

Heuristic Optimization Under Risk with a Focus on Portfolio Optimization: A Literature Review and Bibliometric Analysis (2014–2027)

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Abstract: The present study is a systematic literature review-cum-bibliometric analysis of research on heuristic approaches to portfolio optimization under risk, aimed at mapping how the field has grown, where it is published and which themes drive it. Data were retrieved from Elsevier's Scopus database using the search string "risk AND optimisation AND heuristic" and screened through the PRISMA framework, giving a final sample of 1,901 journal articles and review papers published between 2014 and 2027. Performance analysis and science mapping were carried out in Biblioshiny. Excluding the incomplete year 2027, annual output grew at 18.13% and followed an exponential trend. China, the United States and India are the leading contributors, while IEEE Access, Expert Systems with Applications and the European Journal of Operational Research are the most relevant sources. Thematic and co-occurrence analyses show that the field is anchored around optimization, heuristic algorithms and risk management, with metaheuristic and machine learning sub-themes emerging. Only 143 documents (7.6%) explicitly address portfolio optimization; within this subset, output grew at 8.52% a year, led by Expert Systems with Applications and the European Journal of Operational Research, and by authors from Iran, China, the United States and India. The study closes with research gaps and directions for future work.

Keywords: Portfolio Optimization; Heuristic Algorithms; Metaheuristics; Risk Management; Bibliometric Analysis; Biblioshiny.

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I. INTRODUCTION

A portfolio is a basket of different asset classes which are linked to each other through risk and return. Optimization of a portfolio is a foundational problem in finance. The problem is mainly concerned with the combination of different asset classes, which are to be optimized either to maximize return at a given risk or to minimize risk at a given return. In making such decisions, Markowitz's mean-variance framework can be used (Markowitz, 1952), and the field has since gone far beyond simple linear and quadratic models. The mean-variance framework now incorporates more computationally intensive algorithms, machine learning techniques and risk-comparison models to address complexity and uncertainty in this dynamic financial world.

This research does not propose a new mathematical model. Rather, this paper takes a step back to study and analyze how this topic has developed over time. Bibliometric

research is a systematic, data-driven mapping of literature that traces the evolution of publication trends and identifies influential journals and their countries. It is a conceptual and structural analysis of the field, not a narrow review of a fixed number of papers.

This analysis is based on a dataset of scholarly publications retrieved from Scopus, spanning the period 2014 to 2027. It covers heuristic optimization under risk, with portfolio optimization as the focal application and particular attention to sub-themes explored by the authors, including risk-based approaches, machine learning applications and metaheuristic algorithms. Data cleaning, analysis and visualization were conducted using Biblioshiny, the graphical interface for the bibliometrix R package (Aria and Cuccurullo, 2017).

This paper reports the findings of the bibliometric review using annual scientific production and growth trends,

and then studies the most influential sources and countries. Through cluster and co-occurrence analysis, it studies the thematic and conceptual structure of the field. The review is organized as follows. The next section presents the literature review, followed by the research objectives and the research methodology. The analysis and findings of the review are then discussed.

II. LITERATURE REVIEW

Portfolio optimization has always been closely connected with the question of how an investor can make the best use of limited capital while keeping risk under control. In practice, however, building a portfolio is rarely as simple as choosing assets with high expected returns and assigning them weights. The number of available assets can be very large, market information can be noisy, and investors often have to work with restrictions such as transaction costs, limits on the number of assets, minimum or maximum allocations and diversification requirements. The recent literature retrieved for this study reflects this growing complexity. Instead of relying only on traditional mathematical formulations, researchers are increasingly using heuristic and metaheuristic methods that can search large and complicated solution spaces and adapt to different investment objectives.

This literature has its roots in the mean-variance framework of Markowitz (1952), who offered the first formal treatment of portfolio selection as a compromise between expected return and risk. Several review articles show how the field progressed from there. Mansini, Ogryczak and Speranza (2014) reviewed twenty years of linear programming-based portfolio models, Ertenlice and Kalayci (2018) surveyed the application of swarm intelligence algorithms to portfolio problems, and Kalayci, Ertenlice and Akbay (2019) reviewed the deterministic models built on the mean-variance framework. Together, these reviews reveal a trend in the evolution of the formulation from exact to heuristic and metaheuristic search that is continued by the recent studies outlined below.

There has been considerable progress toward population-based and multi-objective optimization. Hidalgo-Marín, Nebro and García-Nieto (2026) investigate which methods work best for selecting portfolios: NSGA-II, MOEA/D, SMS-EMOA and SMPSO, and they apply their method to an entire historical data set of over 11,000 assets traded on the U.S. exchanges. In their work they represent portfolio construction as a problem with conflicting goals and growing dimensionality and complexity of constraints. The framework is not designed to take the easy way to the solution by focusing on a single dimension only, but it takes into account the trade-offs of building diversified portfolios. It is especially important for real investment decisions as an investor generally has to consider return and risk in combination, and not in isolation. Additionally, the study demonstrates the applicability of evolutionary and swarm-based methods to large-scale financial data, which helps finding optimal solutions when the search space becomes too extensive to consider using simple optimization methods (Hidalgo Marín et al., 2026).

This emphasis on a big and complex search area naturally brings another key development in the literature to the fore—the not-so-insignificant idea of using more than one heuristic technique rather than relying on a single algorithm. In another example, Carvalho, Peixoto and de Freitas (2026) design a hybrid Simulated Annealing–Tabu Search system for downside-risk portfolio optimization with cardinality constraints. They are particularly interesting because there are continuous and discrete decisions in constructing the portfolio. The investor also needs to make the decision as to how much to invest in an asset as well as which assets to invest in. They explore the possible combinations of portfolio weights with Simulated Annealing and obtain a more precise asset-selection process using Tabu Search combined with add-drop-swap operations. S&P 500 data has been used, covering the span of 2020 to 2024, and compared with the hybrid approach and other algorithmic approaches, such as Differential Evolution, Particle Swarm Optimization, Genetic Algorithms, and benchmarks based on mixed-integer programming with exact solutions (Carvalho et al., 2026). This type of combination makes the heuristic approach more practical as one can solve different components of the portfolio problem with different search mechanisms which are appropriate to that particular structure.

This focus on real-world portfolio building is even more pronounced when machine learning is added to the optimization process. In this regard, Hussein et al. (2026) apply deep learning based forecasting and metaheuristic optimization to enhance the Egyptian stock market, focusing on EGX 100 and EGX 33 Sharia-compliant indices. They employ RNN, LSTM, GRU and CNN models for forecasting stock prices and return rates prior to passing stock price information to Golden Jackal Optimization, Electromagnetic Field Optimization and Nuclear Reaction Optimization. What is really interesting is the number of real-life constraints that are incorporated during the stage of optimization: cardinality, allocation boundaries, rounding-to-lot constraints, transaction costs, budget limits and diversification of industries. Based on the reported results, the ability of forecasting methods to predict the out-of-sample R^2 was measured, and it was found that the RNN forecasts the highest value of R^2 , while the optimization method that was tested and found to be able to minimize the mean percentage error was the Golden Jackal Optimization method (Hussein et al., 2026). In this way, prediction and portfolio construction are not two entirely different jobs but are combined.

