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Applications of OR in Portfolio Optimization and Risk Management

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ABSTRACT

This paper presents a bibliometric analysis of the applications of Operations Research (OR) in portfolio optimization and risk management. The data were retrieved from Elsevier's Scopus database and comprise 1,304 documents published between 2016 and 2026 in 619 sources, together with a corpus of 48 review papers. Science mapping was carried out with Bibliometrix and its Biblioshiny interface to examine the growth, authorship and sources of the field and to build a thematic map of its keywords. The number of publications rose from 51 in 2016 to 244 in 2026, an average annual growth rate of 16.95%. Machine learning and risk analysis emerge as the motor themes, risk management and project portfolios form the basic themes, reinforcement learning is a niche theme, and classical optimization and uncertainty modelling are emerging or declining. The review identifies gaps in validation, integration across methods, and consistent terminology, and uses them to propose a research agenda.

Keywords: *Operations Research; Portfolio Optimization; Risk Management; Bibliometric Analysis; Machine Learning.*

1. INTRODUCTION

One of the earliest applications of Operations Research (OR) in finance is portfolio optimisation. Markowitz (1952) posed the problem of asset selection as an issue of choosing among returns and risks, and the mean-variance model generated by the framework is said to be the optimisation model of balancing maximum return against minimum risk (Kim et al., 2024). It is obvious why there was an attraction of the OR framework. An investor has limited resources, assets with uncertain payoffs and restrictions, and needs to find the optimal combination subject to such conditions. This is clearly an instance of mathematical programming, and the field has adopted the problem since then. Kolm et al. (2014), some 60 years after Markowitz's work, reviewed the consequences of meeting the theory with reality and identified three major challenges: transaction costs, portfolio optimisation restrictions, and sensitivity to the input data on returns and covariances. Minor mistakes in inputs generate entirely different portfolios, which is another reason why the classical model has been modified. Actual portfolio allocation problems have their own practical constraints that make exact solutions difficult. Doering et al. (2019) discuss meta-heuristics applied in what the authors call rich portfolio optimisation and risk management, arguing that the use of such algorithms is more and more preferred in case of combinatorial and constrained problem. Other reviews go in the same direction starting from different angles. Senescall and Low (2024) talk about the maturing science of quantitative portfolio management, while Kim et al. (2024) review existing models of optimisation used by

portfolio managers. This leads to the emergence of an area that has a rich OR background, many ways to obtain a solution and no universal way of problem formulation agreed upon by all studies.

The second side of the problem is risk. No portfolio model can be valuable without appropriate measure of risk, which in the modern literature goes far beyond variance. Al Janabi (2021) reviews algorithms for portfolio optimisation under illiquidity constraints and liquidity risk management using the framework of liquidity adjusted value-at-risk. The paper by Cheng et al. (2023) reviews probabilistic methods of portfolio management in future stock markets and Chakrabarty and Nag (2023) analyzes risk measures and portfolio analysis in the context of climate finance. Gökgöz and Atmaca (2017) use the method of lower partial moments in analyzing the risk of portfolios in emerging electricity markets while Bao et al. (2021) conduct a review of risk assessment and risk management in electricity markets. Finally, Biller et al. (2019) prove that the simulation and risk analysis techniques are also applied in industrial OR and illustrate this with the example of production systems design in General Electric. All these studies feature risk estimation that goes directly to the resource allocation process.

There are cases when not everything about the source of uncertainty can be quantified using probabilities. For such cases, OR has another line of research. The review by Gulia et al. (2023) deals with fuzzy-based multi-objective linear programming, and the review of Kaviani and Fakhrehosseini (2020) considers applications of fuzzy logic in portfolio management. These methodologies coexist with a huge amount of data-driven research, and it is not clear how the two will relate. Three reasons may account for this increased interest. First, the classical paradigm has been applied in multiple extensions – with restrictions on position sizes, transaction costs, and other types of risk measurement (Kolm et al., 2014). Second, advances in the application of machine learning and metaheuristics, as well as more affordable computation, make the academics revisit the topic using different methods. Third, volatility in markets has become high enough recently to attract attention to better methods of asset allocation. Although none of these explanations is explored empirically in the paper, all three fit the growth in publications described by the data.

The toolset used for the purposes of the topic has undergone rapid evolution in the recent years. Lee et al. (2024) found that machine learning is beneficial at two stages – return and risk estimation and optimisation itself. Other reviews see artificial intelligence as an extension of modern portfolio theory (Sutiene et al., 2024; Zhao et al., 2025) and address the question of regulation of the AI once it is applied in investments (Mertzanis, 2025). Surveys of deep learning are published within finance (Mienye et al., 2024), and reinforcement learning becomes another topic. AL-Aldaffaie et al. (2026) review the applications of large language models along with reinforcement learning in financial markets. The trend of quantum computing has emerged in this regard, with Kumar et al. (2026) analyzing its trends and applications in finance.

Another reason to consider the whole landscape is that sophistication and usability are not necessarily associated with each other. More sophisticated models bring up issues which are not considered by the classical model. Mertzanis (2025) mentions that the investment management process is transformed through AI but issues related to its architecture, strategy, and governance are yet to be sorted out. Also, Khemlichi et al. (2026) discuss the human factor in human-AI interaction and consider it integral to risk aware portfolio models. The sensitivity of outcomes to estimated parameters had already been discussed by Kolm et al. (2014). Whether the newer techniques offer better results when cost, constraints, and crises are taken into consideration is a matter of concern. Portfolio concept has also been extensively adopted outside finance. Hamdi et al. (2018) discuss supply portfolios within the context of supply chain risk while Vacík et al. (2018) employ efficient frontier rationale for the selection of projects in small and medium-sized enterprises in order to balance between strategy, risk and performance. Micán Rincón et al. (2023) apply a similar reasoning for the project portfolio risk management approach, while forest management (Knoke et al., 2017) and resilience to natural hazards (Gupta & González, 2026) represent other examples. In finance, Oliveira Filho and Poker Junior (2025) identify numerous specialized asset allocation models.

The reason for this review is rooted in the above-mentioned specialization of literature. The current literature on computational techniques applied to portfolio analysis is abundant and increasing, but fragmented according to techniques and areas of application. Almost all existing reviews are either narrative or systematic, and each is dedicated to one particular computational approach – machine learning, reinforcement learning, fuzzy logic or quantum approaches, among others. Their influence is already evident. The metaheuristics review by Doering et al. (2019) and the supply portfolio review by Hamdi et al. (2018) have each been cited 79 times in the corpus of reviews collected for this research, followed by the deep learning review by Mienye et al. (2024). The recent years also see an increase in production: 13 out of 48 reviews collected for this study were published in 2026, which is the largest number of publications in any one year. The limited number of bibliometric analyses is similarly limited in their scope. Micán Rincón et al. (2023) look at project portfolio risk management, Oliveira Filho and Poker Junior (2025) investigate asset allocation, and Kumar et al. (2026) consider quantum computing in finance. To the best of our knowledge, there was no previous attempt at mapping OR applications in portfolio optimisation and risk management, thus there was no overview of the areas where OR still plays a central role, those where it was superseded by AI, and the topics that have little to do with the others.

Bibliometric analysis is a good approach to achieve this goal. It allows to quantify the trends in the production patterns and growth, the contributions of authors and sources, and the interrelationships between keywords (and even categorise them) (Donthu et al., 2021; Zupic & Čater, 2015). It is the extent of this domain that necessitates its use. The collection of data used in this study contains 1,304 papers that have been published in the years from 2016 to 2026 in 619 distinct sources. The number of annual publications increased from 51 in 2016 to 244 in 2026, which equals an average increase of 16.95% per annum (2026 being a partial year). Bibliometrix tool and the bibliometrix's Biblioshiny interface (Aria & Cuccurullo, 2017, 2026) will be used in the analysis. Keywords will be clustered and arranged in a thematic map according to the approach of the strategic diagram (Callon et al., 1991). According to previous studies of science mapping, such maps are also able to follow up on the development process of a field (Cobo et al., 2011).

Therefore, this study has the following objectives:

The first one is to characterize the evolution of the research on OR in portfolio optimization and risk management, its producers and where it gets published. The second one is to characterize its thematic structure by distinguishing between motor, basic, niche and emerging/declining themes and to put this map in contrast with the thematic structure identified in a structured reading of 48 review papers. The third one is to point out gaps that future research should focus on. Thus, the current study provides an overview of the whole field that single technique centered reviews cannot provide, and it uses the gaps it identifies to formulate a research agenda which can be used by researchers in the fields of finance, operations research and computer science. The articles have been searched in Scopus database, and the review corpus has also been taken from the same database. The paper starts with the Introduction section, followed by literature review, then research methodology, then data analysis, followed by future research agenda and finally concludes.

