emerging themes such as behaviourally adjusted optimisation models, bee colony algorithms, and the incorporation of psychological biases into portfolio decision-making. Keyword co-occurrence and thematic analysis reveal four major research clusters: Portfolio Optimisation and Risk Management, Behavioural and Market Dynamics, Asset Allocation and Behavioural Finance, and Computational and Optimisation Techniques. Prominent theoretical perspectives include prospect theory, overconfidence, and loss aversion. The study provides practical implications for both investors and policymakers. Investors may improve risk-adjusted returns by incorporating behavioural insights into investment strategies, while policymakers can leverage these findings to encourage rational investment behaviour and mitigate market inefficiencies. Overall, this review offers a structured and comprehensive foundation for future research in the evolving area of behavioural portfolio optimisation.

Keywords
Behavioural finance, Portfolio optimisation, Investor biases, Market efficiency, Investment decisions, Financial regulation

1. Introduction

Behavioural finance has evolved into a groundbreaking discipline by disputing the market-efficient rational-choice models of conventional financial thinking. According to traditional beliefs, both investors behave rationally by making decisions based on complete and exact information. The methodological analysis in behavioural finance demonstrates that making investment decisions using emotional factors and psychological events results in behaviour contrary to logical investment theory. Dynamic market conditions trigger heightened fear and anxiety, as well as greed reactions, which generate irrational and suboptimal decision-making that contradicts fundamental principles of market efficiency, according to Kanapickienė et al. (2024) and Malkiel (2003). (Mahmood et al., 2024; Nkukpornu et al., 2020). The decision-making processes of investors and financial market behaviours are influenced by three cognitive biases, including overconfidence and the subtypes of loss aversion and herd mentality. Market performance gets affected when traders who face high risk perceptions make numerous trades beyond their normal levels. At the same time very, few traders take market entry or exit positions due to low risk perception. The chosen prejudicial characteristics determine how people measure risk alongside expressing their emotional responses. (Valcanover et al., 2020b; Meziani & Noma, 2018). Markowitz, in 1952, with his Mean-Variance Model came up with the first foundations of modern portfolio theory by suggesting that investors should optimize expected returns and risk amount. Despite its power, the model is based upon the assumption that the markets are efficient and that investors are rational. With the passage of time, behavioural finance has broadened this perspective, revealing that psychological and emotional concerns have a significant role in influencing the investment decision of investors, especially in an uncertain situation (Hu et al., 2024; Tversky and Kahneman, 1974).Emotional biases may severely affect the investment decision of the investors. Investors can stick to under performing assets as an example since they do not want to experience the guilt which comes with realising a loss. The behaviour ends up undermining the performance of a portfolio as a whole (Amir Mohammad Larni-Fooeik et al., 2024). These biases are processes that need to be addressed in a systematic way that will identify the role of biases in investment judgment and ways of integrating biases into the portfolio management systems.By combining the perspectives of behavioural finance and optimisation of portfolios, this study attempts to fill the gap between the traditional theory and the actual behaviour of investment. By so doing, it would help in the understanding the importance of psychological influences on investment decision making today and how this influences recommendations on how to make more adaptive investment strategies in future.

RQ1 How have behavioural finance and portfolio optimisation theories evolved over the past decades, and what role have computational methods played in advancing these fields

RQ2 What are the underlying factors contributing to the significant rise in behaviour financial research

RQ3 How do interdisciplinary research themes, such as risk management, prospect theory, and computational optimisation techniques, influence the development of new financial models and investment strategies?

RQ4 What are the emerging research trends in financial research, such as genetic algorithms and other computational techniques, and how do they address current gaps in portfolio optimisation and market behaviour analysis?

2. Methodology

The methodology includes three stages to examine the trends in behavioural finance research using the particular approaches to guarantee a structure approach with clarity and credibility. The study used the PRISMA method to identify 72 articles in the Web of Science database in 2014-24. The selection method decreased bias factors while retaining only research publications with high quality and significance. A bibliometric analysis utilizing VOS viewer and the Biblioshiny 2.0 from the R-studio program revealed important themes while showing significant patterns and new subject trends. The final part of this research established commonly recognized theories and constructs, and methodologies from behavioural finance while providing insight into current academic practices.

2.1 Selection of Database

Behavioural finance and portfolio optimisation literature research used WoS as its primary database because it provides more reliable sources than Google Scholar and Scopus, which contain researched and unresearched materials (Fatma Hachicha et al., 2024; Kokol, 2023). Massey University employs the Web of Science database for finance and economic analysis because it guarantees top-tier peer-reviewed research with reliability. The primary search phase encompassed behavioural finance, investor psychology and heuristics, overconfidence and herding, and prospect theory. At the same time, Anchoring and Loss Aversion functioned as one term alongside Mental Accounting and Representativeness, followed by Portfolio Optimisation until reaching Portfolio Performance and Investment Decision-Making, afterwards adding Asset Allocation and Behavioural Portfolio Theory and finishing with Mean-Variance Optimisation. The search exclusively retrieved academic reports spanning 2014 to 2024 that belonged to Economics, Business Finance, Management, Science, and Mathematics Applied or Statistics Probability assigned categories in WoS.

2.2 Data Extraction and Data Cleaning

The PRISMA protocol retrieved literature on Behavioural Finance in Portfolio Optimisation, yielding 240 papers, with 72 selected after data cleaning. Research in this domain gained momentum from 2014, a period marked by growing

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recognition of psychological factors in investment decisions and advancements in integrating behavioural insights into portfolio optimisation, making 2014–2024 ideal for systematic study.