This shift towards more adaptive decision making is also evident in reinforcement learning research. Gokilavani et al. (2026) suggest the reward function used in their A3C-LSTM portfolio management is a combination of Sharpe ratio, maximum drawdown and risk-adjusted return. Experiments are performed with S&P 500 data for 2015 to 2023 and in varying markets. This model learns the optimal weights of the portfolio, rather than just looking for a single portfolio. Gao et al. (2026) adopt a similar strategy using their Denoising-Sequence-Correlation Reinforcement Learning approach. They have been able to split the temporal market information from the relationships between assets, and introduce a denoising part for noisy financial information.

Then, to satisfy the budget constraint, a deterministic policy-gradient network generates continuous portfolio weights (Gao et al., 2026). These studies are crucial because financial markets are not static; a sound allocation at one time could be different at another. Reinforcement learning can then be used to think of the optimization of the portfolio as a continuous decision instead of a calculation.

Once portfolio decisions are viewed over time, transaction costs become especially important. Frequent changes in portfolio weights may improve an objective on paper but can also make a strategy expensive to implement. Blomvall, Ekblom and Birge (2026) address this issue through approximate dynamic programming for high-dimensional portfolio choice. Their model considers an investor with constant relative risk aversion, predictable returns, portfolio constraints and proportional heterogeneous transaction costs. The numerical experiments include a risk-free asset and up to ten risky assets over horizons of up to 52 periods. The authors report that their approximate dynamic programming approach performs better than the benchmark heuristics used in the study, while also producing value-function approximations that can be used to calculate dual bounds (Blomvall et al., 2026). This work complements the reinforcement-learning studies because both approaches recognize that portfolio decisions are linked across time and that the cost of changing a portfolio cannot simply be ignored.

In all of these studies, the concept of risk itself is being understood in a more holistic manner. There are models that tend to focus more on variance, but the field of recent literature explored in this report also features models that consider downside risk, maximum drawdown, and risk adjusted performance. Carvalho et al. (2026) explicitly use the downside risk measure, and similarly Gokilavani et al. (2026) use maximum drawdown as part of the reinforcement-learning reward. Simultaneously, Hussein et al. (2026) and Blomvall et al. (2026) demonstrate that the theoretical return-risk relation of a portfolio is not the only factor that can be considered. The quality of a solution can be affected by the cost of trading, the number of assets that can be practically managed, or the limitation of an investor. Heuristic methods come in handy here since they can include multiple of such conditions in a single search process even if the optimization problem becomes hard to solve analytically.

The development of portfolio heuristics is also related to general progress of metaheuristic algorithms. Filtering the literature retrieved for this study, the works related to hybrid optimization methods (RIME-Whale (Arasteh and Rashed, 2026) and multi-swarm particle swarm optimization (MS-PSO) (Sun et al., 2026)) were selected. Not all of these studies are directly related to financial portfolios, but they all tackle problems that are intimately related to the problem of balancing exploration/exploitation and the risk of premature convergence, which are issues relevant to portfolio optimization. Some ongoing challenges in population-based metaheuristic optimization, as identified by the systematic review conducted by Emambocus et al. (2026), include the exploration-exploitation balance, parameter sensitivity, local optima and implementation complexity. These problems are

important in finance because there may be a huge number of combinations in a portfolio search, and an algorithm that decides too early might not find a potentially useful combination. Therefore, researchers are still experimenting with hybrid structures, better initialization and several search operators in an attempt to make heuristic search more reliable.

In recent years, the amount of the literature that addresses the question of how heuristic portfolio optimization can handle nonmathematically expressible preferences has also begun to grow. Saiz, Juan and Panadero (2026) propose generative heuristics, a blend of traditional metaheuristics and semantic evaluation via large language models. Beyond reducing financial risk, their portfolio example also takes into account qualitative factors like sector diversification, geographic exposure, environmental-social-governance quality and overall portfolio coherence. It proposes a method that first proposes solutions that meet quantitative constraints, and then evaluates the qualitative components of these solutions with an LLM-based evaluation (Saiz et al., 2026). This is an interesting extension as investors may have preferences that are real, but not easily discerned or mathematically quantifiable. On the other hand, this line of thinking poses questions regarding consistency, interpretability and validation and how well qualitative judgments can be integrated into an optimization process, which will influence the usefulness of this kind of systems.

All these studies reviewed illustrate a shift in the manner in which portfolio optimization is being considered. Previous notions of mathematically optimal allocations are being broadened to accommodate multiple objectives, fluctuating market conditions, practical limits and imperfect information. The flexibility of the search mechanisms of large multi-objective problems is what makes evolutionary and swarm-based methods suitable. Methods that combine a mix of continuous and discrete decisions, like Simulated Annealing and Tabu Search, are used to handle hybrid decisions. Machine learning introduces an additional forecasting component, reinforcement learning introduces an additional time-evolving component of attention to decisions, and dynamic programming introduces an additional action component of attention to decisions. More recent research even tries to account for qualitative preferences to invest in addition to numerical goals.

Concurrently, the research available does not imply that any single algorithm can offer a solution in all portfolio problems. The method used is highly dependent on the problem structure, the risk type considered, the number of assets, constraints and static or dynamic decisions. One of the recurring problems, however, is not just creating a new algorithm but understanding the performance of the algorithm if it is subjected to realistic conditions. Against this background, some key issues are parameter sensitivity, local optima, computational cost, changing market conditions, and the difficulty of interpretation of increasingly complex models. The studies included in the review also employ different data or market circumstances, so that the conclusions of one study should not necessarily be

extrapolated to another. This suggests that in subsequent research, careful benchmarking, out-of-sample testing and realistic constraints are all particularly crucial.

Overall, the literature presents heuristic portfolio optimization as an increasingly integrated field in which optimization, forecasting and learning are coming together. The research shows that heuristics are valuable not because they eliminate the complexity of portfolio decisions, but because they provide practical ways of working with that

complexity. As financial markets continue to generate larger datasets and more demanding investment requirements, future portfolio optimization is likely to place greater emphasis on adaptive, hybrid and constraint-aware approaches. The main direction emerging from the reviewed studies is therefore toward portfolio systems that are not only mathematically effective, but also flexible enough to reflect the way investment decisions are actually made. A summary of the key studies and earlier review articles in this field is given in Table 1.