2. LITERATURE REVIEW

2.1 Overview of the Review Corpus

Operations Research (OR) has provided the foundations for portfolio theory since the mean–variance model, an optimization model that balances maximum returns against minimum risk (Kim et al., 2024). This review is based on 48 review papers retrieved from Scopus in the period 2016 – 2026. The quantity of recent output has increased rapidly: there were 13 reviews published in 2026, the highest in any year, and 2024 - 2026 dominates the corpus. The scope of the domain is broad, too. Reviews include supply portfolios (Hamdi et al., 2018), electricity markets (Bao et al., 2021), forest management (Knoke et al., 2017) and natural-hazard resilience (Gupta & González, 2026), all of which demonstrate the expansion of portfolio and risk thinking beyond finance.

To provide structure to this literature, a thematic map was generated in bibliometrix (Aria & Cuccurullo, 2017). This follows the strategic diagram (Callon et al., 1991), in which centrality reflects the relevance of each theme to the field and density indicates its level of development. Further science-mapping approaches are outlined in an earlier framework (Cobo et al., 2011) and in the SciMAT software paper (Cobo et al., 2012). Bubble sizes reflect the fuzzy cardinalities of each cluster (Aria et al., 2026) and the framework is detailed in a dedicated primer (Aria & Cuccurullo, 2026). Themes accordingly fall into motor, basic, niche and emerging or declining quadrants.

The impact of reviews cited in the corpus also supports the significance of OR-based literature. The most cited topic-relevant reviews in the corpus include a metaheuristics review (Doering et al., 2019) and a supply portfolio review (Hamdi et al., 2018), each with 79 citations, followed by a review of deep learning in finance (Mienye et al., 2024). This underscores the disproportionate influence of optimization-oriented reviews, even as new AI-focused reviews are gaining increasing attention.

2.2 Motor Themes: Machine Learning and Risk Analysis

The largest motor theme relates machine learning, artificial intelligence and optimization, suggesting that data-driven methods are now the predominant force in the field. Machine learning improves both stages of portfolio optimization, namely the parameter estimation of returns and risk, and the optimization step itself (Lee et al., 2024). AI is also identified as a mechanism to extend modern portfolio theory (Sutiene et al., 2024; Zhao et al., 2025), while its governance implications for investment management have been examined (Mertzanis, 2025). In addition, classical OR approaches are reflected in the use of metaheuristics. These algorithms are increasingly the preferred option for realistic, combinatorial portfolio problems with practical constraints (Doering et al., 2019).

The second motor theme combines risk analysis, portfolio management and portfolio analysis. This cluster exceeds the centrality threshold slightly but is very dense, reflecting its advanced development. This group covers quantitative risk modelling, including a liquidity-adjusted value-at-risk framework (Al Janabi, 2021), Monte Carlo approaches (Cheng et al., 2023), and climate-risk measures (Chakrabarty & Nag, 2023). Quantitative portfolio management is also defined as a maturing discipline (Senescall & Low, 2024), and simulation and risk analysis have been demonstrated in an industrial OR example (Biller et al., 2019). Collectively, these suggest that risk measurement has become inextricably linked with optimization as risk estimates now directly feed into allocation decisions rather than representing an ex-post evaluation.

2.3 Basic Themes: Risk Management and Project Portfolios

The basic quadrant includes risk management, project portfolio and portfolio optimisation. These themes are central but less dense, signifying that they are generic concepts linking various subfields without forming a coherent body of work. Supply portfolio optimization under supply chain risk has been reviewed (Hamdi et al., 2018), while efficient-frontier logic has been applied to balance strategy, risk and performance when selecting projects (Vacík et al., 2018). Project portfolio risk management has been traced as a formal domain (Micán Rincón et al., 2023), and lower partial moments have been applied to electricity markets (Gökgöz & Atmaca, 2017).

2.4 Niche Themes: Reinforcement Learning

Reinforcement learning, along with systematic review, is a niche theme in terms of both high density and low centrality. It is internally well developed, but only weakly connected to the wider field. An attention-enhanced deep reinforcement learning framework for dynamic portfolio optimization has been proposed, which employs a Dirichlet policy to guarantee feasible allocations (Xue & Ye, 2026). Human–AI collaboration in risk- and uncertainty-aware portfolio reinforcement learning has been explored (Khemlichi et al., 2026), and large language model-enhanced reinforcement learning in financial markets has been reviewed (AL-Aldaffaie et al., 2026). The theme is technically complex but has not yet been integrated into mainstream portfolio and risk research.

2.5 Emerging or Declining Themes: Classical Optimization and Uncertainty

The lower-left quadrant contains portfolio optimization, project portfolio management and asset management, along with uncertainty. Its location is ambiguous, since such themes may be either emerging or fading. The evolution and diversity of asset allocation models have been traced, indicating that traditional formulations are fragmenting into specialised variants (Oliveira Filho

& Poker Junior, 2025). OR approaches based on uncertainty, such as fuzzy multi-objective linear programming (Gulia et al., 2023) or fuzzy portfolio models (Kaviani & Fakhrehosseini, 2020), seem to be declining in prominence compared to machine learning. By contrast, quantum computing is an emerging direction (Kumar et al., 2026).

2.6 Research Gap

Despite this volume of reviews, bibliometric evidence is sparse. Only one bibliometric paper on this domain appeared in 2023, and it is confined to project portfolio risk management (Micán Rincón et al., 2023). Other bibliometric work, such as that on asset allocation (Oliveira Filho & Poker Junior, 2025) and on quantum computing in finance (Kumar et al., 2026), covers only narrow sub-areas rather than OR applications as a whole. The extant reviews are narrative or systematic, and tend to split by technique, such as machine learning, reinforcement learning, fuzzy logic or quantum methods, or by application domain. No study has mapped the intellectual structure of OR applications in portfolio optimization and risk management as a whole. The present study fills this void by conducting a bibliometric analysis of the field. Through quantifying how machine learning, metaheuristics, uncertainty modelling and project-level risk management relate to one another, such a study can show where OR remains central, where it is being overtaken by AI, and where under-connected themes deserve future research attention.

3. RESEARCH METHODOLOGY

Many researchers have employed systematic literature review (SLR) techniques to identify and analyze trends within a particular research area. SLR helps researchers understand existing knowledge, synthesize findings from previous studies, and identify research gaps that can guide future research (Paul & Criado, 2020). The research study utilizes one such technique with a goal to identify and analyze the research trends in the applications of OR in Portfolio Optimization.

3.1 Article selection, inclusion, and exclusion criteria

The study applied the Preferred Reporting Items for Systematic and Meta Analysis (PRISMA) technique suggested by (Moher et al., 2010) that provides a systematic framework for searching and filtering literature, thereby minimizing subjective bias from the researcher. The iterative process of selecting the articles for review went through five stages.

As a part of the first stage, a keyword search was conducted on 11th September, 2026 on Scopus database using the research keyword (Portfolio Optimization AND Risk management). The total results were 3068. Next, the research excluded the search results before 2016, though there were publications from 1984. Moreover, the gap years were 1985 and 1986. This year filtering criteria brought the search results down to 2098. Further the study excluded conference papers and other document types except for articles and reviews, thereby bringing down the results to 1351. After that, a language filter was applied and only papers in English were included. This brought down the search results to 1306. Lastly, the source type was selected as journal and the final studies in the analysis were recorded as 1304. Figure 1 shows the search, inclusion, and exclusion criteria in the form of a flow chart.

The final data was then exported from the Scopus database in Research Information Systems (.ris) format and uploaded to Mendeley Desktop for citation and further analysis. Following the verification and updating of author details in Mendeley, the records were exported in BibTeX (.bib) format and imported into Rstudio. Subsequently, data analysis was conducted using R (R Core Team, 2026) within the RStudio integrated development environment. For further analysis, the authors used the bibliometrix package (Aria & Cuccurullo, 2017) via its interactive web interface, biblioshiny (Aria & Cuccurullo, 2026).

3.2 Bibliometric Analysis

The PRISMA flowchart (Page et al., 2021) as shown in Figure 1 was then made using biblioshiny. Moreover, several diagrams such as concurrence networks, heatmaps, etc were made. And for making them, VOSviewer (van Eck & Waltman, 2010), Tableau, Biblioshiny (Aria & Cuccurullo, 2026) were used.

