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OPTIMIZATION TECHNIQUES IN FINANCIAL RISK MANAGEMENT: A BIBLIOMETRIC REVIEW

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Abstract—**Financial risk management has increasingly come to be treated as an optimization problem, and research that brings operations research (OR) methods into finance has grown quickly over the last fifteen years. This paper maps that body of work through a systematic literature review combined with a bibliometric analysis. Articles were retrieved from Scopus and screened using the PRISMA framework, leaving a final dataset of 1,674 journal articles published between 2010 and 2026 across 794 sources. Performance analysis and science mapping were carried out using Biblioshiny and VOSviewer. Publications in the field have grown at an annual rate of 14.08%, with the sharpest rise coming from 2024 onwards. China is the leading contributor by both output and citations, followed by the United States, while India ranks third in output. The European Journal of Operational Research is the most productive source. Thematic mapping identifies optimization, investment and economics as the motor themes of the field, with multi-objective optimization and genetic algorithms emerging. The reviewed literature shows a steady shift away from static mean-variance models towards stochastic, metaheuristic and machine learning based approaches. Based on these patterns, the paper proposes a future research agenda built around three gaps: the limited interpretability of AI-driven risk models, the scarcity of hybrid OR and AI frameworks, and the narrow focus on investment and credit applications at the cost of areas such as supply chain finance and decentralized finance.**

Keywords—**Operations Research; Financial Risk Management; Portfolio Optimization; Machine Learning; Bibliometric Analysis; PRISMA**

I. INTRODUCTION

Financial risk management has long been central to sound business operations and corporate governance. Over the last decade, it has also become one of the most complex functions in the corporate world. Businesses, funds and financial institutions now operate in a digitized, volatile and interconnected environment. They face a wide range of risks: sudden market swings, liquidity crises, credit defaults, macroeconomic shifts, geopolitical instability and changes in consumer behavior. The 2008 global financial crisis showed how quickly systemic risk can spread across borders and asset classes, and how badly portfolios built on simple assumptions can suffer. Work on bank networks has since shown that common asset holdings can pass shocks from one bank to another (Fan & Hu, 2024). Kaucic (2019) notes that the crisis, and the uncertainty that followed, exposed the limits of traditional portfolio theory in handling the many sources of investment risk. Managing these risks therefore takes more than intuition or qualitative judgment. It requires rigorous, data-driven models that protect a firm's capital while still earning competitive returns.

This is where operations research (OR) comes in. OR offers a systematic, quantitative framework for complex financial decisions made under uncertainty and with limited resources. By treating financial risk management as an explicit optimization problem, it helps firms decide how to allocate assets, balance portfolios, assess counterparty credit risk (Gnoatto et al., 2023) and plan long-term investments. Wang et al. (2021) describe the wider operations-finance field in similar terms, as one that jointly optimizes material, monetary and information flows under uncertainty.

Historically, portfolio optimization and risk management relied on deterministic models. The best known is the Markowitz mean-variance framework (Markowitz, 1952), which defined risk as the variance of portfolio returns. These classical models laid the groundwork for understanding the

trade-off between risk and expected return. Modern markets, however, have become too dynamic, nonlinear and turbulent for static models to remain fully effective on their own. Even the estimation side is fragile: Caccioli et al. (2016) show that optimizing a portfolio without accounting for finite liquidity leads to instabilities when coherent risk measures are estimated on finite samples.

The literature reviewed for this study points to a clear shift in how financial risk is measured, modeled and managed. Researchers are moving away from models built on normal distributions toward dynamic approaches that account for extreme downside risk, fat tails and sudden regime changes. Robust and stochastic optimization sit at the centre of this shift. Distributionally robust optimization, for instance, has been applied to corporate loan portfolios to handle data uncertainty and model misspecification (Sun & Kwon, 2024), and downside-focused measures such as semi-quadratic entropy have been built into mean-variance models (Tian et al., 2026).

At the same time, artificial intelligence, machine learning and metaheuristic algorithms are being folded into the traditional OR toolkit. These methods can process large volumes of data quickly and pick up market patterns that classical techniques miss. Survey evidence shows financial institutions using AI and machine learning more in algorithmic trading, risk management and credit scoring (El Hajj & Hammoud, 2023). Particle swarm optimization has been used to find portfolio weights under a mean-value-at-risk model (Amal et al., 2024) and, in a multi-objective form, to manage cardinality-constrained portfolios with risk parity control (Kaucic, 2019).

Because the field has grown so quickly, it is no longer practical to read and synthesize every relevant article by hand. Understanding its current shape, its history and its likely direction calls for a broader, macro-level approach, and a bibliometric review provides one. It allows researchers to study publication trends, influential contributors and conceptual structures across a large body of literature without reading every paper in full. Donthu et al. (2021) recommend bibliometric analysis for exactly this situation, when the scope of a review is broad or the dataset is too large for manual review. By analyzing metadata such as publication years, countries, journals, citations and keyword co-occurrences, it gives a clear overview of how a field is developing over time.

This study maps the literature on optimization techniques in financial risk management. It measures publication growth and citation impact between 2010 and 2026; identifies the leading journals, authors and countries; maps the conceptual structure of the field through thematic mapping and keyword networks; and uses these results to propose a research agenda for researchers, practitioners and policy-makers. The specific objectives are set out in Section III.

The search was run on the Scopus database on 16 September 2026, using the Boolean search string risk management AND investment AND optimization. Scopus was chosen over Web of Science, Google Scholar and PubMed because it provides comprehensive, single-subscription access to content from many specialized databases across disciplines. This makes its records consistent and well suited to bibliometric analysis (Pranckutė, 2021).

Data collection and screening followed the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) framework (Moher et al., 2010). PRISMA sets out transparently how records are identified, screened, checked for eligibility and finally included. The initial search returned 3,500 records, and several exclusion criteria were then applied. First, the timespan was limited to papers published from 2010 onward, since the most important developments in AI and advanced OR models for finance have come in the fifteen years since the 2008 crisis. Second, document types were limited to peer-reviewed articles and reviews, excluding book chapters, conference proceedings and editorials. Third, only English-language publications were kept. This removed more than 80 papers, most of them in Chinese, but allowed the keyword analysis to be carried out consistently. Finally, the source type was limited to academic journals.

These filters produced a dataset of 1,695 articles. The data were then cleaned in Microsoft Excel. Twenty-one records with “NA” or blank values in their keyword fields were removed, because they could not be placed in the thematic or network analyses. The final dataset contains 1,674 articles.

The bibliometric analysis was carried out in Biblioshiny, the web-based interface for the R package bibliometrix (Aria & Cuccurullo, 2017). VOSviewer (van Eck & Waltman, 2010), a tool for building and visualizing bibliometric networks, was used for network visualization and clustering. The analysis followed the four-step framework of Donthu et al. (2021): defining the aims and scope of the review, choosing the techniques (keyword co-occurrence, thematic mapping and trend analysis), collecting and cleaning the data from Scopus, and running the analysis and reporting the findings.

A first look at the dataset shows a dynamic, widely dispersed and collaborative field. The 1,674 articles were published in 794 different sources, from specialized mathematics journals to broad sustainability and economics outlets, and were written by 4,634 researchers. Output has grown at 14.08% a year.

II. LITERATURE REVIEW

Introduction:

Operations Research (OR) has emerged as a key methodology to financial risk management as financial decisions are rife with uncertainty, multiple and conflicting objectives, scarce resources as well as changing constraints. Portfolio selection, asset allocation, risk measurement, rebalancing, credit assessment, and investment planning can be all benefit from casting them 'into optimization and decision problems'. The reviewed literature contributes into the field, recently combines stochastic, robust optimization, and metaheuristics as well as fuzzy, machine learning, and artificial intelligence methods.