Table 1 Summary of Key Studies and Review Articles

Authors	Scope of Study	Type / Year
MANSINI R; OGRYCZAK W; SPERANZA MG (2014)	Review of twenty years of linear-programming-based portfolio optimization models	Review, 2014
ERTENLICE O; KALAYCI CB (2018)	Survey of swarm intelligence algorithms and their applications to portfolio optimization	Review, 2018
KALAYCI CB; ERTENLICE O; AKBAY MA (2019)	Review of deterministic models and applications for mean-variance portfolio optimization	Review, 2019
EMAMBOCUS BAS et al. (2026)	Systematic review of population-based metaheuristics: performance, applications, challenges and future directions	Review, 2026
HIDALGO-MARÍN AJ; NEBRO AJ; GARCÍA-NIETO J (2026)	Multi-objective evolutionary and swarm algorithms (NSGA-II, MOEA/D, SMS-EMOA, SMP SO) for portfolio selection on 11,000+ U.S. assets	Empirical, 2026
CARVALHO SM; PEIXOTO MS; DE FREITAS CM (2026)	Hybrid Simulated Annealing–Tabu Search for downside-risk portfolios with cardinality constraints (S&P 500)	Empirical, 2026
HUSSEIN O et al. (2026)	Deep-learning forecasting combined with metaheuristics under practical constraints (Egyptian stock market)	Empirical, 2026
GOKILAVANI R; ARIVUKKODI R; DEVI M et al. (2026)	A3C-LSTM deep reinforcement learning with Sharpe ratio and drawdown-based reward	Empirical, 2026
GAO N; LIU Y; HE Y; ZHANG J; ZHANG L (2026)	Denoising-sequence-correlation reinforcement learning for continuous portfolio weights	Empirical, 2026
BLOMVAL J; EKBLOM J; BIRGE JR (2026)	Approximate dynamic programming for high-dimensional portfolio choice with transaction costs	Empirical, 2026
SAIZ M; JUAN AA; PANADERO J (2026)	Generative heuristics combining metaheuristics with LLM-based evaluation of qualitative criteria	Empirical, 2026
ARASTE H B; RASHED A (2026)	RIME-Whale hybrid algorithm for global optimization problems	Empirical, 2026

➤ Research Objective

The fundamental aim of this review is to understand how research on heuristic approaches to portfolio optimization under risk has developed, who is driving it and where it is heading. This can be achieved by setting smaller goals as follows:

- To uncover the prevalent publication trends in heuristic portfolio optimization research in terms of time, journals and countries.
- To identify recent methodological developments in heuristic, metaheuristic and learning-based portfolio optimization.
- To map the conceptual structure of the field through thematic mapping and keyword co-occurrence analysis.
- To identify emerging themes, research gaps and potential areas of future research.

III. RESEARCH METHODOLOGY

The Systematic Literature Review (SLR) is a method for aggregating existing information on a subject matter and making sense of it as a whole instead of reading individual studies (Paul and Criado, 2020). The research in this study follows that, employing a bibliometric method to identify the growth of research on portfolio optimization, particularly in regards to risk and optimization methods and heuristic approaches.

➤ Article Selection, Inclusion and Exclusion Criteria

With so much literature in this area it was necessary to have a filter mechanism so that the dataset could be reduced to something manageable. The PRISMA framework was used for this purpose. It provides a straightforward step-by-step approach to narrowing the records that is clearly visible and repeatable by others (Page et al., 2021). The size of the initial data set made PRISMA an ideal fit as it spans four phases: Identification, Screening, Eligibility and Inclusion.

The search was performed on 16 September 2026 in Scopus. The Boolean string used was risk AND optimisation AND heuristic, which was searched in the titles, abstracts and keywords of the Scopus field code (TITLE-ABS-KEY). This resulted in the retrieval of 3409 records, the first of which made up the identification stage.

At this point, screening was started. First, we used a time filter and included only papers published from 2014 to 2027 (the 2027 records being articles in press). The logic behind this was straightforward: optimization and heuristic approaches to risk-based portfolio decisions have progressed rapidly over the past decade, and anything older was likely to be outdated. This reduced the total to 2,901, a 508 record cut.

The next filter was a document-type filter. The articles used were kept as well as the Reviews, and papers from

conferences, book chapters, notes, errata, and retracted work were all excluded due to their lack of peer-review value. This is the largest filter, where 901 records have been filtered out, leaving 2,000 records.

Two more filters were applied at eligibility stage. First, only papers in English were kept as the non-English sources would have made the thematic and keyword analysis later on more difficult. This was down 94 papers to 1,906. Finally, a source-type filter was applied, retaining only the records that were classified as "Academic Journal", and discarding any that had been classified as "Books" or "Non-journal source". Here an additional 5 records were removed, leaving 1901.

Of the 3,409 records identified at the beginning, 1,901 passed through all four steps of PRISMA and are used in this bibliometric analysis (see Figure 1).

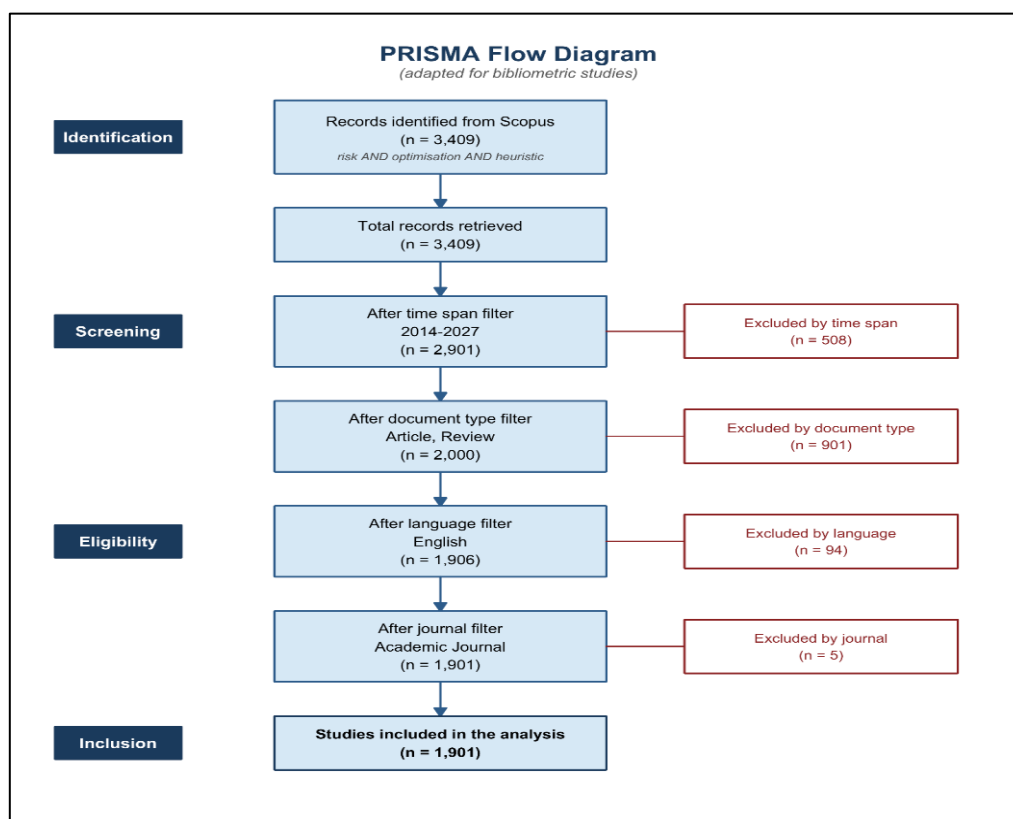


Fig 1 Flow Chart of the Screening Process (Author's Work)

This search was conducted in the Scopus database in preference to other databases such as Web of Science (WoS) or Google Scholar for a number of practical reasons. It has a wider scope of the engineering, business and computer science journals, all of which are relevant, considering how the study of portfolio optimization falls at the crossroads of finance and computational methods. It also enabled the search to be narrowed down to exactly the title, abstract and keyword fields, making it easier to manage the size and content of the initial set of data. Because Scopus data exports very nicely into Mendeley and into Biblioshiny - with little reformatting - the workflow was kept simpler across the tools studied here. The use of a single database is not without its limitations, as there are some papers that may have been referenced in other

papers and not in this one, but this is a necessary and accepted compromise in bibliometric studies of this size and magnitude; and consistency of the metadata is more important than coverage.