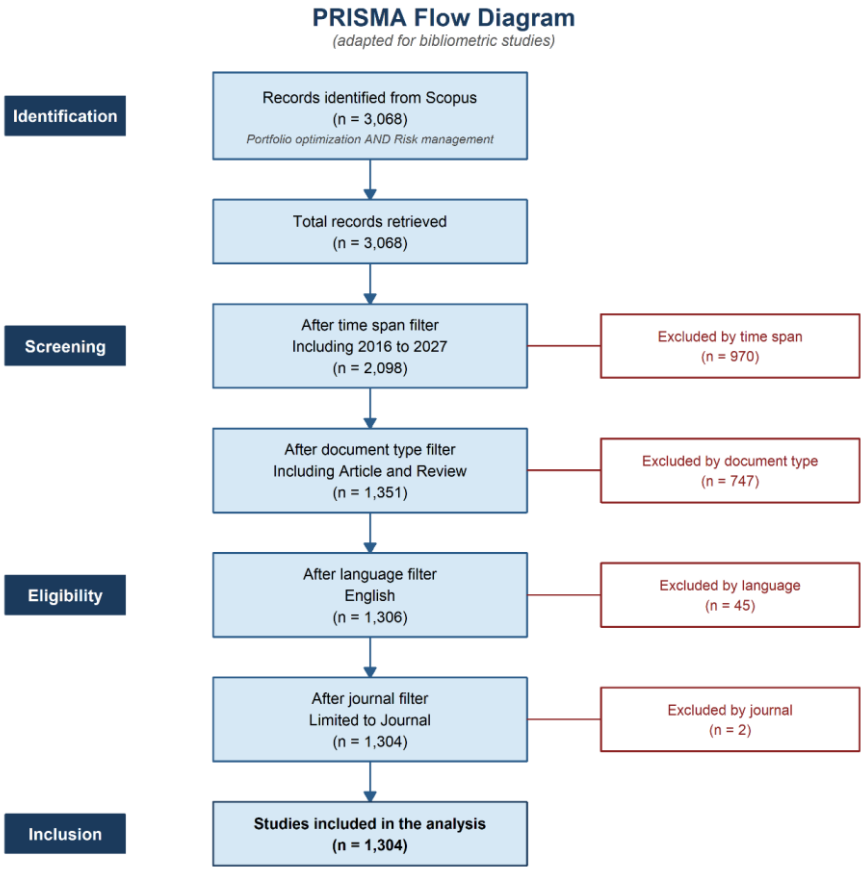

Figure -1: Flowchart of the screening process using Biblioshiny (Aria & Cuccurullo, 2017)

Furthermore, the authors also performed deep analysis of the diagrams in order to understand the emerging fields in the field of finance, such as online portfolio selection, which involves dynamically updating asset weights by combining machine learning return predictions with incoming market data to maintain an optimal risk-return profile (Mehala & Sundar, 2025). Moreover, some more interesting areas like mean-variance theory, which involves building a portfolio with the highest possible return at a given level of risk (Saravanakumar et al., 2026); robust optimization, which involves solving real-world math problems when some of the input data is unknown (Feng & Yang, 2026) and many more were frequently found in the extracted research papers.

4. DATA ANALYSIS

4.1 Annual Growth Rate

The data reveals that the rate of growth of number of publications on Portfolio Optimisation is 16.95% per year. This indicates that the subject is gaining more research interest from 2016 to 2026. This is a fairly large growth rate for any mature stable field of research and is evidence that portfolio optimisation is an active and growing research area.

There are a number of reasons why this might be. First, the classical mean–variance framework has been developed in many directions such as magnitude constraints, transaction costs, and alternative risk measures. Secondly, it is expected that as new techniques in machine learning, metaheuristic algorithms and computing power have come to light that have inspired researchers to revisit the problem in a new way. Third, markets have been volatile during this decade, which could have led to boosted attention on more effective asset allocation methods.

The growth rate, however, is only preliminary for 2026, and may be slightly different from the growth rate reported here. Furthermore, the growth rate is an average for the entire period and reveals nothing about the magnitude of the increase in a few recent years or years or whether growth was slow or fast. It would require further scientific and annual scientific production analysis to clarify this.

4.2 Sources

The 1,304 documents were published in 619 different sources. On average, each source had two documents. It is clear that research on portfolio optimisation is published in broad rather than a small number of publications. Portfolio optimisation involves the application of fields such as finance, economics, operations research, applied mathematics, computer science and engineering. Therefore, researchers from different disciplines tend to publish in the journals that are relevant to their discipline, which perhaps might be the reason for the many sources. The broad geographic distribution also hints that either theoretical or applied researchers find it relevant and that methods are being utilized in a wide range of settings.

One possible implication is that researchers involved in this topic should be looking at a wide variety of journals in order to stay up to date on new developments. However, the small average number of documents per source suggests that a "representative" group of journals may not be as well defined.

4.3 Individual authors of documents or reports

Of the 3605 authors, about 3.8% (137 authors) have produced single authored documents. This suggests that very little research is done by individuals and that most of the research is done in teams of researchers.

The low percentage is comparable to above average mean of 3.13 co-authors per document. It implies the field has moved from the classic individual contribution, as featured in early literature on portfolio selection, to group oriented research that incorporates modelling, computation and data analysis.

4.4 Other Indicators

International co-authorship represents 28.56% of documents, and the documents include 4073 different author's keywords, representing the number of different processes and applications involved in portfolio optimisation. The number of citations per document is 11.94 on average, literature is relatively recent, on average document age of 3.46 years. Lastly, the number of references is listed as 0, indicating that no reference data was present in the data set. Thus, caution should be used when interpreting citation-based analysis, such as co-citation analysis.

4.5 Most Relevant Sources

Table -1: Most relevant sources by number of documents

Rank	Source	Documents	% of 1,304
1	Annals of Operations Research	31	2.4%
2	Mathematics	29	2.2%
3	Computational Economics	23	1.8%
4	European Journal of Operational Research	23	1.8%
5	Expert Systems with Applications	23	1.8%
6	Journal of Risk and Financial Management	18	1.4%
7	IEEE Access	16	1.2%
8	Quantitative Finance	14	1.1%
9	Computers and Industrial Engineering	13	1.0%
10	Journal of Portfolio Management	13	1.0%
11	Insurance: Mathematics and Economics	12	0.9%
12	Applied Sciences (Switzerland)	10	0.8%
13	International Journal of Financial Studies	10	0.8%
14	Risks	10	0.8%
	Total (14 sources)	**245**	**18.8%**

The most productive source, as indicated in the data set above, is Annals of Operations Research with 31 documents (2.4% of the dataset). Next is Mathematics (29 documents), followed by Computational Economics, the European Journal of Operational Research (23 documents) and Expert Systems with Applications (23 documents). The top five sources thus account for approximately 9.9% (129 documents) of the total.

Clearly, the variations in the major sources are not large indicating there are no dominant journals'. Also, the list of 14 sources displayed is only about 2.3% of the 619 sources in the data set, but generates almost 20% of all documents meaning there is a core of journals with a long tail of journals with only a few documents in each.

This implies that the field of portfolio optimisation is closely related to optimisation theory and decision making techniques and that it can often be viewed as a mathematical programming problem. Their role signifies that algorithmic and data-driven methods like algorithmic and metaheuristic methods and machine learning are crucial parts of the literature. The Journal of Portfolio Management is of particular interest, in that it has a practitioner emphasis, and the editors state that the research is also applicable to investment practice. There is also an insurance-related journal included, which suggests that portfolio optimisation techniques are also used in the insurance industry like in Asset–liability management.

4.5.1 Observations on publication venues

Some of the primary sources such as Mathematics, the Journal of Risk and Financial Management, IEEE Access, Applied Sciences, the International Journal of Financial Studies and Risks seem to be open-access journals. These two types make up 93 out of 245 documents (approximately 38%). This suggests that researchers appreciate the visibility and rapidity of open access publishing, but this needs to be compared to the publishers' information. Traditional outlets, however, continue to be important sources, as evidenced by the long-standing journals, Annals of Operations Research and European Journal of Operational Research, which have been among the most productive.

