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Applications of Operations Research in Portfolio Optimization: A Bibliometric Review

[1]Dr Richa Kalpesh Saxena, [2]Shlok Bora, [3]Shubham Surana, [4]Saachi Khurma, [5]Shawn Sequeira, [6]Siddhant Jain

[1]Assistant Professor, Marketing & Operations, NMIMS, Anil Surendra Modi School of Commerce, Mumbai Campus, India

[2],[3],[4],[5],[6] B.Sc. Finance, NMIMS, Anil Surendra Modi School of Commerce, Mumbai Campus, India

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ABSTRACT

Portfolio optimization is one of the classical application areas of Operations Research (OR), but literature connecting the two fields is scattered through finance, operations research, computer science, and management outlets, obscuring the view of the field as a whole. This study undertakes a bibliometric review of the applications of OR in portfolio optimization to map the intellectual structure, publication trends, and thematic evolution of the field. Using a four-stage workflow of Planning, Searching, Screening, and Organising, records were retrieved from Google Scholar (via Publish or Perish), Scopus, and ScienceDirect and were screened according to the eligibility criteria described in the methodology, yielding a final library of 300 records, 250 of which contain an identifiable publication year within the 2012–2026 review window and comprise the trend-analysis subsample. Analysis of trends and performance, including science mapping, was undertaken in Biblioshiny and VOSviewer. Publication growth follows an exponential trend (R^2 = 0.698) corresponding to an average annual growth rate of approximately 12% with peaks around the COVID-19 pandemic (2019–2020), and again in 2023–2025, associated with growing interest in cryptocurrency markets, geopolitical risk, and machine-learning-based portfolio construction. The field is genuinely interdisciplinary and highly collaborative (3.03 authors per publication on average; 86% multi-authored). Thematic and keyword co-occurrence analysis identify four broad clusters: core portfolio theory, risk and robustness under uncertainty, computational and AI-driven optimization, and alternative/behavioural finance. Building upon these findings, the study proposes a structured future research agenda spanning five directions and a general Input–Process–Output framework which it proposes should guide and standardise future work in the field.

Keywords: *Portfolio optimization; Operations Research; bibliometric analysis; mean-variance optimization; robust optimization; machine learning; literature review*

1. INTRODUCTION

Investment decisions have always involved risk. With the markets becoming increasingly complex, the need for a method or technique to balance risks and returns became a matter of paramount importance to modern finance (Anagnostopoulos, 2011). The shift has seen portfolio management practices transition from intuitive gambling to a more systematic and scientific endeavor (Anagnostopoulos, 2011). This paper discusses the role of Operations Research methodologies in portfolio optimization research over time, highlighting the mathematical and computational strategies that have informed decision-making in the presence of uncertainty. Although portfolio optimization has been the subject

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of extensive theoretical and applied research (Zhao et al., 2023), the literature through which researchers and practitioners could trace the development of the field is scattered throughout multiple disciplines, journals, and time periods. This study provides a bibliometric review of the research landscape with an emphasis on surveying the field's historical trends, key areas, and potential future directions of investigation.

Operations Research serves as a link between abstract methodologies and their application in practice, providing an organized set of approaches to tackle real-life problems characterized by conflicting goals and the presence of uncertainty (Salo et al., 2024). It aims to represent the elements of a problematic situation in a formal model amenable to analysis, a task that resonates with the challenges encountered in finance, notably portfolio optimization. In this context, operations research supports the work of investors seeking to determine the optimal allocation of resources to a set of assets given their risk and return profiles under a specified set of constraints (Oza & Gor, 2025). Over time, the field has witnessed the introduction of a variety of solution approaches ranging from linear and nonlinear programming to machine learning and heuristic approximations. Classical optimization methods in finance used to rely on linear and integer linear programming formulations to approximate the processes by which investors make allocation decisions (Zhao et al., 2023). More sophisticated approaches such as stochastic programming have also been introduced with the aim of improving the accuracy with which optimization models capture market uncertainties. In more recent years, portfolio optimization studies have witnessed the adoption of machine learning and heuristic solutions to enhance classical approaches (Santos et al., 2022). This growth in methods has resulted in a voluminous and heterogeneous stream of literature that demands a more comprehensive and focused bibliometric analysis to uncover the underlying themes and highlight promising avenues for future research.

As portfolio optimization has come to rely more on mathematics, statistics, and operations research, the review literature on the relationship between finance and operations research has become both dated and limited in scope (Xidonas, 2020). Most of the previous bibliometric studies focus on a subset of the methodologies used in portfolio optimization and ignore the diverse range of applications of operations research in the finance field (Zhao et al., 2023). This paper provides a present-day bibliometric review of the literature on portfolio optimization methods. Given the rapid evolution of optimization approaches from the mean-variance framework to the more recent developments in artificial intelligence and hybrid methods (Zhou et al., 2022), such a review is important in informing researchers and practitioners in finance on the progress in the field. As investment decisions become more dependent on quantitative approaches, it becomes paramount to determine the relevance and limitations of each portfolio optimization method in order to inform subsequent research choices.