➤ Data Cleaning

Prior to analysis, the dataset was checked for data quality issues. Eleven records missing both Author Keywords (DE) and Keywords Plus (ID) fields were removed before the analyses in Biblioshiny, as keyword completeness is essential for the co-occurrence and thematic mapping analyses. The annual production, thematic and co-occurrence results are therefore based on 1,890 records, while the descriptive statistics in the dataset overview refer to the full set of 1,901

records. No duplicate titles or blank author fields were found. Additionally, records published in 2027 were excluded specifically from the annual growth rate calculation, as this year remained incomplete at the time of analysis; including it would have understated the field's actual growth trend by counting only a partial year's output.

➤ *Bibliometric Analysis*

Once a dataset grows into the thousands, reviewing every paper manually is no longer realistic. At that scale, a purely classical literature review breaks down, as there is too much material spread across too many angles of the topic to process by hand.

There, the tool of bibliometric analysis can be used. It enables large amount of published information to be processed systematically and quantified; it brings out the dominant themes present in the literature and their evolution with time (Donthu et al., 2021). Donthu et al. (2021) describe four stages of conducting such an analysis and this is followed here.

• *Step 1:*

Set the objectives and scope. To prevent data analysis from not addressing the original study questions, it is crucial to understand what the study is seeking to know before entering the data or selecting any technique (Donthu et al., 2021). The emphasis was here on the evolution of research on risk based portfolio optimization with the heuristic method, who is developing it and which journals and countries (drivers of the field) and how the key themes have evolved over time. With 1,901 documents, the dataset is well above the "hundreds or more" threshold that Donthu et al. (2021) suggest for the usefulness of bibliometric analysis compared to manual review of the literature.

• *Step 2:*

Choose the techniques. Two main types of science-mapping methods were used: keyword co-occurrence analysis and thematic mapping, combined with performance analysis. Here there were no attempts to use methods such as co-citation or bibliographic coupling, as the purpose was to illustrate an overall picture of the field, rather than to look for influence between specific papers.

• *Step 3:*

Collect the data. This is the PRISMA process described above with the only difference being that only the database Scopus was used and four filters (time span, document type, language and journal source) influenced the final inclusion criteria, resulting in 1,901 papers.

• *Step 4:*

Analyze the data and share the results. In reality though, analysis and write up are not two distinct phases but rather

they intermingle. Donthu et al. (2021) note that when researchers realize that a point requires further support, they return to the drawing board to make one more chart or table. That's the same mode that is used here too: results are explained as they come, in terms of what they mean for the field, not just listed out.

• *The Following Tools Were Used in this Study:*

- ✓ Scopus (Elsevier): the database used to search and filter the literature, taking the dataset from 3,409 records down to the final 1,901 records.
- ✓ RStudio: runs R, which powers bibliometrix, the package this analysis relies on (Aria and Cuccurullo, 2017). It was not used directly, since Biblioshiny sits on top of it.
- ✓ Biblioshiny: the interface of bibliometrix. The cleaned dataset was run through it to generate publication trends, top journals and countries, keyword networks and thematic maps.
- ✓ Mendeley: used purely for reference management and formatting citations. It had no part in the actual bibliometric analysis.

With the dataset finalized at 1,901 papers, the study moves from methodology to analysis. The major thematic clusters emerging from the literature were identified by mapping of the keywords in pairs as a part of the keyword co-occurrence mapping exercise, using Biblioshiny. Thematic mapping takes this one step further, by plotting these clusters according to how central to the field the theme was, and how developed or new the theme was. In addition, publication trends over 2014–2027, the most relevant sources, authors, countries and affiliations, and a separate subset of portfolio-specific documents were analysed to understand not only what the field discusses but also who drives the conversation and how output has changed from year to year.

A. *Data Set Overview*

➤ *Dataset Overview*

This bibliometric analysis is based on a final set of 1,901 documents from 792 different sources and written by 5,206 authors between 2014 and 2027. Of these 5,206 people, just 2 percent published a paper as the sole author, suggesting that research in this area is a multidisciplinary and collaborative process and not an individual one. This is also confirmed by the presence of a co-authorship rate that is international (32.09%) and the average of 3.91 co-authors per paper. There are 6,477 unique author keywords included in the dataset that are used in the keyword co-occurrence and thematic mapping analyses detailed below in this paper. The average number of citations for each document in the dataset is 18.58; the average age of a document is 3.6 years. These indicators are summarised in Table 2.

Table 2 Main Information About the Dataset (*2027 Records Are Articles in Press)

Description	Results
Timespan	2014–2027*
Sources (journals)	792

Documents	1,901
Annual growth rate, 2014–2026	18.13%
Average document age (years)	3.6
Average citations per document	18.58
Author keywords (DE)	6,477
Authors	5,206
Co-authors per document	3.91
International co-authorship	32.09%

➤ Annual Scientific Production

The analysis of annual scientific production showcases an exponential upward trend in research output in this field between 2014 and 2026, as shown in Figure 2. Publication output grew from 49 articles in 2014 to 362 articles in 2026, with the most rapid growth occurring after 2020. However, when the year 2027 is factored into the timespan, it showcases an annual growth rate of –10.26%. This is because 2027 as a year was not completely recorded at the time of data collection, with only a small number of "article in press" records indexed, which naturally decreased the output for that year. When 2027 is excluded and the growth rate is recalculated over the complete 2014–2026 period, the annual growth rate is a strongly positive 18.13%, which more accurately reflects the field's actual trajectory. It should also be noted that 2026 is itself only partly covered, as the data were collected on 16 September 2026; the 18.13% rate is therefore, if anything, a conservative estimate.

The annual production data was modeled with both linear and exponential trendlines in further analysis to determine how this growth should look and what mathematical model it would fit. The exponential model was significantly better than the linear model, explaining 98.09% of the variance of the research output compared to 85.09% for the linear model, suggesting that the production of research is increasing at an increasing rate. The exponential R^2 gives a statement of how much of the variation in the annual output can be explained using the exponential model: about 98% of the variation can be explained by the exponential model; the model shows an exponential growth rate, not a constant growth rate. This result corroborates the overall growth rate and indicates that heuristic optimization under risk, especially in the context of machine learning and metaheuristic techniques, is a field of research that is far from static and close-ended.