4.6 Sources Production Over Time

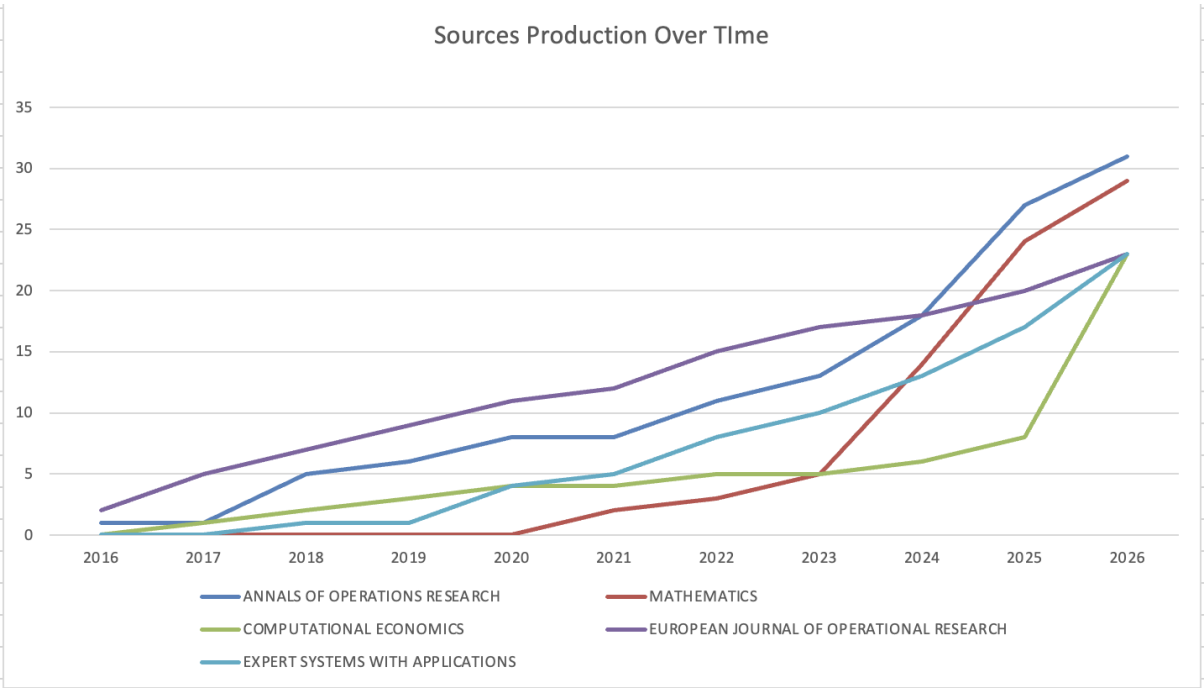

Figure -2: Sources Production over time

Figure 2 represents the production evolution of the five most relevant sources as mentioned in the figure. The lines can only go up or stay flat and the sum of the 2026 values (31, 29, 23, 23 and 23) are the same as the totals in the table of the most relevant sources. How many documents the source published in a specific year is thus indicated by the steepness of each line. The five sources combined published just three documents in 2016, but by 2026 the total number of documents from the five sources was about 129 (9.9% of the total). Growth was very slow until 2021 and was significantly accelerated since 2022.

4.7 Thematic Map

The thematic map is created by the author with the use of bubbles to cluster the keywords into four groups. A bubble has 3 most prominent keywords written on it and the size of each bubble is proportional to the frequency of the keywords in the cluster.

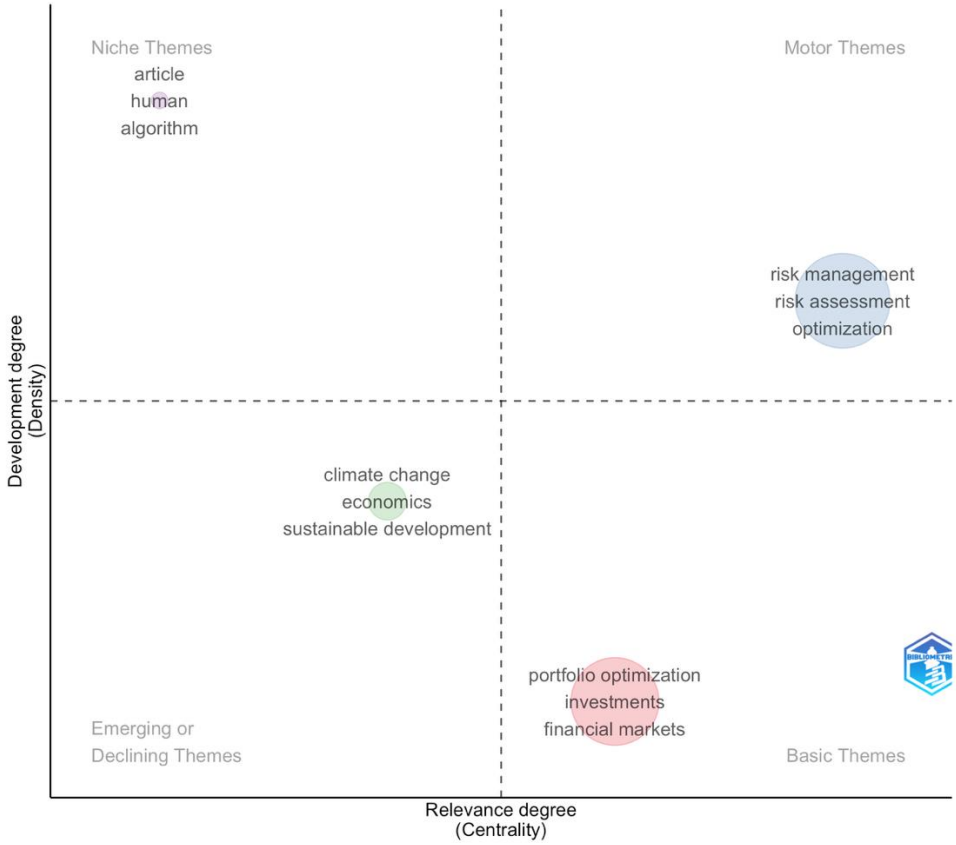

Figure -3: Thematic Map

The four quadrants are briefly explained below.

- Motor themes (upper right): themes that are both central to the field and well developed.
- Basic themes (lower right): themes which have little development internally but are general and central.
- Niche themes (upper left): themes that develop well, but are specialised and marginal.
- Emerging or declining themes (lower left): themes that are not fully developed and not prominent, new or fading.

4.7.1 Risk Management, Risk Assessment and Optimization

This cluster is in the upper right quadrant and, as such, is a motor theme. It is a large bubble and very dense (high) on the map, implying that research on risk occurs often and is tightly interrelated. Moreover, its location far to the right is also an indication of its strong association with the other themes in the field. The presence of risk as a key part of the portfolio optimisation indicates that risk is indeed an important consideration in portfolio construction, as it is for most of the purposes of portfolio construction.

The general term optimization exists in the same group indicates that there is close relationship between the risk measurement and mathematical optimisation methods in the literature. A typical example would be models that minimise variance or conditional value-at-risk.

4.7.2 Portfolio optimization, investments and financial markets.

This cluster is located in the bottom right quadrant and is thus a basic theme. It is one of the two biggest bubbles, indicating these keywords are used with great frequency. It is likely to be highly central, as it includes the central concept of the entire data set. However, its density is the least of the four clusters. This indicates that these keywords are not tightly formed, but rather are used as general terms that relate to a number of sub-topics.

The elementary concepts of such a kind typically form the basis of a line of research. In this instance, the focus words are the context (investments and financial markets) and the primary issue (portfolio optimization) in which the more detailed work is carried out.

4.7.3 Article, Human and Algorithm

This cluster is located in the top left corner and therefore it's a niche theme. It is the smallest bubble on the map, and it has a low centrality but a high density. This means that its keywords have a tight connection to each other but a loose connection with the rest of the field. The words article and human are common indexing terms used by databases, and do not necessarily represent a valid research topic. They may be assigned together and that is why they are high density.

The term algorithm, on the other hand, refers to a specific branch of work about computational procedures. This can be done by a few researchers who are more concerned with the solution methods they design than with the broader literature and who cite one another more frequently than they cite the literature. This interpretation is in line with the leading sources, which include Expert Systems with Applications and Computational Economics, though there is no confirmation in the map of this connection.

4.7.4 Climate Change, Economics and Sustainable Development

The cluster is situated in the bottom left quadrant, near the centre of the map, therefore, it is considered to be an emerging or declining theme. It is a small bubble meaning that the keywords are used less frequently than the other main clusters. The nature of the theme, whether emerging or declining, cannot be displayed on the map.

As the keywords mentioned and the average age of the documents (3.46 years) suggest, however, the cluster is likely a reflection of an emerging interest in sustainability-related investing, including climate-aware portfolio construction and ESG (environmental, social and governance) oriented investing. This is also reflected in the rapid rise of publications after 2022. The bubble's proximity to both the dividing lines also indicates that the theme is likely to shift towards the centre of the field if sustainability research continues to increase.