The VOSviewer keyword analysis visualizes the research landscape and collaboration structure between the authors in the field. The map consists of three major clusters highly related to each other. Words associated with the red cluster are investment, management, system, cost, operation, policy, uncertainty, and development: this cluster forms the main decision-making and operations part of financial risk management. The green cluster consists of return, portfolio, risk management, allocation, asset, volatility, portfolio optimization, financial market: it represents the financial risk management and portfolio optimization stream of research. The blue cluster includes such words as technology, artificial intelligence, machine learning, role, review, methodology: it is associated with an emerging stream of financial risk management research, which integrates computational intelligence methodologies into the OR-based decision-making process. The three clusters are densely connected each other, reflecting the ongoing trend to conceptualize financial risk management as an optimization problem, not just dealing with the measurement of financial risks.

Evolution of Portfolio Optimization and Risk Management:

One of the themes emphasized in the literature reviewed is the shift from traditional portfolio optimization towards more innovative approaches including consideration of such aspects as uncertainty, downside risk dynamics and dynamic markets. While the classical portfolio theory is regarded as a milestone acknowledging the trade-off between expected return and risk, the reviewed literature suggests that a growing number of researchers understand the need to implement more sophisticated uncertainty modelling.

Sharif et al. (2026) have developed the two-stage stochastic optimization approach to the portfolio selection. The novelty of the study is the introduction of the disruption scenarios such as economic sanctions, oil price fluctuation, political instability, and currency depreciation to measure the Conditional Value-at-Risk, the downside risk of the portfolio. In particular, the paper shows the solution that the portfolio optimization should be adjusted given the realized uncertainty that makes the solution useful that integrates the stochastic programming rather than the classic optimization.

The notion of downside risk is further developed in the works of Sheng et al. (2026) and Tian et al. (2026). The former used the semi-Tsallis entropy as the innovative approach to measure the uncertainty in the framework of their study. It explicitly accounts for downside risks and has an additional parameter for the deformation of the expected value. In turn, Tian et al. (2026) have designed the semi-quadratic entropy to measure the downside risk in the mean-variance model that emphasizes the significance of such an approach to the portfolio selection. The papers confirm the shift in the field to the consideration of downside rather than total volatility and present a broad range of new performance measures that have been proposed recently.

Neugebauer (2026) has suggested using the genetic algorithm approach to portfolio optimization in a robust stochastic dominance framework. The novelty of the paper is the integration of the portfolio constraints and the allowance for limited violations of stochastic dominance constraints. It allows the authors to combine the tools of robust optimization and genetic algorithms to solve the mathematical finance problem.

Dynamic Portfolio Management and Rebalancing:

Financial markets are dynamic systems where portfolio decisions cannot be considered as one-time optimizations. Thereby, the literature increasingly considers the dynamic allocation and rebalancing practices.

Bai et al. (2026) advance the field by testing the efficacy of target-volatility approaches and stating the optimal rebalancing thresholds in the presence of transaction costs. Notably, the article argues that it is essential to consider the costs associated with the frequent rebalancing within the optimization process in order to obtain the best possible results in terms of the portfolio risk.

In another article, Kim et al. (2026) attempt to allocate between Bitcoin and the traditional asset classes in a dynamic context of the evolving market environment. The work specifies that it is important to view Bitcoin through the prism of a switching regime and apply the concept to the changing behavior of the risk-return patterns. Similarly, Wattanasin et al. (2026) present a performance analysis comparing the classical Markowitz framework, static and dynamic risk parity, and the differing sets of risk-return paradigms in the changing market regimes. Collectively, these three articles demonstrate that the modern-day context is best addressed through the dynamic paradigms of portfolio optimization.

Lastly, Safari et al. (2026) present a two-step hybrid approach to portfolio selection, which combines the differing risk-return philosophies. In the article, the authors utilize the Data Envelopment Analysis to select the most suitable assets in the universe in the first stage and apply the alternative risk parity models (Conditional Value at Risk, and asymmetric downside risk measures) in the second step to obtain the best possible results. The paper concludes that the hybrid approach outperforms the individual optimizations in most cases.

Artificial Intelligence and Machine Learning in Financial OR:

The VOSviewer maps also indicate that there is a strong relationship between risk management and the financial applications of artificial intelligence (AI) including those of machine learning and deep reinforcement learning. Mahmoud and Surwanti (2026) remarked on the rapid ascent of the applications of AI in investment decision-making in the form of portfolio management, risk assessment, predictive analytics, and algorithmic trading. It is a shift from the operational research (OR) models which are predicated on the application

of predetermined assumptions to machine learning algorithms which can learn patterns from financial market data.

A notable application of machine learning is to predict risk relevant input variables which are needed in optimization models. Reis et al. (2026) proposed a deep learning architecture to forecast multi-asset portfolio covariance matrices for the medium-term horizon. The article used exchange-traded-fund data and a combination of convolutional neural networks, bidirectional long short-term memory networks, and multi-head attention. It is asserted that improved forecasts of covariance matrices improve portfolio decisions since the association between the returns of different assets is a determinant of portfolio risk.

Meanwhile, the extant literature also notes the application of machine learning models to make portfolio decisions including those relating to risk assessment. Kaur et al. (2026) integrated fuzzy least-squares support vector machines and conditional value at risk (CVaR) in a portfolio optimization framework. This is an example of a hybrid machine learning and OR model in finance where the former is used to determine the selection of securities while the latter specifies the model for portfolio risk.

The application of deep reinforcement learning in finance marks a step forward as it reflects a shift in emphasis from portfolio optimization to portfolio management as a whole. Zhu et al. (2026) developed a portfolio rebalancing model using a deep reinforcement learning algorithm and a multi-period Markov decision process. Huang and Jing (2026) applied reinforcement learning in the context of single-stock portfolio optimization. The article by Gao et al. (2026) proposed a deep reinforcement learning framework that separates the temporal patterns of stock prices and their interconnections. It is possible to conclude that deep reinforcement learning facilitates the shift from classical optimization to more holistic portfolio management decisions in finance.

Lastly, the survey highlights that the literature also provides evidence that advanced computational methods should not be considered as replacements for classical OR techniques. Sahu and Bhandari (2026) compared the efficacy of deep reinforcement learning and classical portfolio models in the varying degrees of market efficiency. Such studies emphasize the importance of understanding the limitations of each approach and the impact of dissimilar assumptions about the decision environment on the outcome of the analysis.

Metaheuristic and Hybrid Optimization Approaches:

The increased complexity of financial optimization problems has motivated interest in the use of meta heuristics algorithms. Indeed, Jaiswal et al. (2026) explore the use of meta heuristic and risk-averse optimization techniques to portfolio selection in the face of volatile markets. Chevallier (2026) uses a combination of clustering and Particle Swarm Optimization to deal with allocation portfolio issues and achieve diversification. Neugebauer (2026) implements a genetic algorithm in order to find a solution to a robust portfolio-optimization problem with a stochastic dominance.

Such methods are particularly pertinent in situations where the financial optimization includes several constraints such as portfolio cardinality, investment limits, nonlinear objectives, and multiple risk measures. Indeed, in such circumstances, it can be difficult to find an exact optimization due to the high degree of complexity as the number of assets and constraints increase. This is why one of the main benefits of meta-heuristics is that they can offer alternative computational approaches to find solutions to optimization problems.

The most recent literature seems to agree on the idea that hybridization is the way to proceed. Rather than using one model, practice has shown that the best results are obtained when combining forecasting models, machine learning, risk measures, and optimization algorithms.

For instance, Reis et al. (2026) integrated deep learning to improve covariance forecasts preceding portfolio allocation, while Kaur et al. (2026) employed a machine learning and CVaR approach. Overall, one can see that the literature has shifted towards a more general operations research paradigm in which predictive models provide information that is then processed by optimization models to make decisions.

Expansion Beyond Traditional Market Risk:

In addition, the financial risk management is also changing in the traditional equity-market portfolio risk area. Zhu and Shneor (2026) investigated the credit risk management in the area ofpeer to peer lending, therefore, the results of their study identified the default risk as an essential aspect in the area of finance platforms. As a result, the researchers of the mentioned article applied the systematic review method which shows the increased use of Operational Research and mathematical methods in the study of the alternative financial systems.