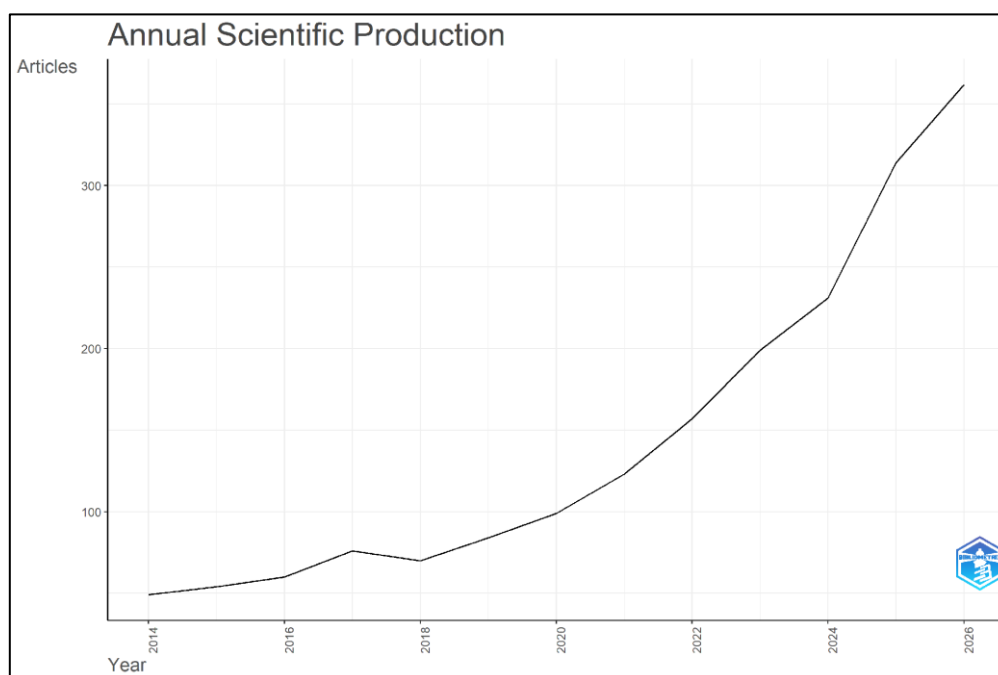


Fig 2 Annual Scientific Production, 2014–2026

➤ Contributing Journals and Countries

The top ten most relevant sources are distributed as follows: IEEE Access (55 documents), Expert Systems with Applications (38) and the European Journal of Operational Research (35) account for the largest contributions. They are followed by Computers and Industrial Engineering (30) and Reliability Engineering and System Safety (25), while the

remaining five sources in the top ten contribute between 18 and 21 documents each, or 100 documents together.

The significance of IEEE Access, a broad, multidisciplinary engineering and computer science journal, signals that a substantial portion of research intersects with computing, engineering and operations research rather than traditional finance alone. Among the top sources, the

European Journal of Operational Research stands out as the most finance- and operations-research-specific venue, and is widely regarded as one of the leading journals for portfolio optimization research specifically. The mix of operations research, computing/AI, reliability engineering and

sustainability journals in the top ten reflects the genuinely interdisciplinary nature of heuristic optimization research under risk, spanning finance, computer science and operations research.

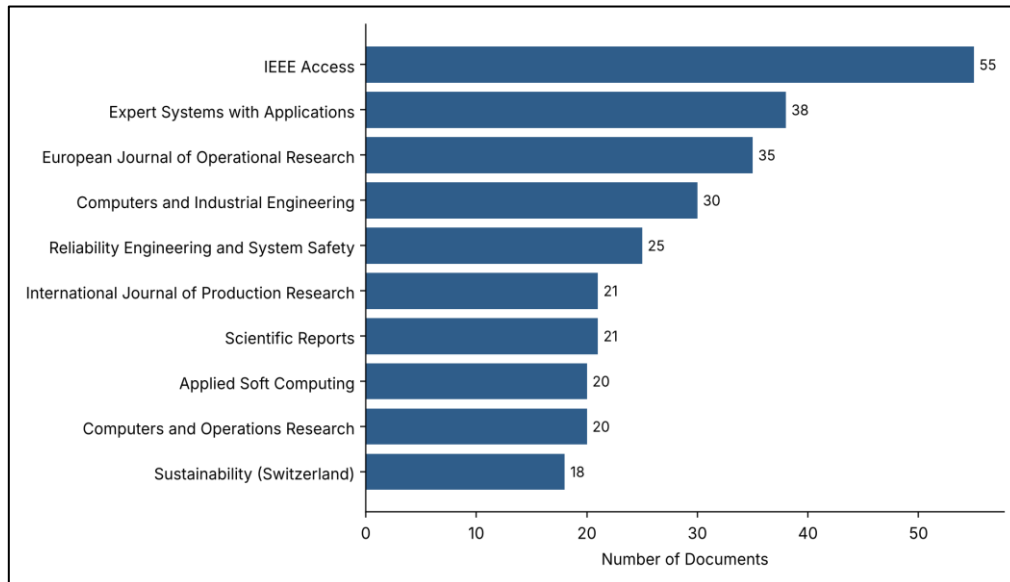


Fig 3 Most Relevant Sources by Number of Documents

Figure 4 illustrates country scientific production, showcasing the geographical spread of production using shades of blue, where darker shades represent higher concentration. China leads by a large extent with 1,532 author-country appearances, followed by the United States (542) and then India (427); China alone contributes 52% of the country production among the top five countries. Table 3 lists the ten most productive countries. It should be noted that this illustration provides the frequency of author-country appearances rather than unique article counts, signaling that this field is collaborative rather than dominated by sole research publishing.

China's dominance, at roughly three times the output of the United States, suggests that Chinese institutions and researchers are the largest single driver of research volume in this field, possibly concentrated in machine learning and metaheuristic sub-themes, which are heavily represented in Chinese computational research. The geographically diverse second tier, spanning North America, South Asia, the Middle East and Europe, is consistent with the international co-authorship rate of 32.09% reported earlier, indicating that this research is not a traditional or region-specific field, but rather a globally distributed one.

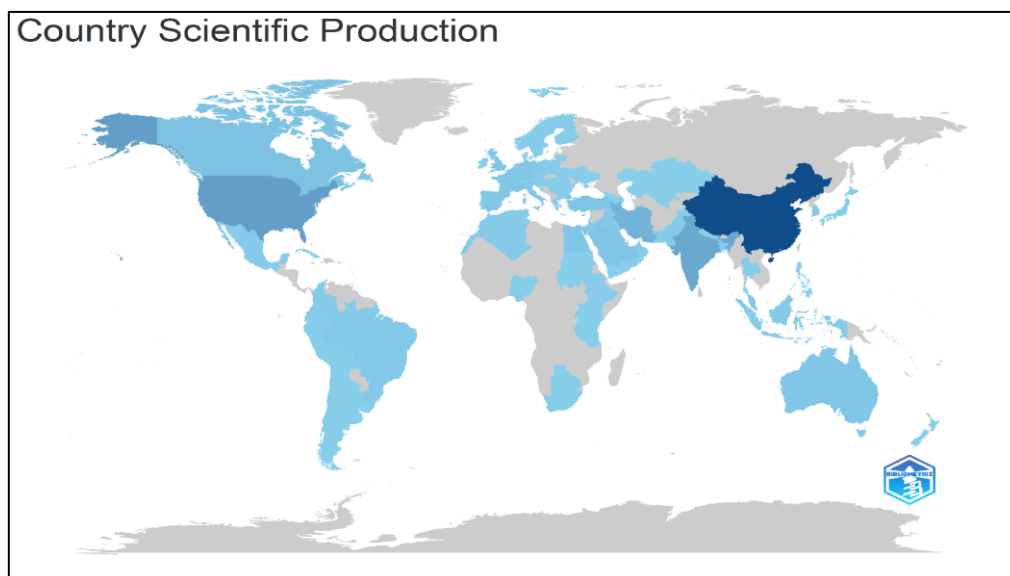


Fig 4 Country Scientific Production

Table 3 Most Contributing Countries (Author-Country Appearances)

Country	Frequency
China	1,532
USA	542
India	427
Iran	303
Canada	136
Turkey	107
United Kingdom	103
Saudi Arabia	101
Italy	92
France	87

At the institutional level, Table 4 presents the top ten productive affiliations, with each document counted once for each institution. Islamic Azad University (48 documents) and the University of Tehran (34) are the leaders, while Beijing

Jiaotong University (26) and Beihang University (22) follow them. The top ten affiliations include seven from China and three from Iran.