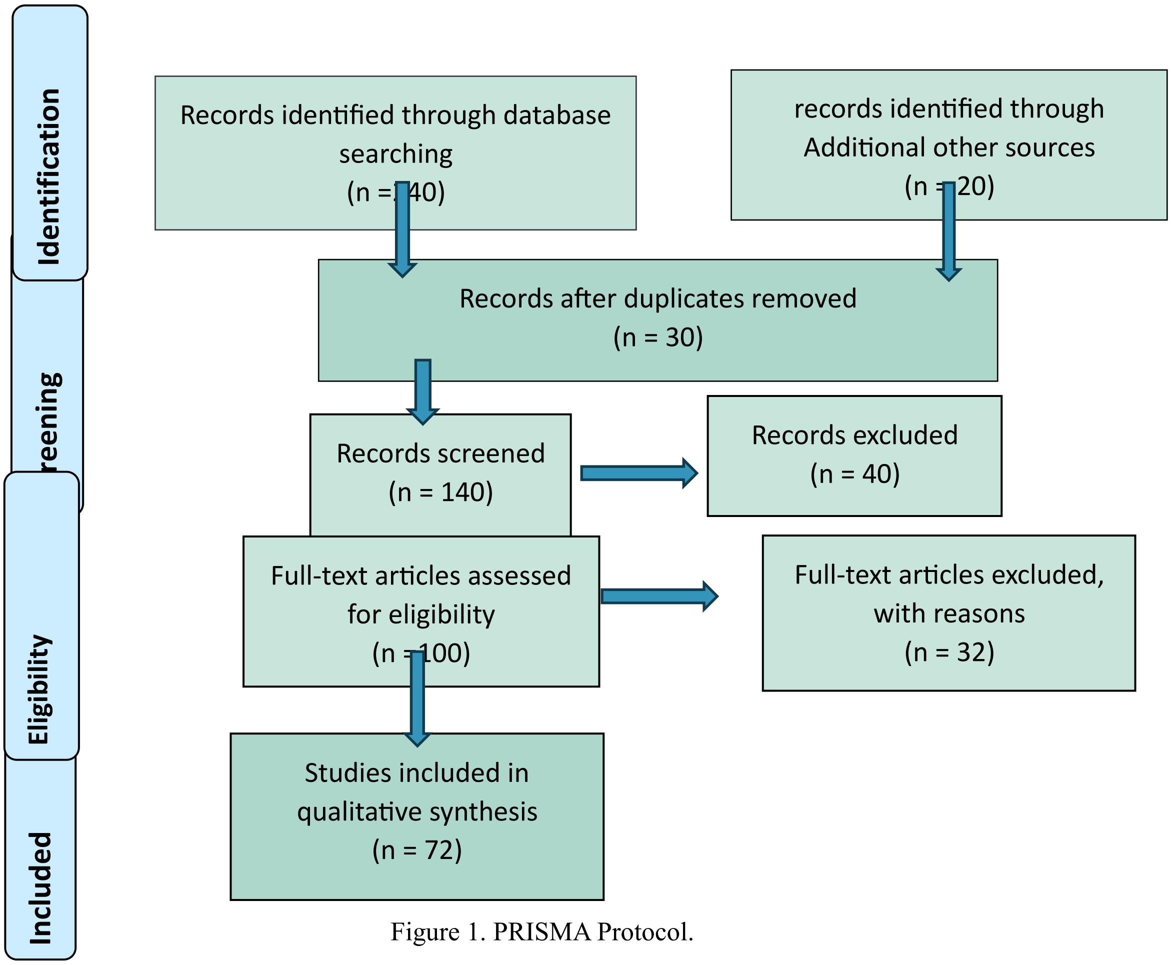

Figure 1. PRISMA Protocol.

3. Findings

The analysis results from annual scientific productions, as well as three-field plots and thematic analysis, form the backbone of this section. The research trends were identified through cluster analysis, but the analysis of methodologies and theoretical properties, along with literature constructs, helped track behavioural finance development in portfolio optimisation. The collected evidence reveals major research themes alongside new fields of inquiry and theoretical concepts that shape this discipline.

3.1 Annual Scientific Productions

This part is devoted to the results of the study. Figure 2 demonstrates the trend in the scientific production over the years. According to the data, the output of research has been gradually increasing since 2004, and the growth rates have been very high every year. As of 2020, the number of publications grows sharply, reaching its peak in 2024, which must be explained by the increased activity of the research or an increase in interest in a certain field of study.

Figure 2: Annual Scientific Production

3.2 Three field plots

This illustration shows the diverse academic connections between financial researchers (AU), research areas (DE) and academic publications (SO) so researchers can see the multiple dimensions of financial research. Auditors Binswanger, Johannes, and Chan Chi Kin produce publications on portfolio optimisation, behavioural finance and risk management, which appear in the European Journal of Operational Research and the Journal of Behavioural Finance (Yeny Rokhilawati et al., 2024). The illustration demonstrates the link between individual scholars who work within particular academic fields with their publication presence throughout different research networks. The diagram presents a comprehensive view of leading authors and core research subjects while listing major academic journals so it supports researchers in detecting publishing trends and suitable academic journals.

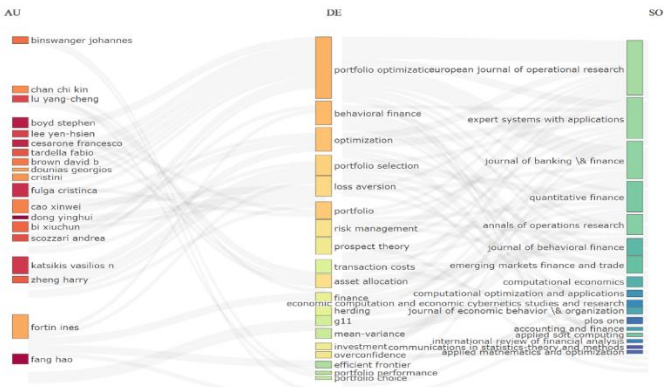

Figure 3: Three Fields Plot

3.3 Thematic Analysis

A thematic map exists to establish semantic links between multiple written documents. The thematic map exists as an informational display method that enhances the understanding of data (Fatma Hachicha et al., 2024). The map's construction depends on keywords, article titles, and abstracts. The diagram places ideas on its two dimensions based on their importance level and familiarity strength.