Papathanasiou and Koutsokostas (2026) analyzed the geopolitical risks and their influence on portfolio optimization and risk management, therefore, providing their results on the abovementioned areas. It can be noted that the scholars determined the influence of portfolio choices on portfolio optimization is being aligned with the approach of using the stochastic optimization method by Sharif et al. (2026). The authors underlined the importance of such factors as political instability, sanctions, and exchange rates which can be crucial in portfolio optimization and risk management.

It can be concluded that the area of financial risk management undergoes significant changes. Volatility, credit risk, liquidity, geopolitical instability, transaction costs, investors' preferences, and technological advancements, can be the multiple factors that should be taken into account. It can be noted that operations research is the appropriate approach to study the financial risk management in multiple areas including the use of multiple mathematical methods and algorithms.

Research Gaps:

Despite the aforementioned advances contained in this article, three gaps can be identified. First, many models are based on the use of historical data and assumptions which may not be applicable during the periods of regime changes which occur in the market. While the use of dynamic and regime aware methods partly address this issue, additional research is required to test and evaluate such models in different markets and settings.

Second, the increased use of AI powered optimization methods requires additional research into the explanation of such methods, as well as considerations of data demands and implementation specifics. In other words, a highly sophisticated algorithm which generates incredible results with little explanation of its inner workings will be of little use to practitioners who do not understand how exactly their financial decisions are being made. This problem can be addressed through additional research and collaboration between finance scholars and operations researchers. The former continue to embrace the explanatory power of traditional operations research, whereas the latter have recently become more interested in the use of AI in operations research. While the former is a growing field, offering incredible possibilities, the latter has much to contribute in terms of flexibility and precision.

Thirdly, the application of such models generates a series of issues, most of which stem from the ability of portfolio managers to operate within the constraints of their work. Bai et al. (2026) specifically mention the fact that their model is designed to explicitly account for the presence of transaction costs. However, in practice, portfolio managers have to consider a variety of constraints in their work, such as liquidity, tax, leverage, market impact, legal, regulatory and execution related constraints, among others. The explicit consideration of such constraints will allow researchers and practitioners to obtain more realistic results.

Finally, as mentioned above, the authors of this article suggest that there is potential for the field of operations research and the use of artificial intelligence to be integrated. Instead of concentrating on the differences between the two approaches, practitioners and scholars should collaborate to combine machine learning and traditional operations research techniques. As mentioned above, the integration of stochastic, robust, fuzzy, and multi-objective mathematical programming into portfolio optimization has the potential to reshape the way in which the problems of portfolio optimization are approached. The use of such AI inspired concepts in finance will enable the fields to benefit from the strengths of predictive analytics, as well as the strengths of traditional operations research and control.

Conclusion:

The reviewed literature proved that Operations Research has come a long way from the relatively static portfolio optimization to the more dynamic, uncertain, and technology-assisted financial risk-management systems. The clusters of the VOSviewer confirm this as they associate investment and management problems with portfolio optimization and management, risk, technology, and artificial intelligence. Stochastic programming, robust optimization, CVaR, entropy-based risk measures, metaheuristics, and machine learning, including reinforcement learning, have been developed to complement the existing methodologies in Financial Decision Engineering to confront the complexity of financial decision-making.

Operations research, therefore, seems pivoting around the operations research and artificial intelligence integration to model the financial decision-making process. In this respect, deep learning can enhance the accuracy of predictions and patterns. By contrast, operations research contributes objective functions, constraints, risk measures, and optimization algorithms to the financial decision-making process. The next research could be dedicated to incorporating such dynamic market regimes, transaction and liquidity costs, explainable AI, and various sources of financial uncertainty to embrace the multifaceted nature of finance. In this way, operations research will remain at the forefront of financial paradigms, being a science of decision-making under uncertainty.

III. RESEARCH OBJECTIVE

The broad aim of this study is to map how optimization techniques from operations research have been applied to financial risk management, and to use that map to show future researchers where the field most needs work. To get there, the study sets out the following objectives:

(1) To measure the growth in publications and citations on optimization techniques in financial risk management between 2010 and 2026.
(2) To identify the most productive and influential journals, authors and countries contributing to this field.
(3) To map the conceptual structure of the literature through thematic mapping and keyword co-occurrence analysis, and to separate its motor, niche, basic and emerging themes.
(4) To trace how the methods used in the field have changed over time, from classical mean-variance models towards stochastic, metaheuristic and machine learning based approaches.
(5) To identify gaps in the existing research and propose a future research agenda for researchers, practitioners and policy-makers.

IV. RESEARCH METHODOLOGY

Systematic Literature Review (SLR) is a structured technique to identify, and evaluate all existing studies on a specific research area (Paul & Rialp, 2020). This study talks about a number of techniques that have been developed to streamline and optimize Financial Risk Management.

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Article Selection, Inclusion And Exclusion Criteria

The database search was conducted on 16 September 2026 on Scopus, using search keywords appearing in the title, abstract, and keywords using PRISMA framework, which clearly indicates data collection as an iterative process, and also indicates systematic review to depend heavily on the scope and quality of included studies(Moher et al., 2010).

The flowchart for the PRISMA is given in Figure 1. The database search revealed publications from the year 1970, however the study excluded the articles before the year 2010. The reason being that the topic seems to have developed majorly in these last two decades. No filtering was done on the subject area. The search revealed the maximum results of 1,262 papers to be in the field of "Computer Science", followed by multidisciplinary topics like Engineering, Mathematics, "Business, Management and Accounting", "Economics, Econometrics, and Finance". There were some papers also published in the fields of "Nursing", "Immunology and Microbiology" as well, containing 1-5 reports each. After further filtering down all the filters as present in Figure 1, we held a total studies dataset of 1,695. It was found that over 80+ papers that were excluded were written in Chinese, which was the next largest dataset present in the language filter after English. Also, over 800 reports of the final dataset were Open access (OA) in Scopus which refers to peer-reviewed research articles and journals that are available online for anyone to read, download, and share for free, without subscription or paywall barriers.

The reason for using Scopus over Web-of-Science, was that Scopus content is accessible with a single subscription without possible modulations. Scopus also includes content from many specialized databases, such as Embase, Compendex, World Textile Index, Fluidex, Geobase, Biobase, and Medline, their content is integrated and equally accessible(Pranckutė, 2021).