Table 4 Most Contributing Affiliations

Affiliation	Documents
Islamic Azad University	48
University of Tehran	34
Beijing Jiaotong University	26
Beihang University	22
The Hong Kong Polytechnic University	20
Tsinghua University	20
Central South University	20
Tongji University	16
Iran University of Science and Technology	16
Jilin University	15

➤ Most Relevant Authors

Table 5 lists the ten most productive authors, counted by the number of documents on which each name appears. Zhang Y leads with 39 documents, followed by Wang J, Wang Y and Li X with 30 each. All ten names are Chinese, which is consistent with China's lead in Table 3. These counts should, however, be read with care. Scopus records authors as a surname with initials, and common Chinese surnames are shared by many different researchers: the 39 documents listed under Zhang Y carry 85 different institutional affiliations, and those under Li X and Wang J carry 75 and 74. The counts

therefore describe name strings rather than single researchers. The fractionalized count, which divides each document equally among its co-authors, gives a more cautious ranking, with Zhang Y (9.05) and Wang J (8.06) still ahead. None of these names is linked to portfolio research in particular, with at most two documents each carrying “portfolio” in the title. Within the 143-document portfolio subset, authorship is spread thinly and no author has more than three documents; the most visible team is Khan, Cao and Li, whose joint work includes the quantum beetle antennae search study (Khan et al., 2021) listed in Table 8.

Table 5 Most Relevant Authors (Documents and Fractionalized Count)

Author	Documents	Fractionalized count
Zhang Y	39	9.05
Wang J	30	8.06
Wang Y	30	7.71
Li X	30	5.84
Liu Y	29	6.56
Zhang J	28	6.42
Wang X	26	5.29
Li Y	25	5.47
Li Z	25	5.40
Li J	24	5.52

➤ Thematic Map

Conceptual clusters were found within the data set and plotted in Figure 5 based on the centrality (relevance) and

density (development) of the data set. The results revealed four clusters as shown in Table 6. The largest and most developed cluster, located in the Motor Themes quadrant, is

around 'optimization', 'heuristic algorithms' and 'heuristic methods', and has a cluster frequency of 7,055, which is the core and well-established theme for the field. On closer analysis of the documents that come with the second cluster ("algorithm", "article" and "human"), it was revealed that these terms are generic methodological terminology that are used in completely different application domains, like civil engineering or healthcare, not a substantive finance theme. The third cluster, "optimisations," "particle swarm optimization (PSO)" and "meta-heuristics algorithms," is in the Emerging or Declining Themes quadrant, which indicates a more specific sub-theme of metaheuristic that is becoming centralised. A fourth, smaller group of themes, including "motion planning," "reinforcement learning" and "resource allocation," is also in the Emerging or Declining Themes quadrant, which reflects the machine learning sub-theme of the field. This clustering's overall Community Detection

Modularity was 0.197. This relatively low score implies that there is a high degree of overlap between the themes rather than distinct groups and would imply a multi-disciplinary field as mathematicians could have used mathematical models from one theme in order to solve problems in another.

In order to test the selected core "optimization" cluster against literature that was important to the cluster, the documents were filtered by the term "portfolio" in the document title. Although the majority of these studies are from other application areas, this central cluster includes the most influential portfolio optimization studies, such as the reviews by Mansini, Ogryczak and Speranza (2014) on linear-programming-based portfolio optimization, Kalayci, Ertenlice and Akbay (2019) on mean-variance portfolio optimization models, and Ertenlice and Kalayci (2018) on swarm intelligence methods for portfolio optimization.

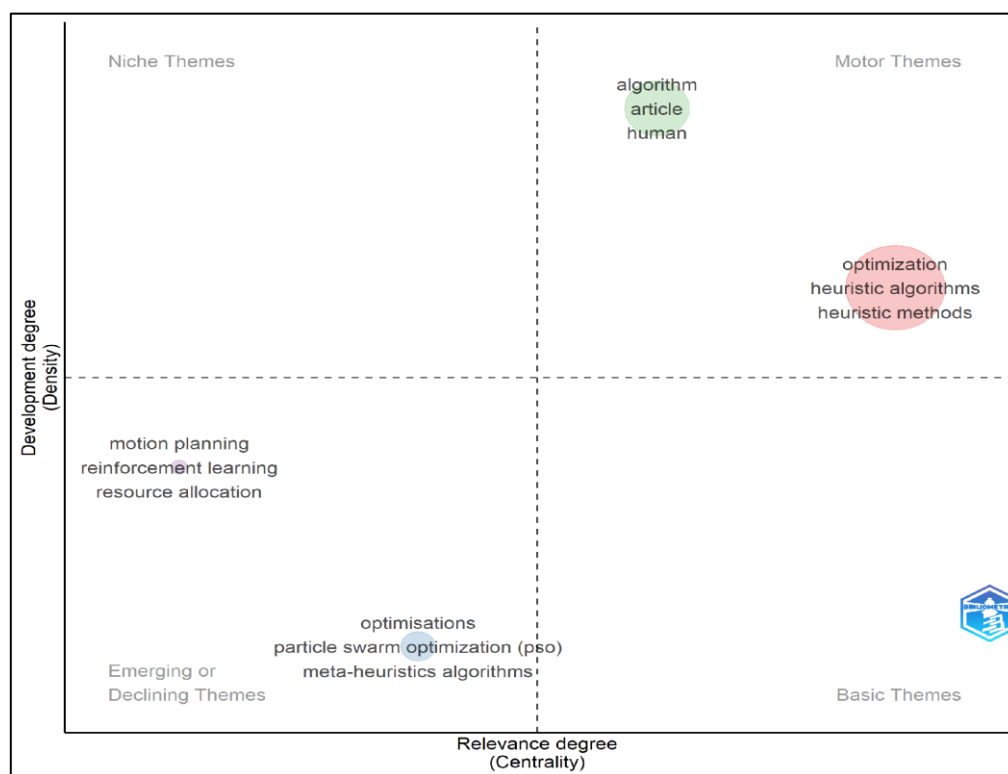


Fig 5 Thematic Map on the Basis of Relevance and Development of Themes

Table 6 Theme Clusters Identified in the Thematic Map

Cluster	Key terms	Quadrant	Interpretation
1	optimization, heuristic algorithms, heuristic methods	Motor theme	Core theme of the field (frequency 7,055)
2	algorithm, article, human	Motor theme	Generic terms from unrelated domains (noise)
3	optimisations, particle swarm optimization (PSO), meta-heuristics algorithms	Emerging or declining	Metaheuristic sub-theme
4	motion planning, reinforcement learning, resource allocation	Emerging or declining	Machine learning sub-theme

➤ Co-Occurrence Analysis

A keyword co-occurrence network was developed to understand the connections between major keywords in greater detail than the thematic map alone. As shown in

Figure 6, the keywords are distributed into three colors: red, blue and green. The red cluster, the largest, is centered on "heuristic algorithms" and "optimization," and notably includes "portfolio optimization" and "investments" as

connected nodes alongside "risk management," "risk analysis," "uncertainty analysis," "decision making," "genetic algorithms" and "particle swarm optimization," confirming that this cluster represents the genuine financial core of the dataset.