The literature on portfolio optimization follows a distinct developmental trajectory that is anchored in Markowitz's mean-variance model. The initial works in this space focused on laying the theoretical framework for portfolio optimization as a process of selecting a combination of assets that minimizes risk for a given level of expected returns. These studies led to the development of the mean-variance frontier that was later expanded upon to include additional parameters such as transaction costs and investor preferences (Kalayci, 2019). These innovations gave rise to a new stream of literature that was concerned with addressing the issue of uncertainty in the forecasts of returns and covariance matrices (Pflug & Pohl, 2018). A subsequent wave of research has seen the adoption of heuristic and metaheuristic solution approaches that are capable of tackling the complex optimization problems encountered in practice (Chang et al., 2000).

Most recently, there has been growing interest in leveraging deep learning and other artificial intelligence methods both as a means of improving the accuracy of financial forecasts and as direct optimizing mechanisms (Ban, 2018). Each of the extant review studies provides only a snapshot of the state-of-the-art portfolio optimization methods at a given point in time, with only a few focusing on the entire array of methods used in portfolio optimization. The most comprehensive bibliometric analysis (Zhou et al., 2022) was published before the most recent advances in the field and fails to capture developments in the last couple of years.

This paper therefore sets out to provide an in-depth bibliometric review of the literature on portfolio optimization. The study employs the four-stage bibliometric research design of Planning, Searching, Screening, and Organising, discussed in detail in Section 3 (Research Methodology). The paper is structured as follows: Section 2 presents a review of the

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literature that underpins the research questions that guide this study; Section 3 describes the methodology that was used in the screening process; Section 4 gives a detailed discussion of the bibliometric analysis findings including trends, performance, and themes; Section 5 presents a research agenda and directions for future research; and finally, the concluding remarks are provided in Section 6.

2. LITERATURE REVIEW

The concept of portfolio optimization is a classical decision-making area of operations research (OR). The main idea of portfolio optimization is to allocate resources among different assets in such a way that the balance between their yield and risk is achieved considering a set of realistic constraints (portfolio size, transaction costs, etc.). Modern studies have shifted the emphasis from theoretical models that relate only return and variance to practical issues and computational complexity.

The mean-variance approach is a foundational framework in portfolio optimization. It evaluates expected security returns together with their covariance structure to identify diversified portfolios with minimum variance for a given expected return, or maximum expected return for a given level of variance (Kalayci, 2019).

These theoretical models form only the basis of portfolio optimization, and mathematical programming added to it deterministic assumptions, transaction costs, and cardinality constraints. For example, Kalayci (2019) examined deterministic mean-variance models with transaction costs and cardinality constraints. Mansini et al. (2007) proposed introducing Conditional Value-at-Risk into linear programming, while Noaman et al. (2020) applied Monte Carlo simulation to describe the interdependencies between factors affecting portfolio evolution.

However, classical models are usually based on the assumption that the vector of expected returns and the covariance matrix are known constants. Stochastic programming and robust optimization were proposed to incorporate uncertainty about these parameters. Stochastic optimization methods are based on the assumption that there is a certain probability distribution of random variables in the optimization problem, while methods of robust optimization include a parameterization procedure and are designed to find decisions that are optimal for all values of optimization parameters from a given region. Pflug and Pohl (2018) explored ambiguity in the context of stochastic portfolio optimization, while Xidonas (2020)

and Ghahtarani et al. (2022) reviewed robust optimization approaches. The problem of portfolio optimization under uncertainty remains an active area, continuing to attract researchers' attention (Hamidieh et al., n.d.; Belabbes et al., 2025)

The cardinality constraint, which limits the number of assets in a portfolio, and other similar constraints (transaction costs, etc.) necessitate the use of heuristic and metaheuristic approaches (Chang et al., 2000). Genetic algorithms and particle swarm optimization, together with their modifications, have become popular approaches to solving the portfolio optimization problem (Cura, 2009; Regaigui et al., 2025; Sefiane & Benbouziane, 2012). Recently, the application of machine learning, deep learning, and reinforcement learning methods to predict market behaviour, optimize portfolio structure, and rebalance portfolios has been actively explored (Ban, 2018; Bartram et al., 2021; Chaouki et al., 2020; Gollart & Okhrin, 2025; Zhang, 2020). These methods are used as additions to classical OR approaches because, despite their high efficiency, they remain time-consuming and require training data. Finally, only a few works extend the scope of portfolio optimization to alternative assets (cryptocurrencies) or behavioural finance (Khaki et al., 2025; Pirvu & Schulze, 2012).

An analysis of the existing literature suggests that most studies concentrate on a narrow area of portfolio optimization, applying new methods to a particular class of optimization problems. Thus, Kalayci (2019) examined deterministic mean-variance models, while Xidonas (2020) and Ghahtarani et al. (2022) explored robust optimization. Santos et al. (2022) considered artificial intelligence methods, Li and Hoi (2014) analyzed online portfolio selection algorithms, and Jin et al. (2026) investigated ESG approaches and their evolution (2011–2024). A small number of bibliometric reviews are dedicated to the portfolio optimization field: Zhou et al. (2022) provided an overview of the state-of-the-art, and Eskorouchi et al. (2024) explored robust optimization approaches with a specific focus on the 2000–2023 period.