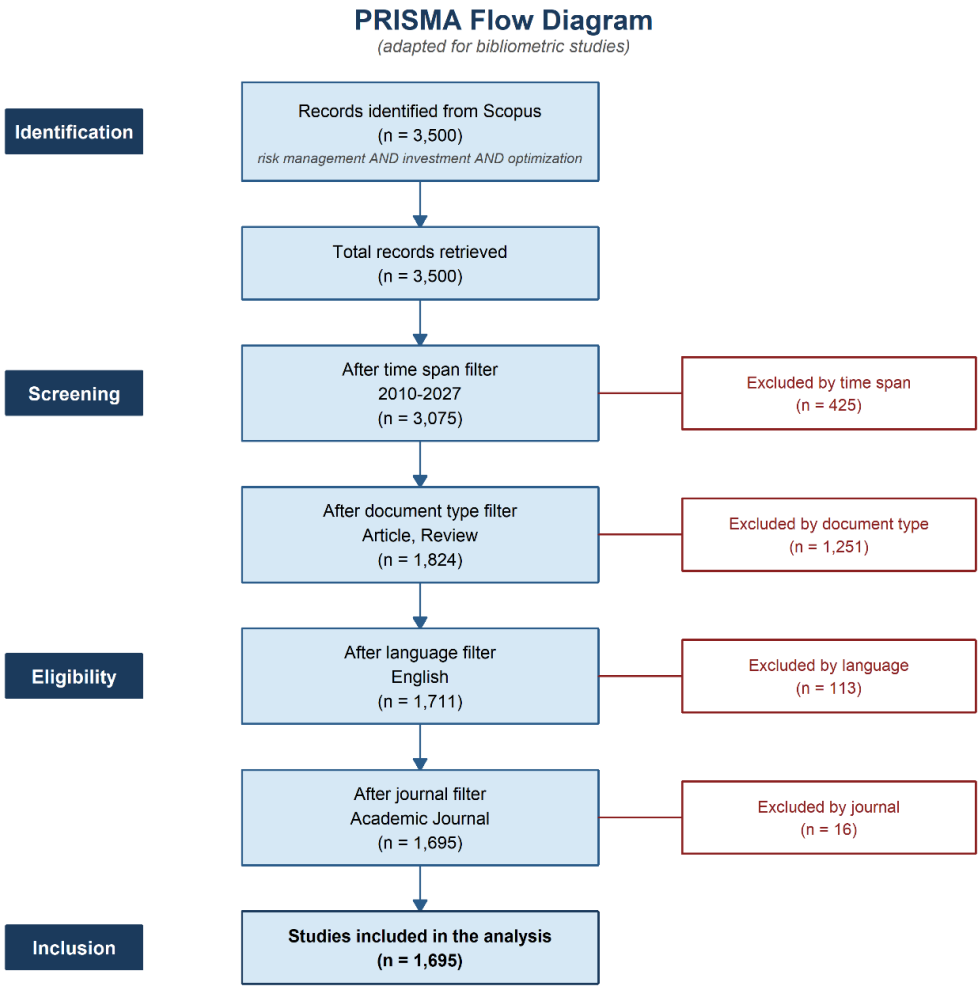


Figure 1 -PRISMA FLOWCHART (CREATED USING BIBLIOSHINY)

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Bibliometric Analysis

The reason for a bibliometric analysis is rather straightforward and simple. We use bibliometric analysis when the scope of review is broad, or when the dataset is too large for manual review, which our dataset clearly fulfills, creating a need for bibliometric analysis using quantitative methods over the use of manual review(Donthu et al., 2021).

Also, considering the proliferation of bibliometrics is fairly recent, as seen through its growth in the fields of "business, management, and accounting," "economics, econometrics, and finance," and "social sciences" on Scopus(Donthu et al., 2021), it creates absolute sense to make a bibliometric analysis using quantitative analysis methods on our data, since the topic chosen also directly correlates with the fields it is used for the most part.

Bibliometric analysis also helps researchers have a set of quantitative data backing to understand their own scope of research(Donthu et al., 2021). Including keywords, progression in number of paperspublished each year, major authors contributing to the topic, or even as to the major fields of work the topic can entail to. The value of a systematic review depends on rigorous methods and the clarity of reporting, as well as on the application of scientific strategies so that possible errors and biases are limited(Moher et al., 2010). Therefore, the fundamental idea of a systematic literature review is that the review is replicable, meaning that another researcher can actually reproduce the whole review process and arrive at the same set of evidence and the same conclusion. (Linnenluecke et al., 2020).

Moving on, (Donthu et al., 2021) suggest a four-step analysis, to successfully fulfill all criteria's of a bibliometric review. This is how this review has followed them:

Step 1 - Define the aims and scope of the bibliometric study

The aim as described above, is to facilitate future research agendas and researchers, with a quantitative analysis of our topic. 1,695 relevant research papers have been used, to conduct the same. Another major scope is to enable visualisations on the quantitative data for a better understanding of the research area.

Step 2 - Choose the techniques

Based on the study's aims, appropriate bibliometric techniques were selected. This entailed the following science-mapping techniques: keyword co-occurrence analysis, thematic mapping, and trend analysis. This study excluded methods used for studying how the database documents are linked to each other, for example co-citation analysis, co-authorship analysis, among many others. Re-iterating on the purpose of the study, we want to see the overall trajectory and direction of the field, which holds more importance than instilling paper linkage, which would turn to be not fruitful towards the scope of the study.

Step 3 - Collect the data

This is well explained earlier along with a PRISMA flowchart. We defined key search terms for the study's scope (risk management AND investment AND optimisation). Scopus was the only database that was used. The inclusion criteria consisted of the following elements: time span, field of study,document type, language, and source type. While we initially started with 3,500 papers, these filters brought us down to the 1,695 papers that were relevant to our scope of the study.

Step 4 - Run the analysis and report the findings

Here, the techniques chosen in step two come into play, i.e. using science-based mapping. Performance analysis and science mapping were conducted together as they go hand in hand (Donthu et al., 2021). The following has also been taken into account, that, the fact that researchers would often realise they need an extra set of data that is visualised (like graphs, charts, mapping's, etc), which would make them need to generate another set of results for the same (Donthu et al., 2021). This is proving to be redundant, urged this review to holdan extra effort in providing clear and pristine analysis to help facilitate future researchers and their agendas. It is the belief of this paper,that this would reduce the amount of time taken by researchers, and also create a smoother process for the same.

Lastly, these were the software's and/or resources that were used for the bibliometric analysis:

1. R Studio - This software enables users to access "Biblioshiny", which was used extensively throughout this analysis.
2. Biblioshiny - Biblioshiny is an free and open-source web-based graphical user interface for the Bibliometrix R package that lets you perform bibliometric and science mapping analysis without writing any code (Aria & Cuccurullo, 2017). Massimo Aria and Corrado Cuccurullo are the co-founders of the same. This played an integral role in making of this review.
3. Mendeley Desktop - This was used as our reference manager. We uploaded all our ".ris" files here for ease of managing, and citing. We also used the "Cite-O-Matic" plugin of Mendeley in MS Word, to efficiently cite our work as we went about the report.PDFs were brought in, citation details were pulled out automatically, and references and in-text citations were produced in the required format (e.g., APA).
4. Scopus - We accessed only the Scopus database by Elsevier, to find our relevant dataset used in this bibliometric review.

How the Keywords Were Collected

To support the research agenda in Section VI, the author keywords (DE) of the 1,674 articles in the final dataset were also harmonised by hand in five steps:

1. Keywords were changed to lower case.
2. Spelling variations were merged, for example, “artificial neural network” and “artificial neural networks”. After checking the source articles, the terms with different meanings remained separate. “Credit risk” means the chance of loan default, while “credit risk assessment” means rating and grouping of borrowers.
3. Counting the number of attention paid to each standardised keyword.
4. Keywords were compared across publication years to identify established topics and those that gained attention between 2022 and 2026.
5. Related keywords were grouped into bigger themes. The theme of Metaheuristic Optimisation includes particle swarm optimisation, genetic algorithm, and multi-objective optimisation.

VOSviewer and Bibliometrix do this automatically. Hand doing is slower and less consistent, but it lets us judge what a term means, which frequency tools cannot. The 2022-2026 cutoff is roughly where large language models and post-pandemic fintech growth came into their own. It's not a hard number and pushing it back a year will change some of the categorisations.

V. DISCUSSION AND IMPLICATIONS

Dataset Summary

Item	Current result
Records in cleaned dataset	1,674
Years	2010–2027
Rows removed during cleaning	21 cells with “NA”as keyword
Skipped publication years	None
Linear R^2	0.6349
Exponential R^2	0.826

The final dataset holds 1,674 articles. Four of them carry a 2027 publication year, most likely articles released online ahead of their journal issue, which is why the summary runs to 2027 while the annual series below ends in 2026. Before any analysis, the records were checked and cleaned in the steps described below.

5.1 Data Preparation

5.1.1 Data import

The BibTeX export from Scopus was loaded into Biblioshiny and then exported to Excel, where every field could be checked line by line.

5.1.2 Data-quality checks

Two checks were run. First, the author keyword (DE) and index keyword (KW) columns were filtered for blank or “NA” entries.

Second, the publication year column was checked for gaps. No year between 2010 and 2026 was missing, so the time series is continuous.

5.1.3 Data cleaning

The keyword check flagged 21 records with “NA” in place of keywords.

These records were removed. Keyword-based methods such as thematic mapping and co-occurrence analysis cannot place an article that has no keywords, and keeping them would have quietly thinned out the clusters.

Removing them is not a judgement on their relevance. The articles may well be on topic; they simply could not contribute to the keyword analyses that drive much of this section.