4.8 Annual Scientific Production

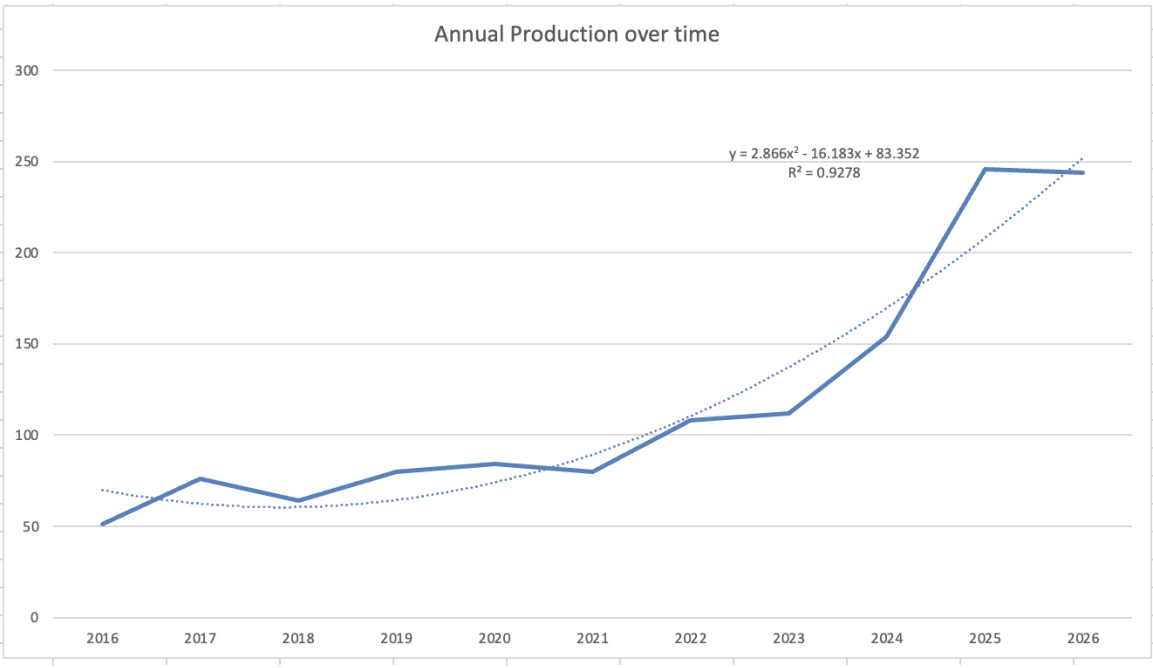

Figure -4: Annual Scientific Production

Table -2: Annual Scientific Production

Year	Documents	Change from previous year
2016	51	–
2017	76	+49.0%
2018	64	−15.8%
2019	80	+25.0%
2020	84	+5.0%
2021	80	−4.8%
2022	108	+35.0%
2023	112	+3.7%
2024	154	+37.5%
2025	246	+59.7%
2026	244	−0.8%

Table 2 indicates that annual output went from 51 documents in 2016 to 244 documents in 2026, showing a 5 times increase. 2025 recorded the highest value of 246 documents. The total number of the documents in the dataset over the entire period is 1,304 documents. The overall increase reflects the annual increase of 16.95%.

The growth pattern can be subdivided into three parts. Growth has been slow and uneven in the first phase (2016-2021). Output ranged between 51 and 84 documents per year, with small decreases in 2018 (−15.8%) and 2021 (−4.8%). Over these 6 years, 435 documents were created, which is roughly a third (33.5%) of the collection of documents. The second phase (2022–2023) saw the output increase to 108 documents in 2022 (+35.0%) and then level off at 112 documents in 2023 (+3.7%). In the third period (2024-2026), the production rate has increased strongly: +59.7% between 2024 and 2025, to reach 246 documents in 2025. These final three years clearly present 644 documents, almost half (49.6%) of all documents published during this period.

It is possible that the rise since 2021 is related to a number of factors including rising interest in machine learning, episodes of market uncertainty, and the growth in the number of journals especially open access journals that publish articles on the subject.

4.8.1 Trendline

The polynomial model fitted was a second order polynomial model for which the equation is $y = 2.866x^2 – 16.183x + 83.352$ and the positive coefficient of the squared term ($R^2 = 0.9278$) suggests that output has been increasing by more and more each year. The curve is a good fit, as based on the value of R^2, the curve accounts for approximately 93% of the variance in the data for annual output. The curve decreases slightly at the start and bottoms out around 2018 as mentioned above, where the rate of change is slow.

The curve is not an exact match with the observed values. It is above the actual values in 2023 and 2024 and below the actual value in 2025, suggesting that the changes in real growth were more abrupt. This fitted value for 2026 (about 252 documents) is however close to the observed value 244.

It is worth to note that 2026 is a partial year. The apparent slowdown between 2025 and 2026 (−0.8%) should not be seen as such. The fact that the number of 2026 is nearing 2025 at the end of this year would indicate that growth is continuing. Also, a polynomial trendline is a descriptive tool and should be used only for describing output within the period being studied.

5. FUTURE RESEARCH AGENDA

This study brings fresh insights to a rapidly growing field. The volume of publications rose from 51 in 2016 to 244 in 2026, an average annual increase of 16.95% and the 1,304 documents reviewed were spread out among 619 sources. But a rising publication rate does not imply that the understanding of practical applications has caught up with the progress in the evidence base. Taken together with a reading of the review literature, the thematic maps suggest a pattern of imbalance that recurs throughout: the methods are increasingly sophisticated, but real-world testing of those methods, their connection to other research areas and common terminology have not evolved as smoothly. The priorities below attempt to address that imbalance. Priorities 1–6 relate to portfolio optimization and risk management, while Priority 7 looks at possible constraints in the evidence base itself.

Table -3: Summary of future research priorities

Priority	Observation from the corpus	Core research question	Proposed approach	Expected contribution
1. From backtests to real investing	Machine learning, AI and optimization form the largest motor theme; studies are mostly judged on historical data	Do reported gains survive transaction costs, changing markets and real constraints?	Walk forward testing; shared benchmark datasets; comparison with simple baselines	Fair, comparable evidence on which methods work in practice
2. Explainability, governance and human oversight	AI is entering investment management, but governance and human–AI collaboration are rarely tested	Which explanations help managers trust a model the right amount, and who is accountable when it fails?	Decision experiments with portfolio and risk managers; case studies of firms using AI	Design and governance principles for usable AI-driven portfolio tools
3. Reinforcement learning is isolated	Reinforcement learning and systematic review sit in the niche quadrant (well developed, weakly connected)	Where does reinforcement learning beat classical optimization, especially in crises?	Head-to-head tests using the same risk measures (VaR, CVaR) and data	Links the niche theme to the main field; shows when the extra complexity pays off
4. Is uncertainty modelling fading?	Uncerainty is a small bubble in the emerging or declining quadrant; fuzzy methods look less visible than ML	Do uncertainty-based models beat ML when data is scarce or noisy?	Thematic evolution over time slices; tests on small-data, high-uncertainty problems; hybrid models	Clarifies whether the theme is declining or just renamed
5. Risk beyond volatility	Risk management and assessment form a motor theme; climate change and sustainability form a small, young cluster	How do liquidity and climate risk change optimal portfolios when modelled together with market risk?	Multi-risk optimization models; scenario analysis.	More realistic risk models that are still explainable
6. Fragmented application areas	Risk management, project portfolio and portfolio optimization sit in the basic quadrant (central but loosely developed)	Which methods transfer between financial, project and supply portfolios?	Cross-domain studies; shared glossary of key terms .	A more connected field with common terminology.
7. Limits of the evidence base	No reference data (co-citation not possible); Scopus only; 2026 is a partial year; 28.56% international co-authorship	How can future bibliometric work get wider, cleaner and more complete data?	Multi-database search; keyword cleaning; full-reference exports; longer time window,	A more reliable base for citation and collaboration analysis.

Priority 1: From backtests to real investing

The biggest motor theme on the thematic map of the 48 review papers is formed by machine learning, artificial intelligence and optimization. Two points of application are identified in the reviews: on the one hand, machine learning is used to estimate returns and risk. On the other hand, machine learning can also be used to solve the optimization step (Kim et al., 2024) . Both of these build on the mean–variance model, which finds the right trade-off between return and risk (Kim et al., 2024) . Recently metaheuristics became popular for the optimization step, mainly in realistic problems with many constraints (Doering et al., 2019) .

The issue here is how such a method or an algorithm is evaluated. In my reading of the corpus, most studies report their results on past data, but relatively few studies test whether the gains survive when one considers trading costs, shifting market conditions, and

the additional constraints that real portfolio managers must follow. This is not a counted result but an interpretation, and is therefore outside the purviewe of this study, which only involves a reading of the abstract. This must be checked again with full-text coding.

Questions worth asking:

- Do reported gains hold up after transaction costs and realistic constraints?
- Do complex models really beat simple baselines, such as equal weighting, over long periods and in crises?

Suggested approach: Walk-forward testing, whereby a model is tested always on data that it was not seen before. At the same time, there should be a set of benchmark datasets that are agreed upon, and the cost of execution should be reported openly. Since metaheuristics are designed to be problem-dependent (Doering et al., 2019) and sought to deal with the messiness of real- world problems, a common test bed would allow different algorithms to be compared against each other for the first time. At present, each paper chooses its own data, which makes it hard to compare the results.