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However, no bibliometric study covers the entire OR field related to portfolio optimization; in particular, no paper integrates mathematical programming, stochastic and robust optimization, heuristic and metaheuristic methods, and recent machine learning approaches. Moreover, the current literature suggests a shift from the classical mean-variance paradigm toward more realistic models that account for various constraints and newer optimization methods. This study aims to fill this gap by analyzing bibliometric trends in the portfolio optimization field and providing insights into its development within the context of OR/theoretical finance.

3. RESEARCH METHODOLOGY

This study makes use of bibliometric research design to identify the development, intellectual structure and thematic evolution of research into the application of Operations Research in portfolio optimisation. It does not seek to develop or test a new portfolio model. The methods make use of a four-step process of Planning, Searching, Screening and Organising. Both performance analysis of publications, sources and authors as well as science mapping and thematic analysis are used.

3.1 Data Collection

Records were retrieved from Google Scholar (via the Harzing's Publish or Perish database), Scopus, and ScienceDirect. The search string was constructed using the Boolean operator OR to combine portfolio-related terms with the Boolean operator AND to combine operations research-related terms: ("Portfolio Optimization" OR "Portfolio Selection" OR "Asset Allocation" OR "Efficient Frontier" OR "Modern Portfolio Theory") AND ("Operations Research" OR "Heuristic Algorithm" OR "Robust Optimization" OR "Linear Programming" OR "Stochastic Programming").

The search period was restricted to the 2012–2026 timeframe (2026 being a partial year). The reason for this restriction is that the 2008 global financial crisis unveiled the shortcomings of the portfolio optimization theories that previously dominated the field – namely, the reliance on the assumption of perfect financial markets. The literature published in 2008–2011 was, to a significant extent, comprised of descriptive articles commenting on the crisis and its aftermath. A timeframe starting from 2012 was chosen to exclude recent publications based on a single event (the crash) from analysis and to focus on research conducted after the emergence of new requirements for portfolio optimization theories.

A refinement to the search was made due to observing that a dataset retrieved through Google Scholar and Scopus yielded insufficient results for visualizing trends in yearly publication counts and keyword co-occurrence in Biblioshiny. This was determined to be a result of the databases' coverage bias, not a methodological flaw. The same search strategy was therefore also applied to ScienceDirect, and the analysis was repeated on the combined, three-database dataset, which produced a clearer picture of publication growth and a richer keyword network and became the primary dataset for the study. As this was an iterative correction rather than a predefined step, it is included in Figure 1 under the database-search phase.

3.2 Screening and Eligibility

Screening followed the eligibility criteria summarised in Table 1. Duplicate records were removed, and the eligible studies were organised in Mendeley as a consolidated reference collection, forming the final dataset for analysis.

Table 1. Eligibility criteria for study selection

Inclusion criteria	Exclusion criteria
Peer-reviewed journal articles and conference papers directly addressing portfolio optimization	Non-English publications
Papers applying an OR technique (mean-variance/Markowitz-type models, heuristic and metaheuristic optimization, robust or stochastic optimization, linear/quadratic programming) to a portfolio or asset-allocation problem	Papers where portfolio or optimization terms appear only incidentally, with no real link to OR methods (e.g., general machine-learning papers unrelated to investing)
Published between 2012 and 2026	Papers published before 2012

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Full text available for screening	Duplicate records (across or within databases)