The cleaned file was then reloaded into Biblioshiny. Its completeness report rated every core field, from Abstract (AB) to DOI (DI), as “good” or better.

5.1.4 Analysis tools

Following the framework of Donthu et al. (2021), the analysis pairs performance analysis, which measures who publishes and who is cited, with science mapping, which shows how ideas in the field connect. The outputs used are grouped below.

Performance analysis

1. Annual Scientific Production
2. Average Article Citations per Year
3. Annual Total Citation per Year
4. Most Relevant Sources
5. Source Dynamics / Sources' Production Over Time
6. Most Relevant Authors
7. Most Global Cited Documents
8. Country Scientific Production
9. Most Cited Countries
10. Country Production Over Time

Word / conceptual analysis

11. Most Relevant Words / Most Frequent Words
12. Words' Frequency Over Time
13. Word Dynamics

Scientific mapping

14. Thematic Map
15. Keyword Co-occurrence Network
16. Density Visualization

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5.1.5 Dataset Overview



Indicator	Latest Biblioshiny output
Timespan	2010–2026
Sources	794
Documents	1,674
Authors	4,634
Authors of single-authored documents	166
International co-authorship	28.62%
Co-authors per document	3.47
Author's Keywords (DE)	12,472
Document average age	4.53 years
Average citations per document	15.43
Annual Growth Rate	14.08%

The overview describes a field that is young, collaborative and growing fast. The 1,674 articles come from 4,634 authors across 794 sources. The average article has 3.47 co-authors, and solo work is rare: only 166 authors appear as sole authors. Close to three in ten articles (28.62%) involve co-authors from more than one country.

The literature is also recent. The average article is just 4.53 years old, and more than 60% of the dataset was published in 2022 or later. Across all articles, the average citation count is 15.43. With annual growth of 14.08%, output in this area roughly doubles every five years.

5.2 Performance Analysis

5.2.1 Annual Scientific Production

Table 1. Annual scientific production, 2010–2026.

Year	Articles
2010	39
2011	36
2012	32
2013	45
2014	51
2015	43
2016	36
2017	70
2018	63
2019	61
2020	82
2021	90
2022	120
2023	92
2024	177
2025	312
2026	321

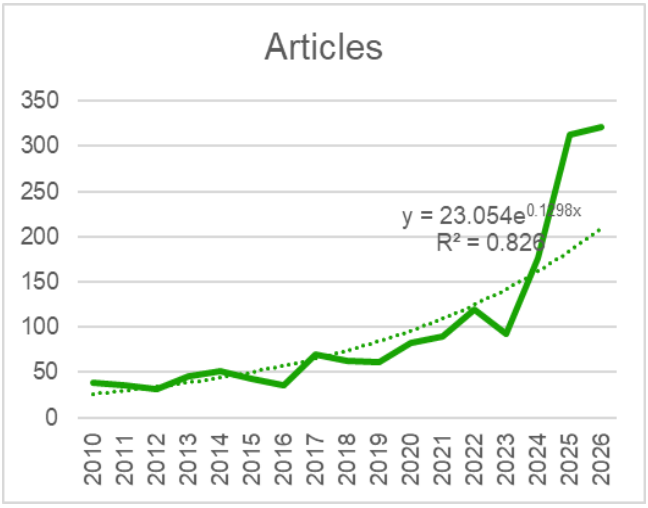


Figure 2. Annual scientific production.

Output has not grown in a straight line. From 2010 to 2016 the field was small and fairly flat, producing between 32 and 51 articles a year. A first step-change came in 2017, when output almost doubled to 70 articles, and it kept rising to 120 by 2022. After a dip to 92 in 2023, the series breaks sharply upward: 177 articles in 2024 and 312 in 2025. That is a 92% jump followed by a further 76%.

The 2026 figure needs care. The search was run on 16 September 2026, so it covers only about eight and a half months. Even so, the 321 articles already recorded exceed the full total for 2025. At the same pace, the year would close at around 450.

An exponential curve fits the series far better than a straight line (R^2 of 0.826 against 0.635). The fitted curve implies growth of roughly 14% a year, close to the 14.08% annual growth rate reported by Biblioshiny. Put simply, almost half of all articles in the dataset (48.5%) were published in the last three years alone.

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5.2.2 Average Article Citations per Year

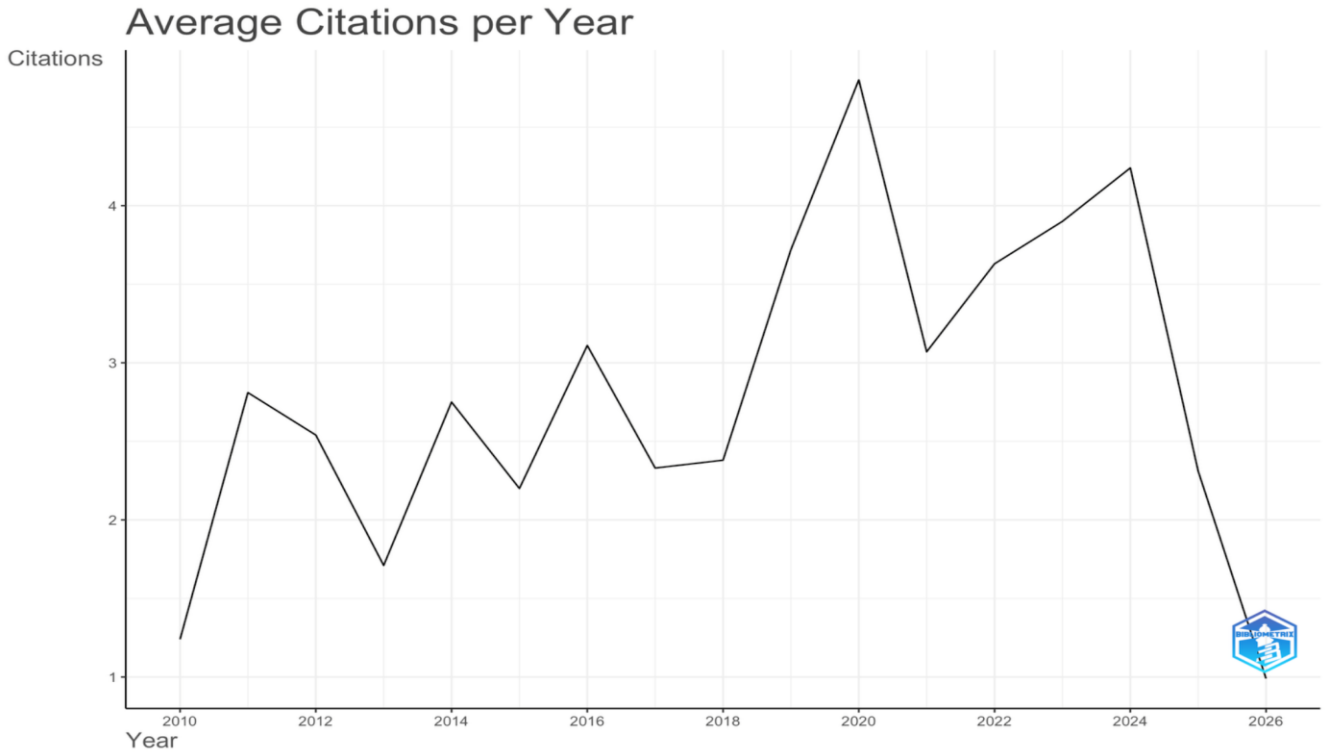


Figure 3. Average article citations per year.

Average citations per year adjust raw citation counts for how long an article has been in print. The measure peaks in 2020 at 4.8 citations a year and stays high for the 2022 to 2024 cohorts. The fall in 2025 and 2026 should not be read as a fall in quality. These articles have simply had very little time to be cited, and given how quickly the field is growing, their counts are likely to rise over the next few years.

5.2.3 Annual Citation Performance

Table 2. Annual citation indicators.