Priority 2: Explainability, governance and human oversight

No one would use a model they could not trust. AI is now moving into investment management, and questions about its structure, strategy and governance are still unanswered (Mertzanis, 2025) . Work on human–AI collaboration in uncertainty- and risk-aware reinforcement learning shows the same trend: the role of the human part of the model is crucial, but the results have not been tested (Khemlichi et al., 2026) .

The gap here, therefore, is that most papers talk about a return or accuracy measure, but not about whether a portfolio manager or risk manager could understand, question and safely override a model's recommendation. Black-box models are particularly dangerous in risk management, because a flaw is hidden until it breaks out in a crisis.

Questions worth asking:

- Which kinds of explanation help managers rely on a model the right amount, neither blindly nor never?
- Who is accountable when an AI-driven allocation fails?

Suggested approach: Decision experiments, whereby portfolio and risk managers are given a set of decisions and the type of explanation and the rules for an override vary from group to group. The decision quality, the override frequency and how closely the trust of the participants corresponded with the model's actual accuracy can be measured. A case study of firms that already use AI would be able to add detail to a real-world application.

Priority 3: Reinforcement learning is isolated from the main field

On the thematic map of the review literature, reinforcement learning and systematic review appear in the niche quadrant. That is, they are well developed in themselves, but weakly connected to the other themes. The last few years have seen several very interesting applications that explain why researchers are excited about this field. One of the framework uses a Dirichlet policy and attention to make sure portfolio weights are always valid (Xue & Ye, 2026) . Another review of large language models and reinforcement learning in financial markets (AL-Aldaffaie et al., 2026) .

The problem here is that this work tends to talk to itself. Little work seems to exist that would compare reinforcement learning with classical optimization methods, using the same measures for risk (e.g. a value-at-risk measure such as VaR or CVaR) and on the same data. Without this, it is not possible for anyone to know when the additional complexity of the approach is actually worth the extra risk of overfitting.

Questions worth asking:

- Where does reinforcement learning beat classical models, and where does it falle behind?
- How does it behave in stress periods that look nothing like its training data?
- Do language-model-based agents bring new risks, such as unstable answers to small changes in wording?

Suggested approach: A controlled comparison of reinforcement learning, classical optimization and machine learning approaches on shared data, including a special interest on crisis periods. The results can be linked to the motor themes to make this niche stop being just that: a separate island.

Priority 4: Is uncertainty modelling really fading?

The uncertainty theme is a small bubble in the lower left of the review map, meaning that this topic is either emerging or disappearing. A single map can not show the difference. Preceding work uses fuzzy approaches, such as fuzzy multi-objective linear programming (Gulia et al., 2023) , and these methods appear to be less visible beside the modern data-driven approaches. Nevertheless, the focus of uncertainty is the core of risk management. No one ever knows returns in advance.

The gap here is that these types of fuzzy and other uncertainty-based OR approaches are rarely compared with the modern data-driven approaches. They may be forgotten due to a fashion issue, and not because they are worse. Nobody has shown this.

Questions worth asking:

- Do uncertainty-based models do better than machine learning when data is scarce, noisy or changing?
- Can the two be combined into hybrid models?

Suggested approach: First, a thematic evolution analysis over a series of time slices, to see whether the theme is really getting smaller, or if it is just getting a new name. Second, a head-to-head comparison on small data and high uncertainty problems, where classical OR methods might do better.

Priority 5: Risk beyond volatility (liquidity, climate and tails)

The risk management and risk assessment topics are the clearest motor theme on the overall map of 1,304 documents, and in that respect, the connection to optimization is close. That is a very good sign. But the kind of risk modelled is often very narrow. Some work looks at liquidity (e.g. a liquidity-adjusted value-at-risk for illiquid markets) (Al Janabi, 2021) . Some other work looks at measures for climate finance (Chakrabarty & Nag, 2023) . On the large map, climate change, economics and sustainable development form a small cluster very close to the centre, but the documents are relatively young (average age 3.46 years), which suggests this is an area where work is expanding.

The gap here is that these types of risks are often looked at separately. A real portfolio is exposed to market risk, liquidity risk, climate risk, and these three risks feed on one another. A portfolio model that includes all these factors, and that at the same time is simple enough for a manager to understand and use, is rare.

Questions worth asking:

- How do liquidity and climate risk change an optimal portfolio when they are modelled together with market risk?
- Is it possible to build such a model without making it too complex to explain?

Suggested approach: A multi-risk optimization model, which can be tested with a scenario analysis, for example with scenarios of climate change and a liquidity squeeze. The biggest problem here is the data, because good data is scarce on climate and liquidity, so the study must state clearly what the assumptions were.

Priority 6: Financial, project and supply portfolios do not talk to each other

The concept of portfolios has been expanding well beyond finance. Supply portfolios are included in reviews on supply chain risk (Hamdi et al., 2018) , and project portfolio and risk management (Micán Rincón et al., 2023) . Within finance itself, asset allocation models are sprouting into many specialised versions (Oliveira Filho & Poker Junior, 2025) . On the maps, risk management, project portfolio and portfolio optimization are in the basic quadrant: central, but losely developed. In playground talk, everyone uses these terms, but not everyone means the same thing in each field.

The gap here is that useful methods get locked inside their field. A method that is useful for selecting suppliers, for example, might also help for choosing assets, or vice versa, but there is little evidence for this, and nobody seems to check.

Questions worth asking:

- Which methods transfer between financial, project and supply portfolios, and which break?
- Can the field agree on shared terms for risk, return and diversification?

Suggested approach: Cross-domain studies that apply one method to several different kinds of portfolios, plus a shared glossary, developed by comparing the use of key words in each area.

Priority 7: Limits of the evidence base

A limitation to this study is that the evidence base is determined by the coverage of the available bibliometric data, and their quality. These constraints do not invalidate the observed patterns, but impact how confident these can be interpreted and generalised. Future research can act on several of these weaknesses.

- No reference data. The dataset does not include reference data, so co-citation analysis was not possible. Any claim based on citations must therefore be read with care. Exporting from another database, which does include full references, would remedy this.
- One database. The Scopus database was used alone. The inclusion of other databases, such as Web of Science, would make the picture wider and fairer.
- Noisy keywords. The niche cluster formed by "article", "human" and "algorithm" mostly represent the labels used by databases, rather than a topic. Cleaning the generic terms before the mapping, as recommended in the guides to bibliometrics (Aria & Cuccurullo, 2017) , would make the maps easier to read and understand.
- A partial year. 2026 is not a full year, and the flat result between 2025 and 2026 says little about what really happened in the intervening time. The review set is small as well, with only 48 papers.
- Collaboration. International co-authorship is only 28.56%, and the average paper has a round 3.1 authors. A later investigation of whether more cross-country and cross-field teams, for example with finance and computer science, result in better and more connected research may be interesting.

6. CONCLUSION

In essence, this paper was written in order to illustrate the application of Operations Research in portfolio optimisation and risk management, as well as its organisational structure. A bibliometric mapping technique was employed using 1,304 publications from 2016-2026 in 619 journals and 48 review papers. As such, the research field is expanding rapidly and becoming more complex, while in some aspects remains underdeveloped and poorly interrelated. This section summarises the conclusions made, provides an interpretation of their implications, and identifies the scope of data used.

The obtained results successfully address all three research questions stated in the introduction. In regards to the field development, growth, authorship and venues, this domain is growing rapidly and is based on collaboration across various venues. With regard to the structure, the topic of risk and optimisation serves as a basis of this field; while portfolio optimisation is a broad foundation. In regard to gaps, the results prove poor validation, poor integration, and inadequate terminology.

The output increased from 51 documents in 2016 to 244 in 2026, growing at an average annual rate of 16.95% and by about fivefold overall. This increase took place in several stages. Until 2021 the increase has been rather weak and irregular, including 435 documents (33.5% of all output) and decreases in 2018 and 2021. The number of publications reached 108 documents in 2022 and 112 documents in 2023. Thereafter, there was a rapid increase to 246 documents in 2025, and three years from 2024 to 2026 contain 644 documents, which are nearly half of all the dataset (49.6%). Second-order polynomial trendline correlates well with the annual number of output ($R^2 = 0.93$), and its value for 2026 is estimated to be about 252 documents, being close to the 244 observed. 2026 figure reflects only a part of the year, therefore the small decrease from 2025 does not signify the slowdown of the trend. The increase after 2021 could have been caused by the diffusion of machine learning, market volatility episodes and open-access publishing, but there is no data to distinguish the reasons.