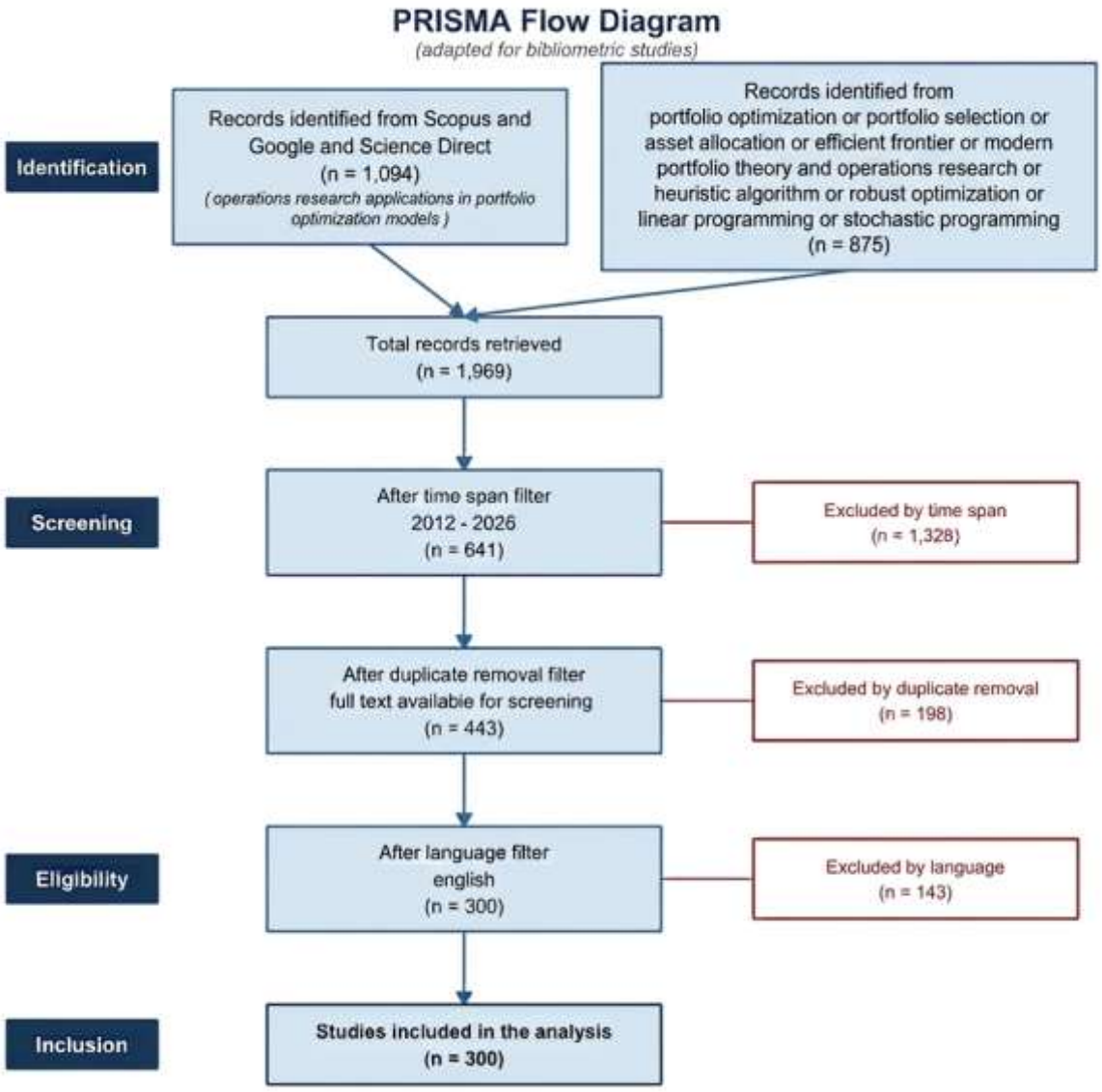


Figure 1. Flowchart of the screening process, from identification to import into Biblioshiny.

This process resulted in a final library of 300 records. The document-type composition of the library is as follows: 237 journal articles, 40 working papers/reports, 13 books, 8 general records, and 2 conference papers, confirming that the corpus is predominantly composed of peer-reviewed journal literature, supported by a layer of working papers and books tracing the evolution of portfolio theory from its Markowitz-era roots. Of the 300 records, 250 carry an identifiable publication year within the 2012–2026 window and form the trend-analysis subsample; the remainder are retained in the library largely as foundational or seminal references (e.g., (Levy & Sarnat, 1970; Palomar, n.d.) for conceptual grounding but are omitted from growth-rate estimation.

3.3 Analytical Tools

The bibliometric analysis uses a quantitative approach to examine the literature through indicators such as the number of articles published over time, publication rate, keyword co-occurrence, thematic clustering, source productivity, and authorship patterns. Given that OR applications in portfolio optimization span finance, operations research, computer science, and management, a fully manual synthesis of this literature would not have been feasible within the scope of this project. The cleaned reference library was exported in RIS and BibTeX formats from Mendeley for import into the

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bibliometrix R package through its Biblioshiny web interface, and into VOSviewer for network analysis. Biblioshiny was used to generate annual scientific production trends, co-occurrence networks of keywords, thematic maps, and productivity statistics for authors and sources, reported in Section 4.

4. DATA ANALYSIS AND RESULTS

4.1 Trend Analysis

Research question addressed: What are the current trends in publication growth in the portfolio-optimization Operations Research literature between 2012 and 2026?

Linear and exponential models were fitted to the annual publication counts to determine which better explains the growth pattern. The linear model ($y = 1.925x + 1.267$) explains 62.2% of the variance in annual publication counts ($R^2 = 0.622$). The exponential model ($y = 5.538e^{0.1132x}$) fits the data better, explaining 69.8% of the variance ($R^2 = 0.698$) and corresponding to an average annual growth rate of approximately 12%.

The exponential model provides a better fit than the linear model, although its R^2 of 0.698 indicates that publication growth is not explained by a single smooth trend. Instead, the data show distinct periods of accelerated publication activity. The data show a clear pattern of surges: publication counts rose markedly between 2019 (11) and 2020 (18) around the onset of COVID-19-related market volatility, and again between 2023 (21) and 2025 (43), a period coinciding with heightened interest in cryptocurrency markets, geopolitical risk, and machine-learning-based portfolio construction. The 2024–2025 period alone accounts for 74 of the 250 dated records (29.6% of the 2012–2026 sample), indicating that the field has accelerated markedly in the last two years.