Researchers measure the significance of the research topic through the analysis of the X-axis parameter. The significance of the main subject becomes visible through this presentation. The Y-axis represents the evolutionary progression rate of individual topics under examination. The density measurement for a topic becomes visible in this system. Research topics can be analyzed through central tendency measures such as mean and median to determine their complete pattern and information content.

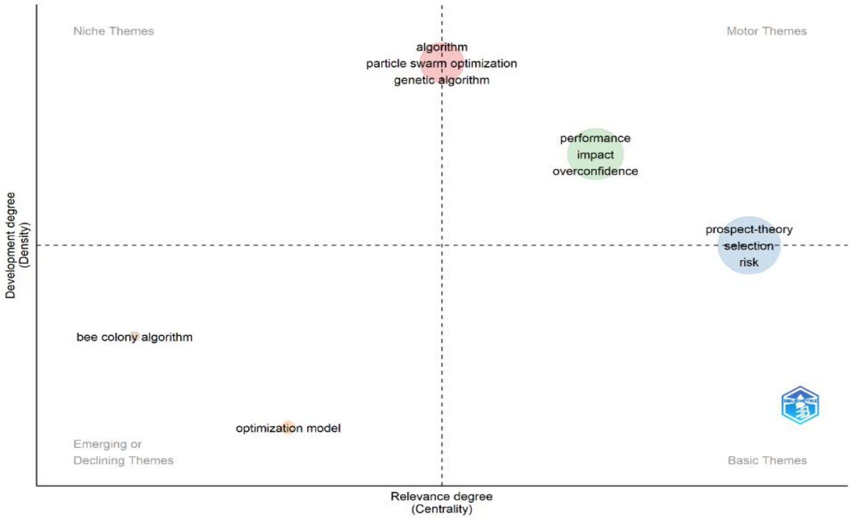

Figure 4. Thematic map

The thematic map categorizes research themes by development (density) and relevance (centrality). Motor themes like “prospect theory,” “risk,” and “selection” are well-developed and highly relevant, while niche themes such as “particle swarm optimisation” and “genetical algorithm” focus on advanced computational techniques. Emerging or declining themes, like “bee colony algorithm” and “optimisation model,” indicate areas with lower relevance and development

Q1: Upper-right Quadrant: Motor Themes

Knowledge development and research innovation depend heavily on the essential and highly central topics present in the Motor topics quadrant. In the field of behavioural economics prospect theory by Tversky and Kahneman (1974), risk according to Mullainathan and Thaler (2000) and selection as explained by Fortin and Hlouskova (2024) serve as significant foundational elements for theoretical research and practical application development. Researchers thoroughly study these themes which show strong connections to behavioural biases together with decision-making solutions under ambiguous conditions (Thaler, 1985) and portfolio optimisation systems (Hali & Yuliati, 2020). As vital fundamental concepts they serve both theoretical functions and serve as functional instruments which propel academic inquiry and unite abstract concepts with practical business challenges.

Q2: Lower-right Quadrant: Basic Themes

The basic themes in the lower-right quadrant stand for important and foundational subjects that underpin the area of study. These basic principles form behavioural finance through their core functionality in interpreting advanced financial operations and portfolio systems (Bihari et al., 2022) (Annin et al., 2024) even though these concepts maintain consistent application rather than generating deep specialization. Research development benefits from fundamental subjects because they produce conceptual and methodological instruments that steer investigators toward crucial risk assessment matters and they examine investor behaviour and decision patterns.

Q3: Lower-left Quadrant: Emerging Themes

Research fields demonstrate minimal advancement as well as limited importance within the Emerging or Declining Themes quadrant which appears in the bottom-left section (Kumar & Choudhary, 2023). Two innovative but untested fields identified in research involve bee colony algorithms(Puerto et al., 2022).(Shanmuganathan, 2020) and optimisation models(Wang et al., 2020). The research field

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enables researchers to perform integrated studies of upcoming subjects that show promise for future applications. The categories of dwindling themes contain subjects which become unimportant because of changes in goals and technological advancements. New interpretations and implementation approaches introduce opportunities to recreate diminishing themes (Buonaiuto et al., 2023). This research field contains emerging fields that need strategic development to establish as future essential scientific areas.

Q4: Upper-left Quadrant: Very Specialised Themes

The upper-left quadrant includes specialized advanced subjects “algorithms” “particle swarm optimisation” and “genetic algorithms” in this field as reported by He & Zhang (2024 but they fail to substantially influence academic discussions outside of the field. The main functions of advanced computational systems incorporate market prediction capabilities together with portfolio restructuring solutions for economic problems (Geboers et al., 2022). Complex system design makes it impossible to evaluate fundamental market concepts and behavioural finance through limited practical usage. Research experts need to analyze these approaches’ connections with core subjects like risk evaluation and decision processes to produce better influence and bridge practical technology gaps (Khayamim et al., 2018).

3.4 Cluster Analysis

The VOS viewer program enabled cluster analysis together with thematic synthesis within this section. Analysis of keyword co-appearance structures the text into four major thematic groups, which the VOS viewer represents through distinct coloured clusters. The different colours in the system denote separate ideas.