Most of this research is done in teams. Only 3.8% of authors (137 of 3,605) have written a single-authored document, the average is 3.13 co-authors per document, and 28.56% of documents have international co-authors. No journal dominates. With 31 papers, Annals of Operations Research ranks first, then Mathematics with 29, while Computational Economics, European Journal of Operational Research, and Expert Systems with Applications rank next with 23 papers each. Only 18.8% of the papers come from the 14 sources with most publications, while those sources make up only 2.3% of 619 sources; thus, a small core of journals has been identified in this study, above the long tail of those having one to two publications. Journals from operations research, computing, finance and insurance can be seen, thus showing that the subject has multiple disciplines involved. The average number of citations per paper is 11.94, and there are 4,073 unique author keywords, reflecting the characteristics of a multidisciplinary field. Almost 38% of papers from the most productive journals (93 out of 245) are from open access journals, which could be due to their desire for fast and visible publication, yet this would need to be verified from publishers' information. From 2016 to 2026, the five most productive journals published three papers in 2016 and almost 129 papers by 2026.

The thematic map for the entire set contains four clusters. The cluster that comprises risk management, risk assessment and optimization is the largest and most compact motor theme, so risk measurement and mathematical optimization are considered together in the research. Portfolio optimization, investment and financial market represent a basic theme. This theme is important and frequently used, but the terms are rather general tags without forming a tightly-knit area of research. The article, human and algorithm niche cluster is rather small and well-integrated within itself, but poorly integrated into other clusters, and almost all keywords are taken from the database indexing, therefore, it does not say much about the content of the research. The fourth cluster consists of the keywords climate change, economics and sustainable development. This cluster is rather small and close to the center of the map. Publications are rather recent (average age of 3.46 years) and there is an increasing tendency in publications starting from 2022, so it seems to be a matter of growing interest in sustainable and climate-friendly investing.

The 48 reviews provide a similar scenario with more details. Machine learning, artificial intelligence, and optimization comprise the largest motor theme, making data-driven methodologies the driving force of the domain (Lee et al., 2024; Doering et al., 2019). The second motor theme includes risk analysis, portfolio management, and portfolio analysis and is highly dense. Risk management, project portfolios, and portfolio optimization are core themes, central but underdeveloped. Reinforcement learning is a niche theme; technically sophisticated (Xue & Ye, 2026) yet sparsely related to the domain. Approaches based on fuzzy logic and other types of uncertainty treatment, together with traditional methodologies for asset and project portfolio management are included in the emerging/declining quadrants. Quantum computing is an emerging direction (Kumar et al., 2026).

They both exhibit the same trend. The methods have been improving much more rapidly than the empirical literature that evaluates their performance and consistency. There are six research gaps. The first gap involves the fact that most of the reported improvements have been done on historical data, and almost none test if they withstand the test of transaction costs, changing markets, and managerial constraints. This assertion is based on the analysis of abstracts and needs to be validated by coding full texts. The second gap is the fact that AI-powered algorithms are rarely examined with respect to the aspects of explainability, governance and oversight (Mertzanis, 2025; Khemlichi et al., 2026). Third, there is very little comparison of reinforcement learning with the classical optimization techniques using the same dataset and risk measures. Fourth, there is little comparison of uncertainty-based models and machine learning, which makes it difficult to ascertain if they are being used less often or simply ignored. Fifth, liquidity, climate and market risk are mostly modelled separately, though a real portfolio faces all of them at once (Al Janabi, 2021; Chakrabarty & Nag, 2023). Sixth, financial, project and supply portfolios use shared vocabulary without agreed meanings, and methods rarely move between them (Hamdi et al., 2018; Micán Rincón et al., 2023).

The first important contribution of this review is the whole field perspective. Earlier reviews have generally been divided into subtopics based on specific techniques used, such as machine learning, reinforcement learning, fuzzy logic, quantum techniques, etc., or by application areas. Placing these in one picture enables seeing relationships between machine learning, metaheuristic algorithms, uncertainty modeling and risk management at the level of the project. Operations research is central when risk measurement meets optimization. AI methods dominate the review results. The distant topics, like reinforcement learning and sustainability topic, need links the most.

For future researchers, establishing connections between different papers may be more productive than building on top of them. Reinforcement learning, for example, is an isolated topic, as well as project and supply portfolios which are rather basic ones. Comparisons of these topics directly to the traditional ones may be useful. A common glossary of such terms as risk, return, and diversification would be useful. For managers, the research indicates that one must be careful with the performance figures until those are evaluated using realistic costs and constraints, as well as whether the people managing the portfolio are capable of understanding the suggestions of the model.

The review corpus reveals a few additional pieces of information. 13 out of 48 reviews were published in 2026, more than in any other year, and the years 2024 through 2026 predominate in the set. The most cited reviews remain the older reviews – Doering et al. (2019) on metaheuristics and Hamdi et al. (2018) on supply portfolios, which both have 79 citations. However, newer reviews

on artificial intelligence and reinforcement learning have not had enough time to accumulate citations yet, and their actual significance can be underestimated.

There are several limitations to the findings. The search included only Scopus database, so publications indexed elsewhere were left out. No reference data was exported, so co-citation analysis was impossible and citation-based findings should be interpreted with caution. Partial counting of 2026 publications, a relatively small set of 48 reviews, and generic indexing keywords introduce some noise in the network maps (Aria & Cuccurullo, 2017). Some interpretations, such as connecting the sustainability cluster with ESG investing, are based on the interpretation of the map itself.

There are two avenues that seem particularly fruitful. One would be to apply both AI-related and classical techniques on common datasets while accounting for transaction costs, crisis times, and explainability. The other would be to link together the isolated and elementary themes with the motor ones, using multi-risk approaches which incorporate market, liquidity, and climate risk, and cross-disciplinary research. Running the same analysis but using Web of Science and all references as well as a complete 2026 would provide a more solid understanding. Should the sustainability cluster continue to grow in size, it may end up becoming one of the motor themes. In either case, the next progress in the area will probably be related not to adding but to combining its elements.

REFERENCES

[1] AL-Aldaffaie, G. H., Taheri, A., Farhadi, A., & Zamanifar, A. (2026). A survey on LLM-enhanced reinforcement learning in financial markets. Discover Artificial Intelligence, 6(1). https://doi.org/10.1007/s44163-026-02018-0

[2] Al Janabi, M. A. M. (2021). Multivariate portfolio optimization under illiquid market prospects: a review of theoretical algorithms and practical techniques for liquidity risk management. Journal of Modelling in Management, 16(1), 288–309. https://doi.org/10.1108/JM2-07-2019-0178

[3] Aria, M., & Cuccurullo, C. (2017). bibliometrix: An R-tool for comprehensive science mapping analysis. Journal of Informetrics, 11(4), 959–975. https://doi.org/10.1016/j.joi.2017.08.007

[4] Aria, M., & Cuccurullo, C. (2026). Science Mapping Analysis: A Primer with Biblioshiny. McGraw-Hill.

[5] Aria, M., D'Aniello, L., Misuraca, M., & Spano, M. (2026). Rethinking thematic evolution in science mapping:An integrated framework for longitudinal analysis. Journal of Informetrics, 20(4), 101877. https://doi.org/10.1016/j.joi.2026.101877

[6] Bao, M., Ding, Y., Zhou, X., Guo, C., & Shao, C. (2021). Risk assessment and management of electricity markets: A review with suggestions. CSEE Journal of Power and Energy Systems, 7(6), 1322–1333. https://doi.org/10.17775/CSEEJPES.2020.04250

[7] Biller, B., Hartig, M., Olson, R. J., Sandvik, P., Trant, G., Sui, Y., & Minnick, A. (2019). General electric uses simulation and risk analysis for silicon carbide production system design. INFORMS Journal on Applied Analytics, 49(3), 117–128. https://doi.org/10.1287/inte.2019.0995

[8] Callon, M., Courtial, J. P., & Laville, F. (1991). Co-word analysis as a tool for describing the network of interactions between basic and technological research: The case of polymer chemsitry. Scientometrics, 22(1), 155–205. https://doi.org/10.1007/BF02019280

[9] Chakrabarty, S. P., & Nag, S. (2023). Risk measures and portfolio analysis in the paradigm of climate finance: a review. SN Business and Economics, 3(3). https://doi.org/10.1007/s43546-023-00449-w

[10] Cheng, L., Shadabfar, M., & Sioofy Khoojine, A. (2023). A State-of-the-Art Review of Probabilistic Portfolio Management for Future Stock Markets. Mathematics, 11(5). https://doi.org/10.3390/math11051148

[11] Cobo, M. J., López-Herrera, A. G., Herrera-Viedma, E., & Herrera, F. (2011). An approach for detecting, quantifying, and visualizing the evolution of a research field: A practical application to the Fuzzy Sets Theory field. Journal of Informetrics, 5(1), 146–166. https://doi.org/10.1016/j.joi.2010.10.002