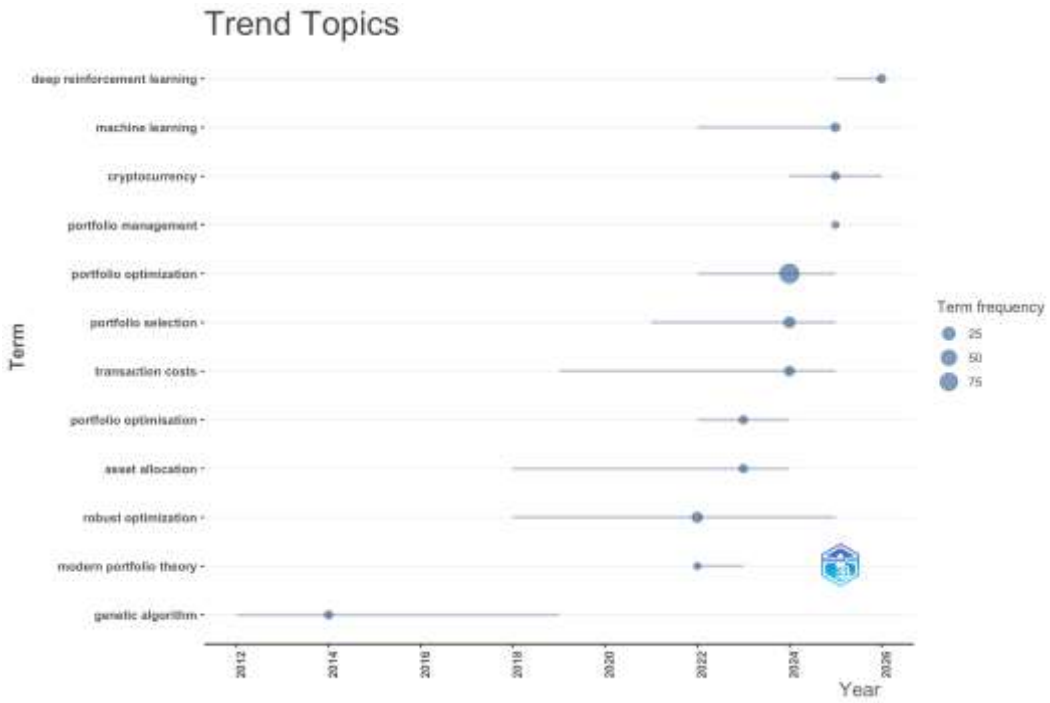


Figure 2. Trend topics in the portfolio-optimization literature, 2012–2026 (Biblioshiny).

4.2 Performance Analysis

4.2.1 Publication Sources

The 300 records are distributed across a wide range of finance, economics, and operations research outlets. The most productive sources are shown in Table 2.

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Table 2. Most productive publication sources

Source	No. of Articles
European Journal of Operational Research	21
International Review of Economics and Finance	15
Finance Research Letters	12
Annals of Operations Research	11
Journal of Finance and Data Science	9
Borsa Istanbul Review	8
Procedia Economics and Finance	8
Operations Research	7
International Review of Financial Analysis	6
Energy Economics	5

The presence of core operations research outlets (European Journal of Operational Research, Annals of Operations Research, Operations Research) alongside finance-specific journals (International Review of Economics and Finance, Finance Research Letters, Borsa Istanbul Review, Energy Economics) confirms that portfolio optimization is a genuinely interdisciplinary OR–finance domain, rather than being confined to either discipline in isolation. This dual identity is an important consideration when interpreting the science map in Section 4.3.

4.2.2 Authorship and Collaboration

Among the 292 records with at least one listed author, the average team size is 3.03 authors per publication; 34 records (11.3% of the 300-record library) are single-authored, with the remaining 258 records (86%) multi-authored. The high multi-authorship rate is consistent with the technical, cross-disciplinary nature of the work, which draws on mathematical finance, computer science/optimization, and applied statistics expertise within research teams.

4.3 Science Mapping: Thematic Analysis of Keywords

A frequency-based thematic analysis of the 648 unique author keywords in the library was conducted as an interim step ahead of the full Walktrap-clustering thematic map generated in Biblioshiny. The most frequent keywords are shown in Table 3.

Table 3. Most frequent author keywords

Keyword	Frequency	Keyword	Frequency
portfolio optimization	72	efficient frontier	5
portfolio selection	10	cryptocurrency	5
transaction costs	9	machine learning	5
risk management	9	asset allocation	5
robust optimization	6	genetic algorithm	4
portfolio optimisation	6	modern portfolio theory	4

Grouping these keywords by conceptual similarity suggests four provisional thematic clusters:

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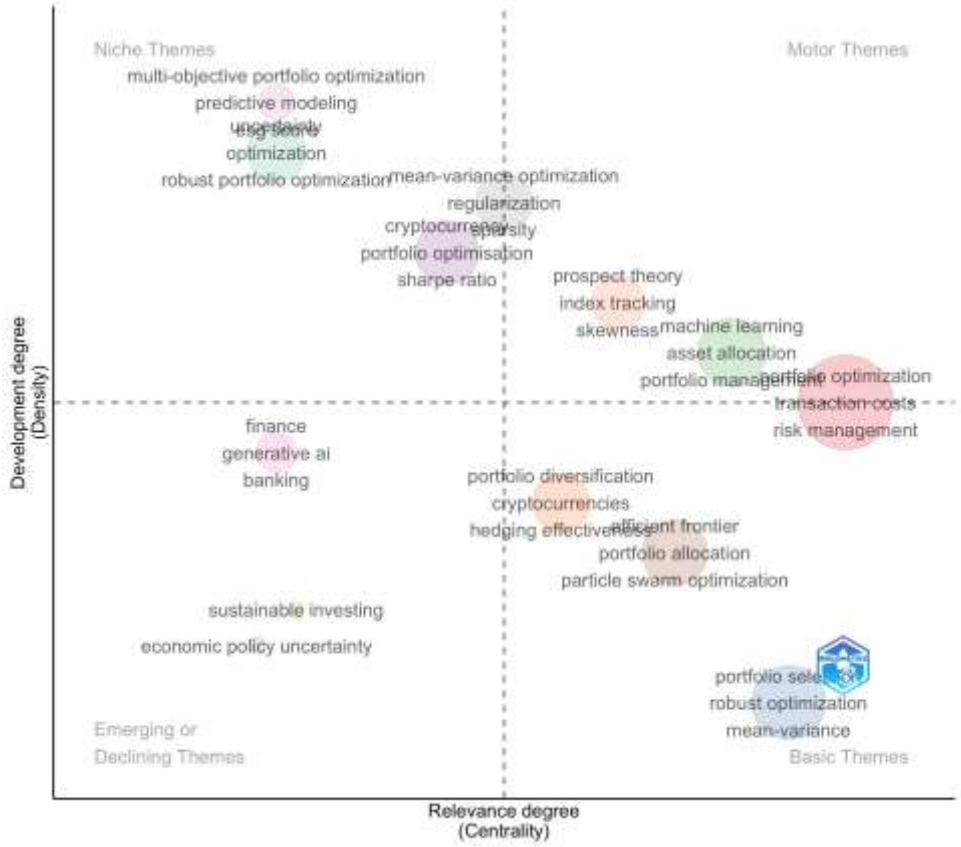