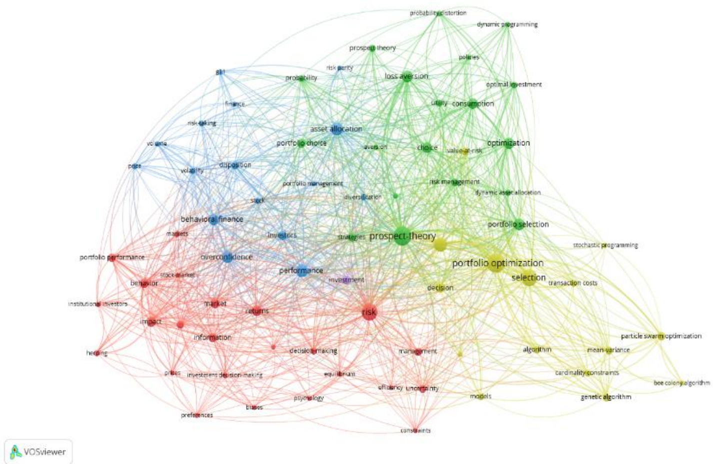

Figure 5. Cluster analysis

1. Green Cluster (Portfolio Optimisation and Risk Management)

The Green Cluster executes portfolio optimisation through behavioural finance and quantitative risk management methods. Two essential methods for successful risk and return management include Value-at-risk and portfolio selection. Investors make choices in unpredictable conditions primarily because of their psychological biases, such as prospect theory and loss aversion, According to Nkukpornu et al. (2020). Consumer preferences derived from utility theory enable investors to find strategies aligning with their financial goals and danger comfort zones (Verlaine, 2022). Computational methods through dynamic asset allocation along with optimisation models refine decision-making through enhanced financial planning accuracy in complex market conditions (Shanmuganathan, 2020). This cluster develops data-based individualized financial choices by combining behavioural understanding with strict quantitative methods.

2. Red Cluster (Behavioural and Market Dynamics)

Major components of The Red Cluster investigation base their research on market movement and investor trends through psychological dynamics including cognitive errors. Through several behavioural patterns which include "overconfidence" together with "herding" and "behaviour" the financial industry makes its dependency on heuristics possible. FOMO and social influence create market trends from following others but excessive confidence often produces overtrading in market participants (Mahmood et al., 2024). Market efficiency and rationality principles become subject to evaluation based on how psychological elements affect financial behaviour (Nkukpornu et al., 2020). The research cluster examines how market price discrepancies and asset inefficiencies form through irrational actions through investigations of wide-ranging market trends and price volatility and information transmission (Verlaine, 2022). The biases held by institutional investors show potential to change the structure of financial markets thus strengthening the overall effects that emerge (Pandey and Sharma, 2024).

3. Blue Cluster (Asset Allocation and Behavioural Finance)

When markets show uncertainty The Blue Cluster uses classical finance principles to examine investment behaviour related to asset management decisions integrated with behavioural finance concepts. Investing decisions consist of integration between quantitative data and human psychological elements as supported by finance literature and volatility and portfolio performance theories (Corzo et al., 2024). Investors demonstrate the disposition effect through cognitive biases because they show a tendency to sell their profitable investments before time yet keep their non-performing assets (Almansour et al., 2023). The strategies investors apply toward uncertainty events combine with their loss aversion mechanisms and gain responses based on their tolerance toward risk which determines their final asset distribution choices (Dennie van Dolder and Jurgen Vandenbroucke, 2024). By incorporating behavioural elements into the cluster it achieves better comprehensive evaluation for market analysis and portfolio supervision (Elgebeily et al., 2021).

4. Yellow Cluster (Optimisation Techniques and Computational Approaches)

Recent advances in computational techniques- sometimes referred to as the Yellow Cluster by a few studies- have transformed the field of portfolio management by adding more sophisticated optimisation techniques. The methods of asset selection and portfolio construction have also become more often based on applying the techniques of mean-variance optimisation, particle swarm optimisation, and genetic algorithms, each of which has its own benefits in operating within a complex financial system (Chen et al., 2021). Genetic algorithms are based on similar principles of natural selection to search extensive solution spaces, whereas the idea of particle swarm optimisation is developed around collective behaviour models, so that it can search efficient portfolios in a relatively small amount of time (Albadr et al., 2020).The approaches to analytics also help investors to handle the challenges of asset allocation, cost, and market-related constraints, thereby reinforcing the quality of financial decisions (Wang et al., 2020). Protecting portfolios is also supported by optimisation processes which are effective in the absence of hypotheses especially when stochastic programming is utilized to integrate risk factors in the form of probability. These processes are accompanied by the growing relevance of artificial intelligence and machine-learning solutions in the analysis of large volumes of data, prediction of business output, and risk management in rapidly changing trading contexts (Shanmuganathan, 2020; R. Annapurna and Savitha Basri, 2024).

3.5 Methodology Assessment

The evaluation focuses on dominant approaches employed in both behavioural finance and portfolio optimisation. Research methods are studied to determine which practices generate maximum effectiveness. The analysis of these methodologies demonstrates essential knowledge regarding ways that investment models handle behavioural biases during decision-making processes.

Table 1 showcases recent portfolio optimisation and behavioural finance research methods which involve using innovative combinations of behavioural technology. Traditional Mean-Variance Optimisation serves as the foundation while

Bayesian Learning and Metaheuristic Algorithms and Behavioural Portfolio Models function to address biases and dynamic adjustments and complicated limitations. Strong risk management emerges from stochastic optimisation and machine learning models that process time series while social network and cluster analysis boost portfolio diversity through collaborative decision processes. The Augmented Epsilon Constraint Method demonstrates why data-centric adaptive behaviour-informed methods are progressively preferred in current research for finding Pareto-efficient solutions.