Year	Mean citations/article	Articles	Mean citations/year	Citable years
2010	21.13	39	1.24	17
2011	45.03	36	2.81	16
2012	38.03	32	2.54	15
2013	23.89	45	1.71	14
2014	35.73	51	2.75	13
2015	26.4	43	2.2	12
2016	34.19	36	3.11	10
2017	23.33	70	2.33	10
2018	21.4	63	2.38	9
2019	29.75	61	3.72	8
2020	33.63	82	4.8	7
2021	18.42	90	3.07	6
2022	18.17	120	3.63	5
2023	15.59	92	3.9	4
2024	12.72	177	4.24	3
2025	4.62	312	2.31	2
2026	0.99	321	0.99	1

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Table 2 separates two effects that are easy to confuse: how much each cohort has been cited, and how quickly. On total impact, older work leads. The 2011 cohort averages 45 citations per article, and the articles from 2010 to 2016, only 17% of the dataset, hold 35% of all citations.

On speed, the newer cohorts hold their own. Articles from 2024 are already gathering 4.24 citations a year, the second-highest rate in the series after 2020. Recent work is being picked up quickly, not ignored. The articles published from 2024 onward make up almost half of the dataset but hold only 16% of its citations so far. That gap is citation lag, and it should narrow as these papers age.

5.2.4 Most Relevant Sources

Table 3. Ten most productive sources.

Rank	Source	Documents
1	EUROPEAN JOURNAL OF OPERATIONAL RESEARCH	39
2	EXPERT SYSTEMS WITH APPLICATIONS	27
3	IEEE ACCESS	22
4	SUSTAINABILITY (SWITZERLAND)	22
5	ENERGIES	19
6	ANNALS OF OPERATIONS RESEARCH	18
7	APPLIED ENERGY	18
8	ENERGY ECONOMICS	17
9	MATHEMATICS	17
10	COMPUTERS AND INDUSTRIAL ENGINEERING	15

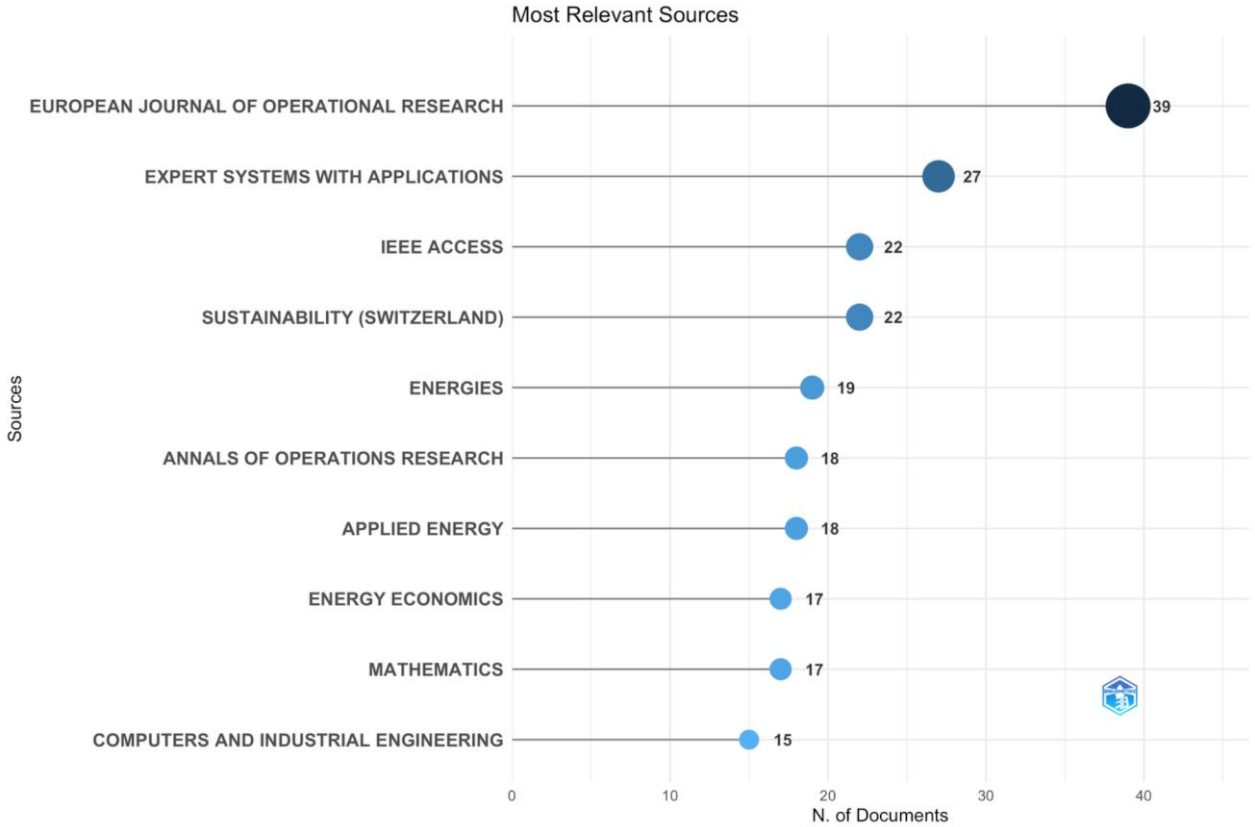


Figure 4. Most relevant sources.

The European Journal of Operational Research is the leading outlet with 39 articles, though its lead over Expert Systems with Applications (27) is modest. More telling is how thinly the literature is spread. The ten most productive sources account for only 214 articles, about 13% of the dataset, and the 794 sources average barely two articles each.

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The mix of journals matters as much as the counts. Energies, Applied Energy and Energy Economics together publish 54 articles, more than the leading journal on its own. Risk-aware optimization has clearly become a working tool in energy and sustainability research, not only in finance and operations research.

5.2.5 Sources' Production Over Time

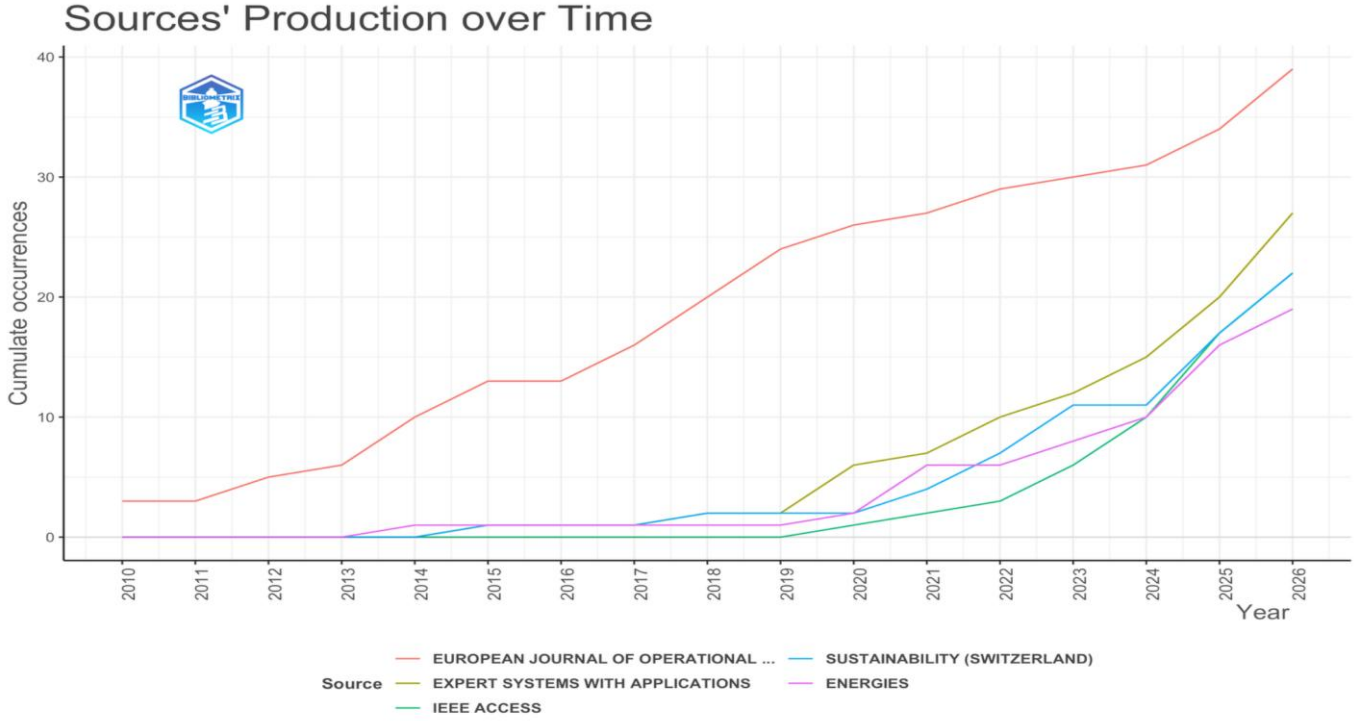


Figure 5. Sources' production over time.