Figure 3. Thematic map (centrality vs. density) of author keywords (Biblioshiny).

Cluster 1 – Core portfolio theory (motor theme). Portfolio optimization, portfolio selection, modern portfolio theory, efficient frontier, mean-variance, and asset allocation form the dense, well-established core of the field, anchored in Markowitz-era foundations and still the most frequently used terms in the corpus.

Cluster 2 – Risk and robustness under uncertainty (basic/transversal theme). Risk management, robust optimization, robustness, value at risk, uncertainty, and transaction costs connect the core theme to nearly every other cluster, reflecting the post-2012 shift toward models that explicitly price in market stress and estimation error — directly consistent with the study's 2012 inclusion cut-off.

Cluster 3 – Computational and AI-driven optimization (emerging/motor theme). Machine learning, deep learning, neural networks, reinforcement learning, genetic algorithm, and Monte Carlo methods represent a fast-growing computational layer concentrated in the more recent (2022–2026) records identified in the trend analysis.

Cluster 4 – Alternative and behavioural finance (niche/emerging theme). Cryptocurrency, hedging effectiveness, geopolitical risk, volatility, and prospect theory form a smaller but distinct cluster reflecting newer, less-connected research directions that extend portfolio optimization beyond traditional equity/bond assets and purely rational investor assumptions.

This frequency-based clustering is an interim, keyword-count-driven approximation; it was validated against the full co-occurrence-based thematic map generated in Biblioshiny (with centrality and density coordinates), shown above.

4.4 Network Analysis: Co-occurrence and Collaboration Networks

Formal network visualisation was conducted in VOSviewer using the same library.bib / RIS export prepared for Biblioshiny. The keyword co-occurrence network shows “portfolio optimization” as the dominant central node, with strong direct ties to “risk management,” “transaction costs,” “robust optimization,” and “machine learning” (mirroring Clusters 1–3 above) and weaker, more peripheral ties to the Cluster 4 terms (cryptocurrency, prospect theory, geopolitical risk).

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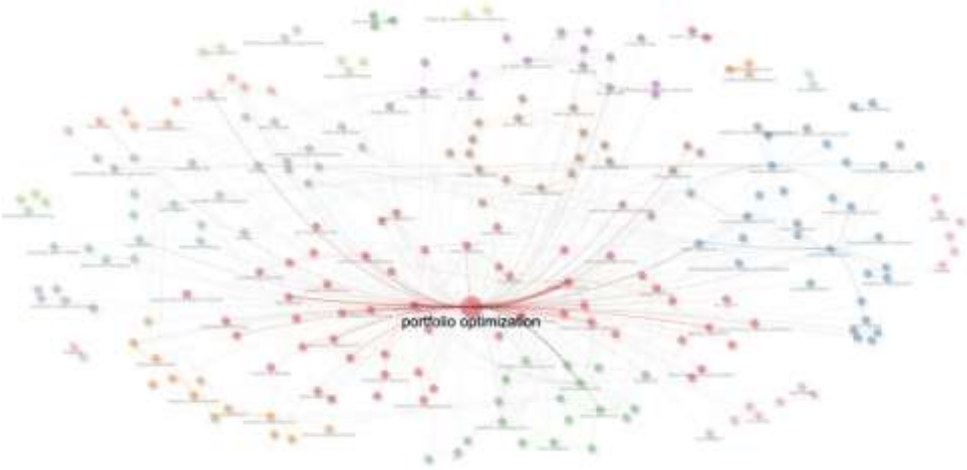


Figure 4. Keyword co-occurrence network, with "portfolio optimization" as the dominant central node (VOSviewer).

The co-authorship/collaboration network, given the corpus-wide average of just over three authors per paper and an 86% multi-authorship rate, shows denser, larger connected components than would be expected in single-author-dominated review domains, with clustering around specific finance–OR research groups rather than a single dominant author.