Table 1: Portfolio Optimisation Methodologies Used in Behavioural Finance Research

S. No.	Methodology	Description	Source
1	Mean-Variance (MV) Optimisation	Foundational method for portfolio optimisation aiming to balance risk and return, originally proposed by Harry Markowitz.	(Abdul Hali & Yuliati, 2020), (Chaweewanchon & Chaysiri, 2022), (Anis et al., 2024)
2	Behavioural Portfolio Models (BPM)	Models incorporating investor psychology, preferences, and biases (e.g., loss aversion, overconfidence).	(Fortin & Jaroslava Hlouskova, 2024), (Gao et al., 2024), (Grant et al., 2024), (Hu et al., 2024), (Luca Vincenzo Ballestra et al., 2024)
3	Bayesian Learning	Updates beliefs about asset returns dynamically, especially under biased beliefs, like overconfidence and overextrapolation.	(Kato et al., 2024), (Escobar-Anel et al., 2024), (Herrera et al., 2022), (Blajer-Gołębiewska et al., 2024)
4	Metaheuristic Algorithms	Advanced optimisation algorithms inspired by nature or heuristics (e.g., Black Widow Algorithm, IQBAS, mating attraction, differential evolution).	(Cai & Xiong, 2024), (Chen, 2023), (Filiz et al., 2018), (Ivanova & Dospatliev, 2018), (Martino & Ventre, 2023)
5	Time-Series Models	Combines high-frequency return data with machine learning techniques (e.g., CNN, RNN) or Copula-based models for interdependence structure analysis.	(Ortiz et al., 2021), (S. Vinoth & Gopalakrishnan Chinnasamy, 2024), (Wang et al., 2022), (Zhang et al., 2023)
6	Stochastic Optimisation with Behavioural Biases	Incorporates biases like regret and loss aversion into stochastic multi-objective optimisation models.	(Zhang, 2024), (Wang et al., 2011), (W. Brent Lindquist et al., 2022), (Torriani et al., 2022), (Srinivasan Karthikeyan, 2023), (Sarpong, 2019)
7	Cluster Analysis with Random Matrix Theory (RMT)	Identifies mesoscopic market structures by filtering random and systemic co-movements, leading to stable portfolio construction.	(Oliinyk & Kozmenko, 2019), (Mazhara, 2023), (Martino & Ventre, 2023)
8	Rank-Dependent Expected Utility	Accounts for non-convex utility functions with distortion functions to optimize under incentive schemes like option compensation.	(Torriani et al., 2022), (Wang et al., 2024), (Young et al., 2022), (Ababio, 2019), (Aguirre & Aguirre, 2023), (Akkaya, 2021)
9	Social Network Analysis in Large-Scale Group Decision-Making (SN-LSGDM-PO)	Uses multi-clustering and social network theory for consensus building among diverse stakeholders.	(Blajer-Gołębiewska et al., 2024), (Cai & Xiong, 2024), (Herrera et al., 2022), (Hübner & Lejeune, 2022), (Jiang et al., 2023)
10	Augmented Epsilon Constraint (AEC) Method	Converts multi-objective portfolio optimisation into single-objective models to identify Pareto-efficient solutions.	(Amir Mohammad Larni-Fooeik et al., 2024), (Kashaev & Aguiar, 2022), (Pandey & Sharma, 2024), (Fortin & Jaroslava Hlouskova, 2024), (Zervoudi, 2017)

Economic Sciences
https://economic-sciences.com
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3.6 Literature Constructs

This section evaluates central ideas from portfolio optimisation together with behavioural financial concepts. Knowledge of basic theoretical and empirical ideas helps explain the influence of behavioural biases on investment decisions. Our understanding of these concepts streamlines our ability to determine their financial impact on results and portfolios.The two concepts that have been used most frequently in finance applications are behavioural finance and portfolio optimisation, as shown in Table 2. The main research areas for portfolio performance focus on overconfidence and overextrapolation as well as Bayesian learning while portfolio diversification mainly studies investor demographics together with portfolio size. The study of risk preferences and incentive fee rates is presented in Optimal Investment Policies alongside the analysis of digital payments and implementation of financial literacy and information focus in Financial Market Participation. Research about herding behaviour that links with market stress and macroeconomic shocks appears frequently in studies demonstrating the key aspects of current investigations in this field.

Table 2: Dependent Constructs Used in Behavioural Portfolio Optimisation Studies

S. No.	Variable Name	Description	Citations
1	Portfolio Performance	Measures the returns, risk-adjusted returns, or overall performance of an investment portfolio.	(Abdul Hali and Yuliati, 2020), (Ekeland et al., 2012), (Gan et al., 2014), (Buonaiuto et al., 2023)
2	Portfolio Diversification	Refers to the extent to which an investor allocates investments across various asset classes.	(Anwar et al., 2017), (Filiz et al., 2018), (Ghmari et al., 2024)
3	Optimal Investment Policies	Strategies aimed at achieving the best possible returns while managing risk and other factors.	(Mazhara, 2023), (Jing et al., 2023), (Ortiz et al., 2021), (Chen, 2023)
4	Financial Market Participation	The act of engaging in financial markets through investments or trading.	(Datta, 2024), (Ahmad, 2022), (Bashar Yaser Almansour, 2015)
5	Herding Behaviour towards Systematic Risk Factors	Collective movement of investors following market trends, often leading to inefficiencies.	(Goyal & Kansal, 2024), (Abdin et al., 2017), (Aguirre & Aguirre, 2023), (Ahmad et al., 2020)

Table 3: Independent Constructs Examined in Behavioural Portfolio Optimisation Research

S. No.	Variable Name	Description	Citations
1	Overconfidence	The tendency of investors to overestimate their knowledge and decision-making abilities.	(Costa et al., 2017)
2	Overextrapolation	Drawing overly optimistic or pessimistic conclusions based on limited past trends.	(Almansour et al., 2023)
3	Bayesian Learning	Incorporating prior beliefs and evidence to update probabilities in decision-making.	(Blajer-Gołębiewska et al., 2024)
4	Gender	Examines how gender differences influence investment decisions and diversification strategies.	(Maknickienė and Rapkevičiūtė, 2022)
5	Investor Characteristics	Factors like income, education, age, and experience that affect investment decisions.	(Wu and Westerholm, 2024)
6	Portfolio Size	The size or value of an investor's portfolio as a determinant of diversification behaviour.	(Filiz et al., 2018)
7	Incentive Fee Rates	Compensation structures influencing optimal investment policies.	(Filiz et al., 2018)
8	Probability Distortion	Misjudgement of probabilities in investment decision-making.	(Gavrilakis and Floros, 2021)