The European Journal of Operational Research has published on the topic steadily throughout the period and has stayed in front. Expert Systems with Applications shows the sharpest change, accelerating after 2019. That timing mirrors the field's wider turn toward machine learning and intelligent systems. The remaining journals grow steadily from around 2013.

5.2.6 Most Relevant Authors

Table 4. Ten most relevant author records.

Rank	Author record	Documents
1	WANG Y	26
2	LIU J	22
3	LI Y	19
4	WANG X	17
5	WANG J	16
6	LI X	15
7	WANG Z	13
8	ZHANG Y	13
9	LI H	12
10	WANG H	12

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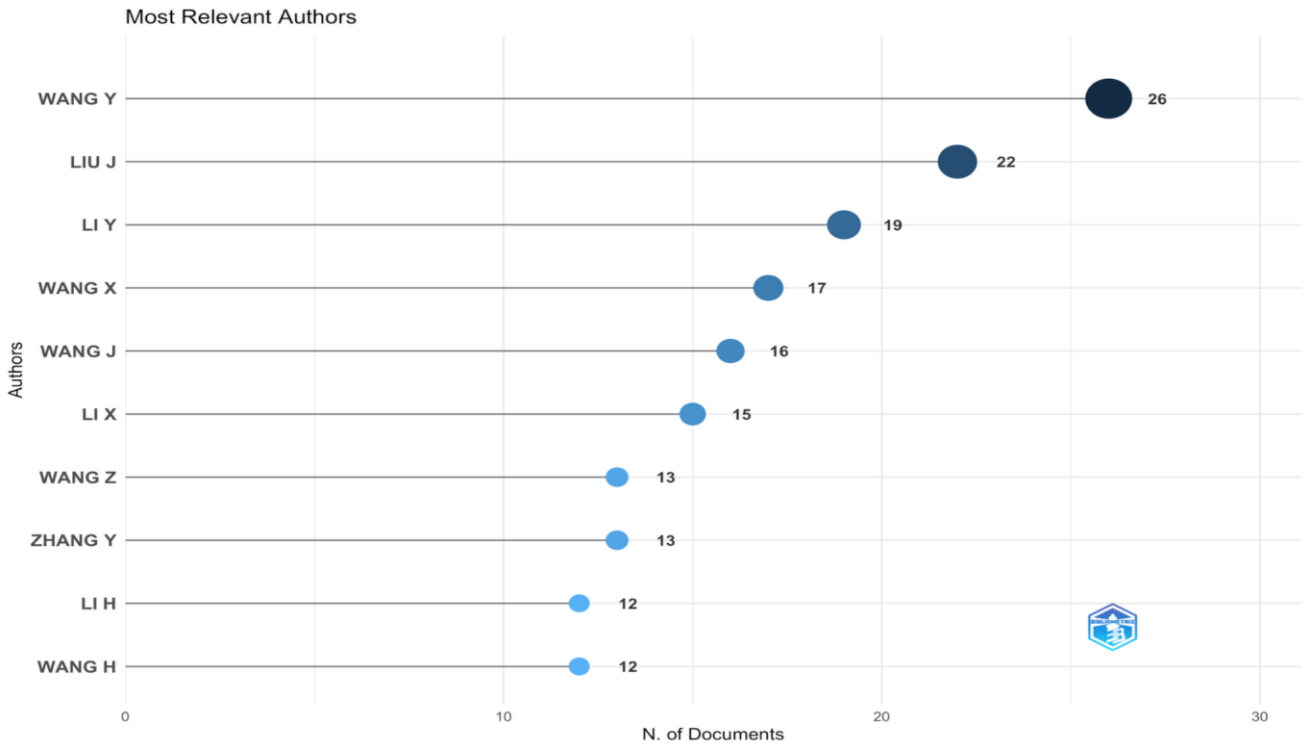


Figure 6. Most relevant authors.

Wang Y leads the author list with 26 documents, followed by Liu J with 22 and Li Y with 19. No single author dominates. Two caveats apply to this ranking. First, Biblioshiny identifies authors by surname and initials, so common names such as Wang Y or Li X may combine several different researchers. Second, every name in the top ten is Chinese, which matches the country results in section 5.2.8. The list is better read as a sign of China's research volume than as a ranking of individual leaders.

5.2.7 Most Globally Cited Documents

Table 5. Ten most globally cited documents.

Rank	Document	Global citations
1	KOLM PN, 2014, EUR J OPER RES	503
2	JACKSON I, 2024, INT J PROD RES	404
3	CHENG D, 2022, PATTERN RECOGN	402
4	GEBRESLASSIE BH, 2012, AICHE J	232
5	HUANG CF, 2012, APPL SOFT COMPUT J	229
6	ARNOLD U, 2015, RENEW ENERGY	212
7	HERMAN JD, 2014, WATER RESOUR RES	202
8	JABBARZADEH A, 2016, TRANSP RES PART B METHODOL	201
9	WANG W, 2020, EXPERT SYS APPL	198
10	DAL-MAS M, 2011, BIOMASS BIOENERGY	179

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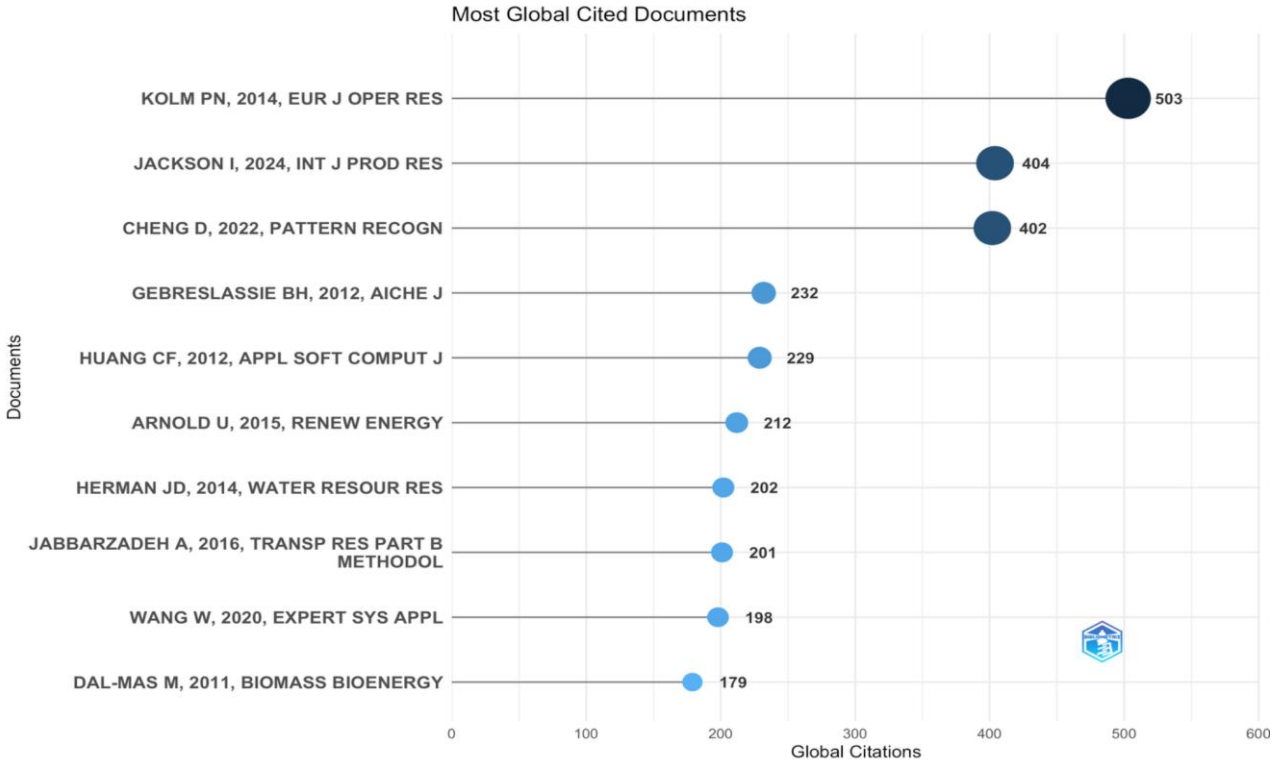