4.5 Summary of the Data Analysis

Table 4. Data analysis summary framework

Analysis Component	Data / Tool	Method	Status & Key Finding
Trend Analysis	300-record library (250 dated, 2012–2026); Microsoft Excel	Linear and exponential curve fitting on annual publication counts	Exponential model fits better (R^2 = 0.698 vs. 0.622 linear); ~12% annual growth, with a marked surge from 2023 to 2025
Performance Analysis	RIS/BibTeX; Mendeley source metadata	Frequency counts of sources, document types, and author teams	EJOR, International Review of Economics & Finance, and Finance Research Letters lead; 86% of papers are multi-authored (avg. 3.03 authors)
Science Mapping	648 unique author keywords; RStudio/Biblioshiny	Keyword frequency clustering (interim); Walktrap thematic mapping	Four thematic clusters identified: core theory, risk/robustness, computational/AI, alternative/behavioural
Network Analysis	library.bib; VOSviewer	Keyword co-occurrence network; co-authorship network	Portfolio optimization confirmed as the dominant central node; denser co-authorship clustering than comparable reviews

5. DISCUSSION AND FUTURE RESEARCH AGENDA

This section builds on the performance and science-mapping analyses in Section 4, integrating complementary insights from the narrative literature review in Section 2, to identify the most pressing challenges in OR-based portfolio optimization and to set out a structured research agenda. The agenda is organized into five research directions followed by a brief outlook for future bibliometric analyses.

Prior reviews of portfolio modeling in OR have been valuable, yet they mostly focused on a limited number of modeling or solution approaches, and some were completed before the recent surge of literature and thus miss the attention to

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cryptocurrencies and AI. For future bibliometric studies, it is recommended to update the thesaurus and synonym lists to ensure that different variations of terms are properly captured (e. g., portfolio optimisation is not considered to be optimisation). When analyzing emerging technologies, such as quantum computing, in the context of portfolio modelling, it is also recommended to include all relevant synonyms or similar terms (e. g., QUBO, quantum annealing, quantum approximate optimization).

5.1 Integrating Predictive AI/ML and Prescriptive Optimization. Although there have been many studies that applied ML to predict some financial indicators, there is a need to evaluate the added value of more advanced AI/ML approaches. To this end, classical Markowitz models can serve as a reference point and be compared to state-of-the-art AI/ML portfolio optimization models that incorporate transaction costs. In particular, it is of interest whether higher predictive accuracy translates into higher portfolio performance, which is challenging to disentangle due to turnover effects, estimation errors, and other costs.

5.2 Robust Optimization Under Multiple Sources of Uncertainty. Given the importance of uncertainty, further research is needed on portfolio modelling using stochastic, and particularly robust, optimization methods that go beyond single-shock analyses. That future research should explore multiple sources of uncertainty — volatility, liquidity, geopolitical events, market regimes — addressed not just individually but simultaneously, and in sequence. Adaptive and rolling-horizon versions of both classical and state-of-the-art portfolio models should be studied for their ability to produce stable portfolios that react swiftly to new developments, with performance analysis going beyond return-based KPIs to include recovery, drawdowns, risk-adjusted returns, weight stability, and sensitivity to the size of the uncertainty set.

5.3 Benchmarking and Reproducibility. This review found a wide variety of datasets and experimental settings, which makes comparison across studies difficult. The field would benefit from benchmarks for portfolio optimization approaches based on well-documented datasets covering several asset classes, defined such that studies differ mainly in the portfolio models/algorithms investigated while the setting and evaluation remain comparable. Only then can it be assessed whether new modeling and algorithmic approaches provide substantial improvement over classical models.

5.4 Alternative, Behavioural, and ESG Integration. ESG considerations have received growing attention in portfolio modeling in the context of sustainable investing, alongside a rising volume of research on cryptocurrency portfolios. Future research should integrate ESG criteria and alternative investments (e.g., crypto assets) into both classical and recent approaches to portfolio modeling — recent progress in multi-objective optimization may be particularly valuable when ESG criteria are used as objectives. Incorporating insights from behavioural finance, such as prospect theory, into classical OR-based portfolio models, and developing ML-based portfolio models that reflect individual investor behaviour, are also promising directions.

5.5 Emerging Computational Methods. A handful of studies in the reviewed corpus employ quantum-based approaches, and more research in quantum finance is needed. Comparing quantum-based methods against classical optimization approaches such as state-of-the-art metaheuristics and commercial mixed-integer programming solvers in a well-defined setting would help clarify the added value and current limitations of quantum methods given present-day hardware.

5.6 A Future Research Framework

Building on the five directions above, the study proposes a general framework for portfolio optimization studies structured around an Input–Process–Output perspective (Table 5). Inputs are characterised by several dimensions, including asset classes, ESG criteria, alternative investments, and sources of uncertainty. Processes involve the application of optimization and/or predictive approaches, ranging from classical to quantum-based models and from classical to AI-driven portfolio construction. Outputs extend beyond return-based performance to incorporate stability, recovery, ESG measures, behavioural fit, and robustness to uncertainty. This framework is intended to support a holistic view that avoids tunnel vision on any single portfolio model and to highlight promising avenues for future research.