The blue cluster is essentially noise, as identified in the thematic map; it comprises keywords such as "algorithm," "human," "article" and "controlled study," which represent clinical-study terminology and have no direct bearing on the core topic of portfolio optimization.

The green cluster, comprising "machine learning," "artificial intelligence," "forecasting," "learning algorithms" and "reinforcement learning," represents the intersection between optimization and the machine learning sub-theme, which is currently small but growing fast.

Filtering documents within this network by the title term "portfolio" surfaced further supporting citations, including Hall, Long, Qi and Sim's (2015) study on managing underperformance risk in project portfolio selection, and Vercher and Bermúdez's (2015) portfolio optimization model using a credibility mean-absolute semi-deviation measure, both of which connect the risk sub-theme directly to portfolio optimization. Zhao, Chen, Zhan, Kwong and Zhang's (2021) study on multi-population co-evolutionary particle swarm optimization for multi-objective cardinality-constrained portfolios further supports the metaheuristic sub-theme. Together, these results help justify that, even though there is some cross-disciplinary noise in the dataset, the portfolio optimization literature sits within the core cluster of managing risk and uncertainty by deploying heuristic and metaheuristic models.

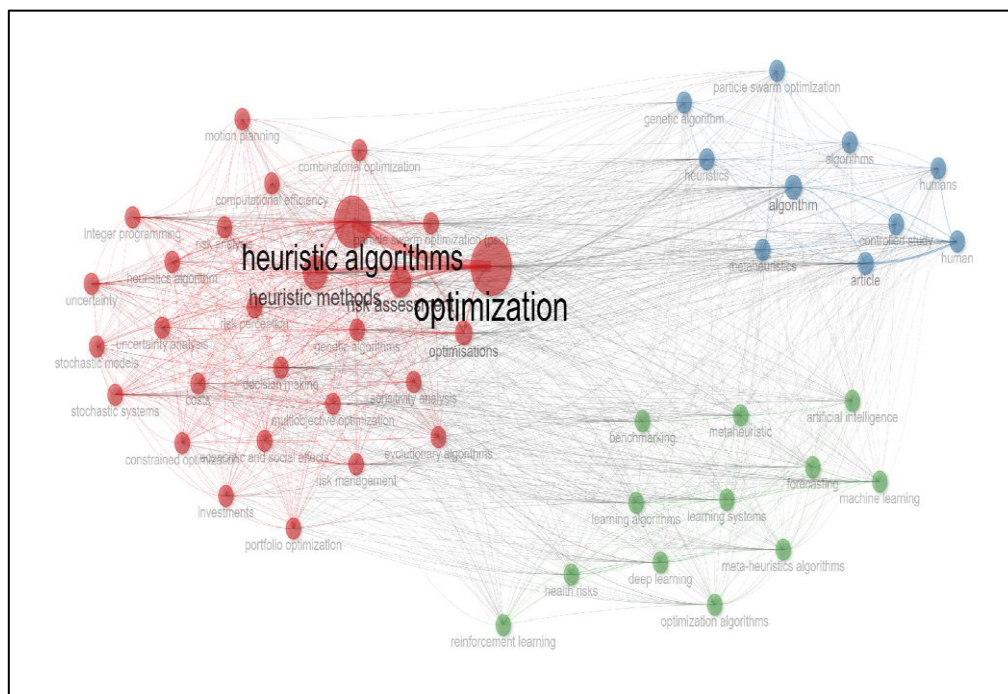


Fig 6 Co-Occurrence Network

Table 7 lists the most frequent author keywords. "Optimization" (109 occurrences), "machine learning" (66) and "multi-objective optimization" (61) lead, followed by named metaheuristics such as "genetic algorithm" (51) and

"particle swarm optimization" (49). "Portfolio optimization" appears 43 times, alongside application terms such as "path planning" and "feature selection", which again shows that the dataset spans several application domains.

Table 7 Most Frequent Author Keywords

Author keyword	Occurrences
optimization	109
machine learning	66
multi-objective optimization	61
genetic algorithm	51
particle swarm optimization	49
metaheuristics	46
portfolio optimization	43
path planning	43
robust optimization	39
heuristics	39

➤ Portfolio Optimization Subset

Because the search string did not include the term "portfolio," the full dataset spans many application domains. The most-cited documents overall come from energy pricing, tunnelling, supply-chain design and vehicle routing; for example, Wei et al.'s (2015) study of smart-grid retail pricing has 371 citations. To examine portfolio research directly, the 1,890 records were filtered for the term "portfolio" in the title, abstract or keywords. This left 143 documents (7.6% of the dataset), a small number of which concern project or other non-financial portfolios.

Output in this subset grew from 6 documents in 2014 to 16 in 2026, peaking at 20 in 2025, an annual growth rate of 8.52%, which is less than half the rate of the full dataset (Figure 7). The leading sources are Expert Systems with Applications (7 documents) and the European Journal of Operational Research (6), followed by Applied Soft Computing and Quantitative Finance, so portfolio work is concentrated in operations research and finance journals

rather than in broad engineering outlets such as IEEE Access. Counting documents with at least one author from each country, Iran (26) and China (25) lead, followed by the United States (16) and India (15). Apart from "portfolio optimization" (43) and "portfolio selection" (17), the most frequent author keywords in this subset are "genetic algorithm", "particle swarm optimization", "Sharpe ratio", "risk parity" and "conditional value-at-risk", showing that portfolio studies combine metaheuristic search with established risk measures.

Table 8 lists the most-cited portfolio documents. The three most-cited are the review articles by Mansini, Ogryczak and Speranza (2014), Kalayci, Ertenlice and Akbay (2019) and Ertenlice and Kalayci (2018), which confirms their role as the foundation of the field. The remaining studies apply quantum beetle antennae search, swarm optimization, deep reinforcement learning hyper-heuristics and heuristic index tracking, which matches the methodological trends identified in the literature review.