[12] Cobo, M. J., López-Herrera, A. G., Herrera-Viedma, E., & Herrera, F. (2012). SciMAT: A new science mapping analysis software tool. Journal of the American Society for Information Science and Technology, 63(8), 1609–1630. https://doi.org/10.1002/asi.22688

[13] Doering, J., Kizys, R., Juan, A. A., Fitó, À., & Polat, O. (2019). Metaheuristics for rich portfolio optimisation and risk management: Current state and future trends. Operations Research Perspectives, 6. https://doi.org/10.1016/j.orp.2019.100121

[14] Donthu, N., Kumar, S., Mukherjee, D., Pandey, N., & Lim, W. M. (2021). How to conduct a bibliometric analysis: An overview and guidelines. Journal of Business Research, 133, 285–296. https://doi.org/10.1016/j.jbusres.2021.04.070

[15] Feng, X., & Yang, S. (2026). The Evolution of Portfolio Theory Under Risk & Uncertainty: From Mean–Variance to AI-Augmented Investing. Journal of Economic Surveys. https://doi.org/10.1111/joes.70148

[16] Gökgöz, F., & Atmaca, M. E. (2017). Portfolio optimization under lower partial moments in emerging electricity markets: Evidence from Turkey. Renewable and Sustainable Energy Reviews, 67, 437–449. https://doi.org/10.1016/j.rser.2016.09.029

[17] Gulia, P., Kumar, R., Viriyasitavat, W., Aledaily, A. N., Yadav, K., Kaur, A., & Dhiman, G. (2023). A Systematic Review on Fuzzy-Based Multi-objective Linear programming Methodologies: Concepts, Challenges and Applications. Archives of Computational Methods in Engineering, 30(8), 4983–5022. https://doi.org/10.1007/s11831-023-09966-1

[18] Gupta, H. Sen, & González, A. D. (2026). Systems optimization for enhancing community resilience to natural hazards: a review of integrated modeling approaches. Environment Systems and Decisions, 46(1). https://doi.org/10.1007/s10669-026-10074-1

[19] Hamdi, F., Ghorbel, A., Masmoudi, F., & Dupont, L. (2018). Optimization of a supply portfolio in the context of supply chain risk management: literature review. Journal of Intelligent Manufacturing, 29(4), 763–788. https://doi.org/10.1007/s10845-015-1128-3

[20] Kaviani, M., & Fakhrehosseini, S. F. (2020). Application of Fuzzy Logic in Portfolio Management: Evidence from Iranian Researches. Journal of Fuzzy Extension and Applications, 1(2), 108–111. https://doi.org/10.22105/jfea.2020.249372.1012

[21] Khemlichi, F., Idrissi Khamlichi, Y., & Elhaj Ben Ali, S. (2026). Human–AI Collaboration in Risk- and Uncertainty-Aware Portfolio Reinforcement Learning: A Critical Review. Information (Switzerland), 17(5). https://doi.org/10.3390/info17050476

[22] Kim, J. H., Lee, Y., Kim, W. C., Kang, T., & Fabozzi, F. J. (2024). An Overview of Optimization Models for Portfolio Management. Journal of Portfolio Management, 51(2), 101–117. https://doi.org/10.3905/jpm.2024.1.643

[23] Knoke, T., Messerer, K., & Paul, C. (2017). The Role of Economic Diversification in Forest Ecosystem Management. Current Forestry Reports, 3(2), 93–106. https://doi.org/10.1007/s40725-017-0054-3

[24] Kolm, P. N., Tütüncü, R., & Fabozzi, F. J. (2014). 60 years of portfolio optimization: Practical challenges and current trends. European Journal of Operational Research, 234(2), 356–371. https://doi.org/10.1016/j.ejor.2013.10.060

[25] Kumar, V. L., Reddy, D. S., & Kumar, J. P. S. (2026). Quantum Computing in Finance: A Scientometric Exploration of Emerging Trends and Applications in Financial Markets. SN Computer Science, 7(6). https://doi.org/10.1007/s42979-026-05216-w

[26] Lee, Y., Kim, J. H., Kim, W. C., & Fabozzi, F. J. (2024). An Overview of Machine Learning for Portfolio Optimization. Journal of Portfolio Management, 51(2), 131–148. https://doi.org/10.3905/jpm.2024.1.639

[27] Markowitz, H. (1952). Portfolio selection. The Journal of Finance, 7(1), 77–91. https://doi.org/10.2307/2975974

[28] Mehala, V., & Sundar, D. (2025). Developing advanced model for portfolio optimization and return prediction using nested adaptive efficient CapsNet with spatial attention. Intelligent Decision Technologies, 19(6), 3804–3825. https://doi.org/10.1177/18724981251388889

[29] Mertzanis, C. (2025). Artificial intelligence and investment management: Structure, strategy, and governance. International Review of Financial Analysis, 107. https://doi.org/10.1016/j.irfa.2025.104599

[30] Micán Rincón, C. A., Rubiano-Ovalle, O., Delgado Hurtado, C., & Andrade-Eraso, C. A. (2023). Project portfolio risk management. Bibliometry and collaboration Scientometric domain analysis. Heliyon, 9(9). https://doi.org/10.1016/j.heliyon.2023.e19136

[31] Mienye, E., Jere, N., Obaido, G., Mienye, I. D., & Aruleba, K. (2024). Deep Learning in Finance: A Survey of Applications and Techniques. AI (Switzerland), 5(4), 2066–2091. https://doi.org/10.3390/ai5040101

[32] Moher, D., Liberati, A., Tetzlaff, J., & Altman, D. G. (2010). Preferred reporting items for systematic reviews and meta-analyses: The PRISMA statement. International Journal of Surgery, 8(5), 336–341. https://doi.org/10.1016/j.ijsu.2010.02.007

[33] Oliveira Filho, B. G. de, & Poker Junior, J. H. (2025). Asset allocation models: evolution and diversity – a systematic literature review. Journal of Capital Markets Studies, 1–19. https://doi.org/10.1108/JCMS-05-2025-0067

[34] Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., Shamseer, L., Tetzlaff, J. M., Akl, E. A., Brennan, S. E., Chou, R., Glanville, J., Grimshaw, J. M., Hróbjartsson, A., Lalu, M. M., Li, T., Loder, E. W., Mayo-Wilson, E., McDonald, S., … Moher, D. (2021). The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. BMJ, n71. https://doi.org/10.1136/bmj.n71

[35] Paul, J., & Criado, A. R. (2020). The art of writing literature review: What do we know and what do we need to know? International Business Review, 29(4). https://doi.org/10.1016/j.ibusrev.2020.101717

[36] R Core Team. (2026). R: A Language and Environment for Statistical Computing. R Foundation for Statistical Computing. https://doi.org/10.32614/R.manuals

[37] Saravanakumar, A., M, A. R., Chandana, A. V., Yashaswini, E., & Abirami, K. (2026). Proximal Policy Optimization for Risk-Adjusted Stock Portfolio Optimization: A Reinforcement Learning Approach. Computational Economics. https://doi.org/10.1007/s10614-026-11355-2

[38] Senescall, M., & Low, R. K. Y. (2024). Quantitative Portfolio Management: Review and Outlook. Mathematics, 12(18). https://doi.org/10.3390/math12182897

[39] Sutiene, K., Schwendner, P., Sipos, C., Lorenzo, L., Mirchev, M., Lameski, P., Kabasinskas, A., Tidjani, C., Ozturkkal, B., & Cerneviciene, J. (2024). Enhancing portfolio management using artificial intelligence: literature review. Frontiers in Artificial Intelligence, 7. https://doi.org/10.3389/frai.2024.1371502

[40] Vacík, E., Špaček, M., Fotr, J., & Kracík, L. (2018). Project portfolio optimization as a part of strategy implementation process in small and medium-sized enterprises: A methodology of the selection of projects with the aim to balance strategy, risk and performance. E a M: Ekonomie a Management, 21(3), 107–123. https://doi.org/10.15240/tul/001/2018-3-007

[41] van Eck, N. J., & Waltman, L. (2010). Software survey: VOSviewer, a computer program for bibliometric mapping. Scientometrics, 84(2), 523–538. https://doi.org/10.1007/s11192-009-0146-3

[42] Xue, P., & Ye, Y. (2026). Attention-enhanced reinforcement learning for dynamic portfolio optimization. Intelligent Systems with Applications, 29. https://doi.org/10.1016/j.iswa.2025.200622

[43] Zhao, Y., Wang, J., Wang, Y., & Lv, M. (2025). How to optimize modern portfolio theory? A systematic review and research agenda. Expert Systems with Applications, 263. https://doi.org/10.1016/j.eswa.2024.125780

[44] Zupic, I., & Čater, T. (2015). Bibliometric methods in management and organization. Organizational Research Methods, 18(3), 429–472. https://doi.org/10.1177/1094428114562629