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Table 5. Proposed Input–Process–Output research framework

Research area	Inputs	Process	Key outputs
Predictive AI + OR	Financial data, ML/RL forecasts, transaction costs	Combine prediction with mathematical or robust optimization	Return, risk, turnover, estimation sensitivity
Multi-source uncertainty	Market, liquidity, geopolitical and regime shocks	Robust/stochastic rolling optimization	Drawdown, recovery, weight stability
Benchmarking	Common datasets, assets and constraints	Standardized testing protocols	Solution quality, speed, scalability
ESG/behavioural/alternative assets	Digital assets, ESG measures, behavioural parameters	Multi-objective optimization	Risk-adjusted return, ESG measures, behavioural fit
Emerging computation	Large portfolios, quantum/AI methods	Compare with classical and heuristic methods	Speed, scalability, solution quality
Search standardization	Keyword variants and emerging terminology	Updated thesaurus and validation	Better coverage and reproducibility

6. CONCLUSION AND LIMITATIONS

6.1 Summary of Findings

This study investigated bibliometric trends in the application of Operations Research techniques to portfolio optimisation, seeking answers to three research questions: (1) How has this area grown in terms of publications? (2) What are the core themes, and how do they relate? And (3) what does the structure of authorship, journals and collaboration say about how this research area has developed?

A dataset of 300 records was collated from Google Scholar, Scopus and ScienceDirect and screened/organised through a four-step bibliometric process, before analysis using Biblioshiny and VOSviewer. Publication growth is better approximated by an exponential curve than linear ($R^2 = 0.698$), with distinct surges in popularity. There are two obvious surges in popularity; the first being in 2019–20, corresponding to market turmoil caused by the COVID-19 pandemic, and a second surge in 2023–25, suggesting increased interest in the areas of cryptocurrency, geopolitical risk, and machine-learning-based portfolio techniques.

The performance analysis highlights this as a truly interdisciplinary field, bridging core OR and finance journals, with most papers being multi-authored (3.03 authors per publication on average; 86% multi-authored). Thematic mapping and network analysis identified four broad clusters: a strong, established core of classical portfolio theory; a cluster focused on risk and robustness under uncertainty; a fast-growing cluster covering computational and AI based optimisation; and a smaller cluster covering alternative and behavioural approaches to portfolio optimisation, including cryptocurrency and prospect-theory-based models. The keyword network confirms that portfolio optimisation remains the core of this field, closely tied to the areas of risk management and robust optimisation, while newer topics such as cryptocurrencies and geopolitical risk are comparatively peripheral. Taken together, these findings suggest that this field has not replaced its classical methods but has developed around them, building newer computational and uncertainty-focused approaches on a still-relevant foundation.

The foundational portfolio theory laid by Harry Markowitz has generated substantial research activity, leading to a set of novel, elaborate, and promising modelling and optimization approaches. The exponential (but uneven) increase in publications over the past decade is testimony to the continued relevance of this topic. The increasing complexity and sophistication of newer approaches requires a thorough evaluation against classical portfolio models using well-defined, publicly available benchmarks to ensure the added value of novel approaches can be properly evaluated.

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6.2 Implications

In terms of implications, this study offers, for the first time, a field-level bibliometric map which binds together methods previously studied in isolation and extends the timeline to include the rise of computational and AI-based techniques. This gives researchers a clearer starting point for situating their own work in the field, as well as identifying areas — such as the alternative and behavioural finance cluster identified in this study — that are underexplored. For practitioners, especially portfolio managers and financial professionals increasingly reliant on computational techniques, this study offers a way to differentiate which techniques are established in the research from those which are still developing, which is useful in determining where to focus efforts or which academic ideas are sufficiently mature to adopt in practice. The finding that classical and computational methods are growing side by side, rather than one replacing the other, is also relevant to how portfolio optimization is taught: understanding the fundamentals of mean-variance theory remains necessary even as newer tools are introduced. We encourage researchers to adopt the Input–Process–Output structure proposed in Section 5.6 when publishing future work, to facilitate comparison and provide a more structured, holistic picture of the state of the art.

6.3 Limitations

A number of limitations are worth noting in this study. First, data were collated only from Google Scholar, Scopus, and ScienceDirect; other databases such as Web of Science were not used, so this study cannot claim to include every relevant paper in the field — not least since this combination was adopted after an initial two-database search failed to yield sufficient data for a meaningful trend and keyword analysis. Second, the RIS/BibTeX export did not carry citation-count metadata consistently, so a citation-based performance analysis (most-cited papers or authors) could not be produced from the current export and would require a supplementary Scopus or Web of Science citation pull. A third limitation relates to keyword variants that had not been harmonised at the time of the interim thematic analysis (e.g., ‘portfolio optimization’ vs. ‘portfolio optimisation’, ‘cryptocurrency’ vs. ‘cryptocurrencies’ appearing as separate entries), which were merged prior to the final thematic map to improve keyword consistency. A fourth limitation is that a small number of records (27 of the 300) lacked a machine-readable publication year and were excluded from the trend-analysis subsample; these were checked and back-filled in Mendeley ahead of the final analysis where possible. Finally, as with any research project of this scope, there were practical limitations to this work: the time available to complete the review, the team’s developing familiarity with bibliometric tools, and limited access to some subscription-based databases and premium citation tools. The findings of this study should be regarded as a considered, but partial, account of the literature the authors were able to access and review, rather than as an exhaustive record of everything written on Operations Research in portfolio optimization.

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