9	Risk-Seeking Degree	The extent to which investors are willing to take on higher risk for potential rewards.	(Gorzon et al., 2024)
10	Risk-Aversion Degree	The extent to which investors avoid taking risks.	(Ivanova andDospatliev, 2018), (Kashaev & Aguiar, 2022)
11	Digital Payments	The use of digital payment platforms and their impact on financial market participation.	(Adil et al., 2021)
12	Subjective Financial Literacy	An individual's self-assessed understanding of financial concepts.	(Ahmad and Shah, 2020)
13	Attention to Financial Information	The degree of investor focus on market updates and financial news.	(Aguirre and Aguirre, 2023)
14	Macroeconomic Shocks	Economic events that influence systematic risk factors and investor behaviour.	(Xu, Guan, et al., 2024)
15	Market Stress	High market volatility impacting investor behaviour.	(Herrera et al., 2022)
16	Risk Factor Loadings	Sensitivity of an asset to systematic risk factors.	(Jiang and Jin, 2020), (Blajer-Gołębiewska et al., 2024)

3.7 Theoretical Underpinnings

Researchers predominantly use major behavioural finance and portfolio optimisation theories for their evaluations. An examination of theory demonstrates how these frameworks have developed understanding about investor conduct and cognitive errors as well as choice processes. Research theories generate deep understanding of asset optimisation processes through their exploration into how human behaviour affects financial decision-making approaches

The analysis will use theories from behavioural fiancé and portfolio optimisation (Table 4) to build its foundation. Behavioural Finance Theory studies irrational choices which result from psychological elements such as overconfidence along with herding behaviour. Investors allocate their assets according to Bayesian Learning Theory by making belief updates based on incomplete information as well as changing their reinsurance requirements. The power of Modern Portfolio Theory remains vital for risk-return optimisation because it understands the valuable benefits of portfolio diversification. The investigations of Prospect Theory focus on human decision making under uncertainty through studying both loss-avoidance tendencies and probable value misperceptions. The expanded Capital Asset Pricing Model reveals investor behaviour during social influence situations and the impact of economic events on systematic risk elements to enhance portfolio management in different finance markets.

Table 4: Theoretical Foundations of Behavioural Portfolio Optimisation

SR.NO	Theory	Explanation	Source
1	Behavioural Finance Theory	Explains how psychological biases (e.g., overconfidence, overextrapolation, herding) influence investor decisions, portfolio construction, and asset allocation, deviating from rational expectations.	(Kanapickienė et al., 2024), (Jia, 2023), (Hersh Shefrin, 2024), (Gorzon et al., 2024), (Gavrilakis and Floros, 2021), (Jia, 2023)
2	Bayesian Learning Theory	Focuses on how investors update their beliefs (posterior mean and variance) based on incomplete information, influencing optimal reinsurance and asset allocation strategies.	(Escobar-Anel et al., 2024), (Kato et al., 2024), (Jiang and Jin, 2020), (Liu and Son, 2024), (Zhang et al., 2023)
3	Modern Portfolio Theory (MPT)	Originating from Markowitz's mean-variance optimisation framework, this theory explores the trade-off between risk and return in portfolio construction,	(Ababio, 2019), (Aguirre and Aguirre, 2023), (AmirMohammad Larni-Fooeik et al., 2024), (Arora and R Madhumathi, 2023), (Chen,

		emphasizing diversification and efficiency.	2023), (Filiz et al., 2018), (Ghmari et al., 2024)
4	Prospect Theory	Examines how investors make decisions under risk and uncertainty, incorporating concepts such as loss aversion, probability distortion, and S-shaped utility functions, influencing narrow framing and asset allocation.	(Arora and R Madhumathi, 2023), (Brummer and Oppermann, 2024), (Filiz et al., 2018), (Grant et al., 2024), (Hübner & Lejeune, 2022), (Kashaev & Aguiar, 2022), (Li, 2024)
5	Capital Asset Pricing Model (CAPM) Extensions	Investigates herding behaviour and systematic risk factors, highlighting how macroeconomic shocks and risk factor correlations impact investment strategies and asset allocation in various markets.	(Chen et al., 2021),(Escobar-Anel et al., 2024),(Fortin and Jaroslava Hlouskova, 2024)

4. Conceptual Framework

Figure 6. Conceptual framework

Investors' conduct under behavioural finance influence generates numerous suboptimal decisions that create consequences for market outcomes. The widespread investor bias of overconfidence drives investors to misjudge their ability, leading to excessive trading and risk-taking and poor outcomes and higher transaction costs (Xu et al., 2024; Valcanover et al., 2020b). Loss-averse investors face difficulties in their portfolio development as they keep ill-performing assets for too long yet dump profitable assets prematurely to capture profits (Zervoudi, 2017; Verlaine, 2022). During previous financial crises people engaged in herd behaviour to avoid individual research leading to altered market prices and market bubbles and collapses (Alamsyah et al., 2023; Ahmad and Wu, 2022). The fixation on irrelevant reference points including original purchase prices from anchoring bias affects rational decision-making because market conditions keep changing (Bihari et al., 2022; Vazirani et al., 2023). The combination of emotional decision-making with factors of fear or greed boosts investor bias to levels that create hasty decisions that oppose long-term investment targets (R Annapurna and Savitha Basri, 2024; Mullainathan and Thaler, 2000). Availability heuristic operates as an inaccurate rational decision-making mechanism because it allows fast-available news to control investor choices leading to irrational market reactions (Costa et al., 2017; Wu and Westerholm, 2024).