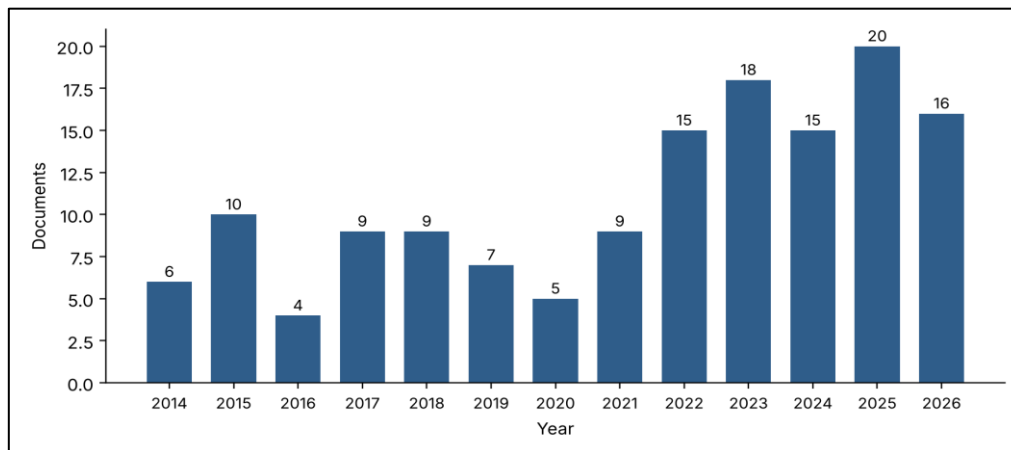


Fig 7 Annual Production of Portfolio Optimization Documents, 2014–2026

Table 8 Most-Cited Documents in the Portfolio Optimization Subset

Document	Source	Citations
Mansini R et al. (2014), Twenty years of linear programming based portfolio optimization	European Journal of Operational Research	177
Kalayci CB et al. (2019), A comprehensive review of deterministic models and applications for mean-variance portfolio optimization	Expert Systems with Applications	162
Ertenlice O and Kalayci CB (2018), A survey of swarm intelligence for portfolio optimization	Swarm and Evolutionary Computation	152
Khan AT et al. (2021), Quantum beetle antennae search for the constrained portfolio optimization problem	Science China Information Sciences	95
Vercher E and Bermúdez JD (2015), Portfolio optimization using a credibility mean-absolute semi-deviation model	Expert Systems with Applications	89
Hall NG et al. (2015), Managing underperformance risk in project portfolio selection	Operations Research	88
Soler-Dominguez A et al. (2017), A survey on financial applications of metaheuristics	ACM Computing Surveys	76
Zhao H et al. (2021), Multiple populations co-evolutionary PSO for cardinality constrained portfolio optimization	Neurocomputing	71
Cui T et al. (2024), Multi-period portfolio optimization using a deep reinforcement learning hyper-heuristic approach	Technological Forecasting and Social Change	70
Filippi C et al. (2016), A heuristic framework for the bi-objective enhanced index tracking problem	Omega	67

IV. DISCUSSIONS AND IMPLICATIONS

➤ Findings

- Publication output rose from 49 articles in 2014 to 362 in 2026, an annual growth rate of 18.13%, and an exponential trendline fits this growth far better than a linear one. The field is expanding rapidly rather than maturing.
- Research in the field is highly collaborative and international, with an average of 3.91 co-authors per paper and 32.09% international co-authorship. China is the largest contributor, followed by the United States and India.
- The field is published mainly in computing, engineering and operations research journals rather than traditional finance outlets. IEEE Access is the most relevant source, while the European Journal of Operational Research is the leading operations research venue.
- The core conceptual structure is built around optimization, heuristic algorithms and risk management. Metaheuristic (particle swarm optimization) and machine learning (reinforcement learning) themes sit in the emerging quadrant, which matches the hybrid and learning-based methods discussed in the literature review.
- Only 143 documents (7.6%) explicitly address portfolio optimization. This subset grows more slowly (8.52% a year), is published mainly in operations research and finance journals, is led by Iran and China, and rests on three highly cited review articles.
- A broad search string brings in cross-disciplinary noise, such as clinical-study and engineering terms. Future reviews of this field would benefit from portfolio-specific search terms.

➤ Research Gaps and Future Research Agenda

- Most of the studies reviewed test their methods on a single market or index, such as the S&P 500 or the Egyptian Exchange. Comparative studies across developed and emerging markets remain limited among the studies reviewed.
- Machine learning and metaheuristic themes are still in the emerging quadrant of the thematic map, so their integration with risk-based portfolio models is not yet mature.
- The literature reviewed calls for more benchmarking of new heuristics against one another on common datasets, with realistic constraints and out-of-sample testing.
- Qualitative investor preferences, such as ESG quality, are only beginning to be included through approaches like generative heuristics, and their reliability is untested.
- Future bibliometric work could combine Scopus with Web of Science and use portfolio-specific search terms with co-citation analysis to trace the intellectual roots of the field.

➤ Implications

This systematic literature review, combined with bibliometric analysis, gives an objective picture of how

heuristic approaches to portfolio optimization under risk have developed. For practitioners, the literature shows that heuristic and metaheuristic methods are useful mainly because they can handle realistic constraints, such as cardinality limits, transaction costs and lot sizes, that make exact optimization difficult. For researchers, the emerging position of machine learning and metaheuristic themes points to clear opportunities, but the literature also warns that parameter sensitivity, local optima, interpretability and out-of-sample performance remain open problems. Careful benchmarking across markets is therefore needed before results from one setting are applied to another. Finally, India is the third-largest contributor to the field, which offers scope for stronger collaboration between Indian institutions and the leading research groups in China and the United States.

V. CONCLUSION AND LIMITATIONS

This review of 1,901 documents, published from 2014 to 2027 in the field of heuristic optimization under risk, with a focused look at portfolio optimization, shows an exponentially growing field of research, expanding at a rate of 18.13%. This field of study is highly collaborative and researched throughout the world, with very few papers published by individual researchers. Research in this field is currently led largely by China. This field also draws on an interdisciplinary mix of computer engineering and operations research journals, rather than being confined to traditional finance outlets. Thematic and co-occurrence analysis confirms that, even after accounting for some cross-disciplinary noise present in the dataset, the core conceptual structure of optimization, risk and heuristic methods is dominant and rapidly growing, alongside a smaller but growing sub-theme of machine learning. Within this, portfolio optimization forms a smaller but steadily growing subset of 143 documents, anchored by a few highly cited reviews. These findings help us understand how research on portfolio optimization and its wider methodological field has developed in a systematic manner.

In terms of the four objectives set out in Section 3, the study finds the following. (1) Publication trends: output grew at 18.13% a year between 2014 and 2026, is spread across 792 sources led by IEEE Access, Expert Systems with Applications and the European Journal of Operational Research, and comes mainly from China, the United States and India. (2) Methodological developments: recent work has moved from exact formulations towards multi-objective evolutionary algorithms, hybrid metaheuristics such as Simulated Annealing-Tabu Search, deep-learning forecasting combined with metaheuristics, reinforcement learning and, most recently, generative heuristics that use large language models. (3) Conceptual structure: the thematic map and co-occurrence network place optimization, heuristic algorithms and risk management at the core of the field, with portfolio optimization and investments connected to this core cluster. (4) Emerging themes and gaps: metaheuristic (particle swarm optimization) and machine learning (reinforcement learning) themes are emerging, while comparisons across markets, common benchmarks and the

treatment of qualitative investor preferences remain open research gaps.

The study has some limitations. Only one database, Elsevier's Scopus, was used, which limits the number of documents on which the analysis could be done. The search string did not include the term "portfolio," so the dataset covers heuristic optimization under risk more broadly; only 143 of the 1,890 analyzed records (7.6%) explicitly address portfolio optimization, and the portfolio subset was identified by a simple term filter rather than full-text screening. The analysis also relied on keyword-based methods rather than co-citation or bibliographic coupling. Finally, the data were collected on 16 September 2026, so 2026 is only partly covered and 2027 contains only articles in press; 2027 was therefore excluded from the growth rate calculation, and the reported growth rate is likely to be conservative. Author names were also not disambiguated, so author-level counts may combine different researchers who share a surname and initials.

➤ *Declarations*

➤ *Conflict of Interest:*

The authors declare no conflict of interest.

➤ *Funding:*

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➤ *Use of Generative AI:*

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