Psychological knowledge must be visualised in order to reduce these biases in portfolio management practices. The construction of portfolio models with investor biases (like overconfidence and loss aversion) is expected to match investor risk thresholds precisely (Meziani and Noma, 2018; Shanmuganathan, 2020). Education of investors about cognitive biases fulfills two fundamental purposes: it helps to get to know their unconscious responses better and allows them to make more rational investment decisions (Mahmood et al., 2024; Kanapickiene et al., 2024). Intervention of financial literacy programs with behavioural finance principles expands the investing decisions and minimizes cognitive biases that impact investment decisions as indicated by Eko Pranajaya et al., 2024; Yeny Rokhilawati et al., 2024. Robo-advisors offer an effective data-driven advice to investors through technology as a solution that assists them to stay focused on long-term goals(Vazirani et al., 2023).Financial institutions can predict market scenario biases and enhance investor behaviour understanding through behavioural data analytics. The result of such improvements leads to enhanced investment results because analysis allows the development of better investment approaches which target psychological factors(Broby, 2022; Mohan and Varghese, 2023). Financial returns and market efficiency increase as investors use analysis data to control their portfolios towards both risk interests and financial goals. (Corzo et al., 2024; Dennie van Dolder and Jurgen Vandenbroucke, 2024). Addressing behavioural biases leads to an enhanced efficiency of the financial system that allows assets to price according to actual economic fundamentals. Better risk management and effective decision-making improve individual investor outcomes through the integration of proper analysis (Almansour et al., 2023; Ben Ameur et al., 2024). A unified approach of reasoned analysis leaves the financial market better off since biases diminish thus preventing choices that stem from gut feelings or mental distortions.

5. Discussion

The paper is a review of the development of behavioural finance in the field of portfolio optimisation through the conduction of a bibliometric study of 240 articles in the Web of Science database by applying PRISMA protocol. The data were analyzed using Bibliophagy 2.0 and VOS viewer that served to identify large thematic clusters, collaboration trends between authors, and similar methodological strategies. These findings are interpreted and what they imply on how knowledge in this field has changed as time goes is discussed in the following.The results show that behavioural finance has become a focus of research in the modern portfolio management. The classical theory of investment has developed on the premise that investors are rational, and that markets are efficient, yet this premise has been violated by the growing behavioural literature that documents numerous violations of these assumptions. The bibliometric analysis identifies overconfidence, herding, anchoring, and loss aversion as the most studied biases that influence the portfolio decisions and risk perceptions. A combination of these arguments leads to the timeliness of the role played by psychological factors in the attempt to find out why investors are likely to underdiversify in a manner that is appropriate as well as why asset prices are in some cases not related to the underlying fundamentals.The other noticeable trend that has been evident in the analysis is the heightened use of computational methods and behavioural concepts. Recent publications can be seen as an emerging tendency in integrating the classical forms of optimisation with the software of artificial-intelligence (Bayesian learning, genetic algorithms, machine-learning-based forecasting). This change is reflective of a greater change within the industry: scientists no longer merely identify biases in behaviour, but it is an attempt to model these tendencies and they are being implemented directly in investment decision-making. The union of the wisdom of behaviour with the methods of analysis of a more advanced nature also is proving helpful in forecasting the behaviour in which investors will act and create a portfolio that is better adjusted to the variations of market sentiment and condition. The increasing overlap of behavioural finance and data science, thus, heralds and desirable direction of research and business growth of the field of portfolio management.The increasing importance of financial literacy in balancing behavioural biases is also evident in the bibliometric support. The examination of the emerging markets, especially India and China, has shown that the investors who are better financially educated can study their psychological behaviour more effectively and can be aware of it. This trend is an indication that education and awareness can result in more disciplined portfolio choices and it can help restrain market distortions based on collective behavioural reactions. Financial literacy, in this regard, is also a behavioural defence mechanism and a structural constituent of investment performance, which connects the psychological aspects, the individual learning, and the market-wide results.The aspects of the culture and context are also significant in determining how the biases of behaviour manifest in the financial choices. Research in developing economies indicates that biases or herding and loss aversion can be affected by social norms, uncertainty in the economy, as well as regulatory frameworks. In collectivist environments, such as group behaviour may be valued more by investors, whilst risk-averse behaviour is likely to be increased in high volatility markets. The above observations indicate that behavioural finance should be considered in the local cultural and economic context because psychological biases do not follow the same pattern in different market settings.The cooperation and citation patterns also indicate that behavioural portfolio research is becoming more interdisciplinary. Economists, psychologists, and computer scientists are collaborating to study the role of emotions, human cognitions, and computer aids to examine how these elements affect the behaviour of investments. Such interdisciplinary interaction is contributing to the development of a more balanced picture of the actual decision making process of investors and no longer depending on models based on rationality. The broader diversification of the authors and institutions behind this work is also an indicator of emerging international interest in the connection between behavioural knowledge and newer fields like sustainable finance and technology-based investment approaches.

6. Conclusion

Studies on portfolio optimisation in the behavioural finance framework have been on the rise in recent years. The paper under the analysis involved 240 entries to Web of Science database analysed in Bibliophagy 2.0 and VOSviewer, where the documents were chosen according to PRISMA protocol to map the current work and understand the gaps in the research area. The key conceptual frameworks and methodological tools that characterize contemporary research trends have been identified in the review, and include the intense role of psychological biases (overconfidence, loss aversion, herding and anchoring) in investment decisions resulting in the portfolio decisions made by investors being not the most optimal portfolios. A number of researchers have proposed the use of computational techniques, such as Bayesian learning algorithms and genetic algorithms, to predict these biases and enhance the results of optimisation. It is also observed in the analysis that financial literacy is an influential factor in the process of cognitive distortion moderate, and the evidence indicates that investors with higher financial literacy are more effective in their decision-making in regards to their portfolio choices. Regardless of these developments, more studies are to be done to comprehend the interaction of behavioural biases with complex computational mechanisms especially in growing economies in which culture and economic factors can influence investor behaviour in different ways. A study of these dynamics may be useful in creating more adaptive and context-dependent portfolio strategies.

7. Implications of the Study

The results of this paper have significant implications to regulators, practitioners in the industry, and academic researchers. In the context of academic studies, the findings indicate that multidisciplinary research, which involves the combination of traditional financial theory, behavioural insights, and sophisticated computational methods should be a priority (Bi et al., 2023). This kind of integration may be able to provide a more realistic picture of market behaviour. As a practitioner, one can apply the cognition bias and decision making heuristic knowledge to create portfolio strategies that can guide them through uncertainties, and reinforce their investment decisions. Regulatory-wise, the behavioural aspects of the study indicate that those features of the investor psychology can be taken into account when formulating policies that are supposed to ensure the stability of the market (Bouteska et al., 2023).

7.1 Implications for Investors

The research emphasizes the need to combine behavioural knowledge with computational models and conventional financial analysis in the design of investment strategies (Amir Mohammad Larni-Fooeik et al., 2024). To the investors, it is important to identify personal cognitive biases, in particular overconfidence and loss aversion because loss aversion and overconfidence can be mitigated by specific methods. Other behavioural ideas like the Prospect Theory can be a particularly insightful guide as it enables investors to learn how they are emotionally reacting to losses and gains, which will result in more rational and steady decision-making (Bi et al., 2023).

The use of analytical tools which are advanced also helps in this process. Genetic algorithms and dynamic programming (among others) could be used to help create portfolios that have better long-term risk management performance (Annin et al., 2024). Investors that are keen on the trends in AI-based portfolio management and sustainable investment strategies are thus better placed to record resilient and informed financial outcomes.

7.2 Implications for Policymakers

The implications of the results on policymakers are that the regulatory systems must take into account the findings of the behavioural finance in order to make the markets more efficient. Namely, augmenting financial education is that, as it may reduce most biases such as overconfidence and losses aversion to engaging in more appropriate investment choices. The behavioural tendencies associated with the process of portfolio optimisation can also be overcome through motivation of using advanced computational technologies such as genetic algorithms and Bayesian learning.Regulation within emerging markets ought to put into interventions the local cultural and economic conditions, which is prone to condition the manner in which investors respond to any uncertainty and risk. Another step of promoting FinTech projects that involve the application of behavioural indicators may promote more reasonable and informed decision-making, too. Finally, cross-disciplinary collaboration, in particular, between behavioural finance and computational research, should be encouraged to enable the construction of more data-driven and adaptive market stabilising mechanisms.

8. Future Research Directions

The next section establishes key points of intersection between the portfolio optimisation techniques and behavioural finance studies in the future. Behavioural knowledge increases the precision of projections in cases where superior computational strategies which combine AI and machine learning techniques are involved. The study of financial literacy programs in different countries, in particular, emerging economies gives an insight into the activity of investors. The comparison of the effects of bias across countries will help the researchers to find out the difference between the bias across countries, thereby making investment models and policy choices more effective.

Table 5: Future Research Directions

S.NO		
	Cluster 1 'Red': Impact of Behavioural Biases on Investment Performance	Focus on the impact of behavioural biases like overconfidence and loss aversion in emerging economies, such as India (Corzo et al., 2024).
		Investigate how biases like herding and anchoring influence risk-adjusted returns in developing countries (Mahmood et al., 2024).
		Explore how financial literacy programs, behavioural interventions, or AI tools can mitigate the effects of biases (Mahmood et al., 2024).
2	Cluster 2 'Blue': Investor Sentiment and Stock Market Volatility	-Examine the relationship between investor sentiment and stock price volatility in emerging markets and high-volatility sectors (Varghese & Mohan, 2023).
		- Conduct cross-country comparisons to assess how cultural differences impact sentiment and decision-making in non-Western markets (Jiang et al., 2023).
		- Investigate the role of social media and digital platforms in amplifying or mitigating market volatility.
3	Cluster 3 'Green': Behavioural Data Analytics for Investment Decision-Making	- Utilize big data and AI to predict investor psychology and biases, enhancing investment decision-making (Podille et al., 2024).
		- Develop models integrating behavioural biases with financial data (e.g., stock performance) to improve predictive accuracy (Shanmuganathan, 2020).
		- Focus on AI-driven tools that analyze investor behaviour and sentiment to optimize portfolios and reduce biases.
4	Cluster 4 'Yellow': Financial Literacy and Behavioural Bias Mitigation	- Investigate the role of financial literacy in mitigating biases like overconfidence and loss aversion in emerging markets (Mahmood et al., 2024).
		- Examine the effectiveness of financial literacy interventions, such as workshops or digital platforms, in improving decision-making.
		- Study the link between financial literacy and investor confidence in mitigating the impact of behavioural biases.

9. Limitations

Some shortcomings and ways of research that can be pursued in the future concerning behavioural finance and portfolio optimisation are also established in this study and are summarised in Table 5. Despite having some useful information about the developments in the field, the review has some limitations. The use of the Web of Science database alone also has a weakness, in that it can fail to capture an important work in progress, or published in a non-dominant outlet, especially in new, or very specialised fields of research. Consequently, it is possible that not all trends in the general scientific environment will be reflected.Also, self-reported information could be used in a few of the underlying studies and therefore, there could be reliability issues because the responses to these items are likely to be affected by the problem of recall or social desirability. The extensive use of cross-sectional research designs also limits the possibility of making causal conclusions or tracking the development of behavioural patterns with time. Lastly, due to the nature of the segment of the financial market that is analysed via the review, the results cannot be easily extrapolated to other types of asset classes or industries.

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