Figure 7. Most globally cited documents.

The most cited article is Kolm et al. (2014) in the European Journal of Operational Research, with 503 citations. It reviews sixty years of portfolio optimization and its practical challenges, and it serves as a common reference point for later work. The papers ranked second and third, published in 2024 and 2022, stand out for their speed: each passed 400 citations within a few years of appearing.

The list also shows how far this research travels. Alongside operations research and AI journals, it includes outlets in chemical engineering, renewable energy, water resources, transportation and bioenergy. Some of the field's most visible work applies risk-aware optimization to physical investment decisions, such as energy systems, water infrastructure and supply networks, rather than to financial portfolios alone. As always, citation counts measure visibility rather than quality, and older papers have had longer to collect them.

5.2.8 Country Analysis

Table 6. Ten most productive countries.

Rank	Country	Articles
1	CHINA	960
2	USA	488
3	INDIA	205
4	UK	172
5	IRAN	140
6	GERMANY	126
7	ITALY	114
8	UKRAINE	113
9	AUSTRALIA	105
10	CANADA	103

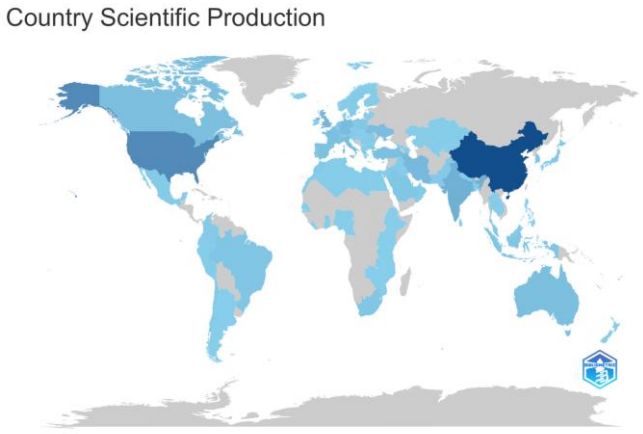


Figure 8. Country scientific production.

China leads scientific production by a wide margin, with 960 author appearances against 488 for the United States. India is third with 205, ahead of the United Kingdom, Iran and Germany. This measure counts the country of every author, so an article with several Chinese co-authors adds several times

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to China's total. Even allowing for that, the weight of Asian research in this field is unmistakable.

Table 7. Ten most cited countries.

Rank	Country	Citations
1	CHINA	5908
2	USA	4374
3	ITALY	1419
4	UNITED KINGDOM	1114
5	IRAN	970
6	GERMANY	917
7	CANADA	738
8	SPAIN	526
9	FRANCE	468
10	INDIA	447

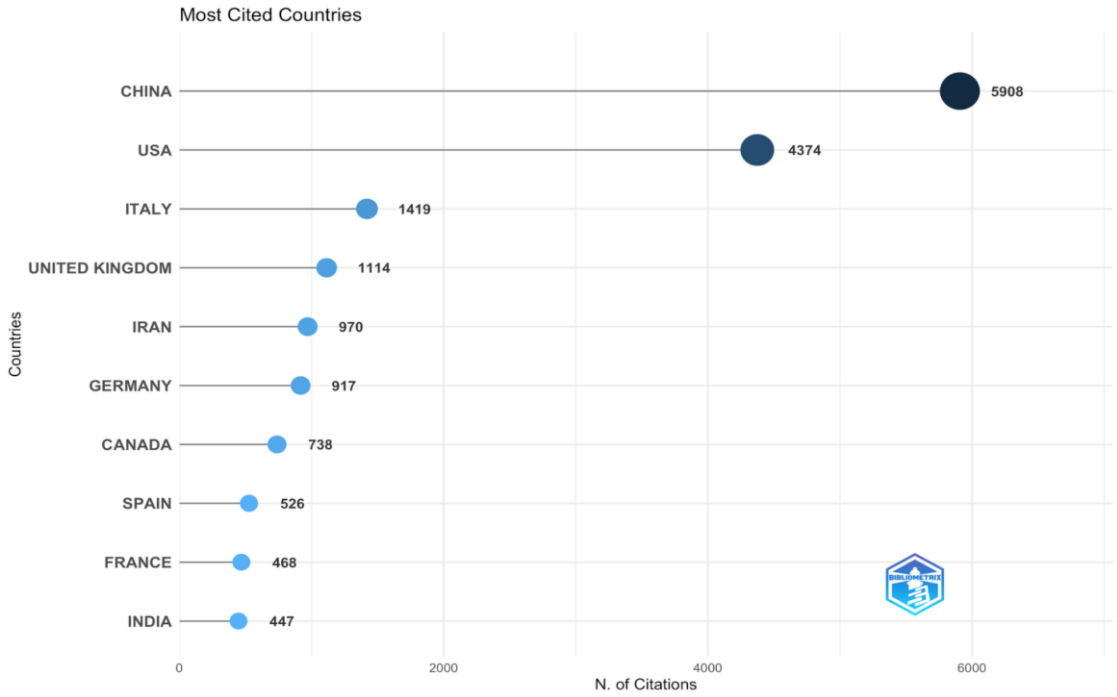


Figure 9. Most cited countries.

Production and citations measure different things. Production shows how much a country publishes, while citations show how much others draw on that work. The two do not move together. China leads on both, with 5,908 citations, but the United States collects 4,374 citations from a much smaller body of work. Italy is the clearest case of impact outrunning volume: it ranks seventh for production but third for citations.

5.2.9 Corresponding Authors' Countries and International Collaboration

Table 8. Corresponding authors' countries: single-country (SCP) and multiple-country (MCP) publications.

Rank	Country	Articles	SCP	MCP
1	CHINA	398	301	97
2	USA	148	121	27
3	IRAN	76	62	14
4	UNITED KINGDOM	58	32	26
5	INDIA	51	40	11
6	GERMANY	48	34	14
7	ITALY	48	33	15
8	CANADA	44	31	13
9	TURKEY	34	25	9
10	SPAIN	33	22	11

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MCP percentage: China 24.37%; USA 18.24%; Iran 18.42%; United Kingdom 44.83%; India 21.57%; Germany 29.17%; Italy 31.25%; Canada 29.55%; Turkey 26.47%; Spain 33.33%. Here each article is assigned to the country of its corresponding author. SCP counts articles written within a single country, and MCP counts articles involving co-authors from more than one.

The largest research systems turn out to be the most self-contained. China's 398 articles, almost a quarter of the whole dataset, are 76% single-country work. The United States is even more inward-looking, with only 18% of its articles involving a foreign co-author. The United Kingdom sits at the other end. Close to half of its output (44.83%) is internationally co-authored, the highest share in the top ten, and Italy and Spain also work with partners abroad on about a third of their articles.

5.2.10 Country Production Over Time

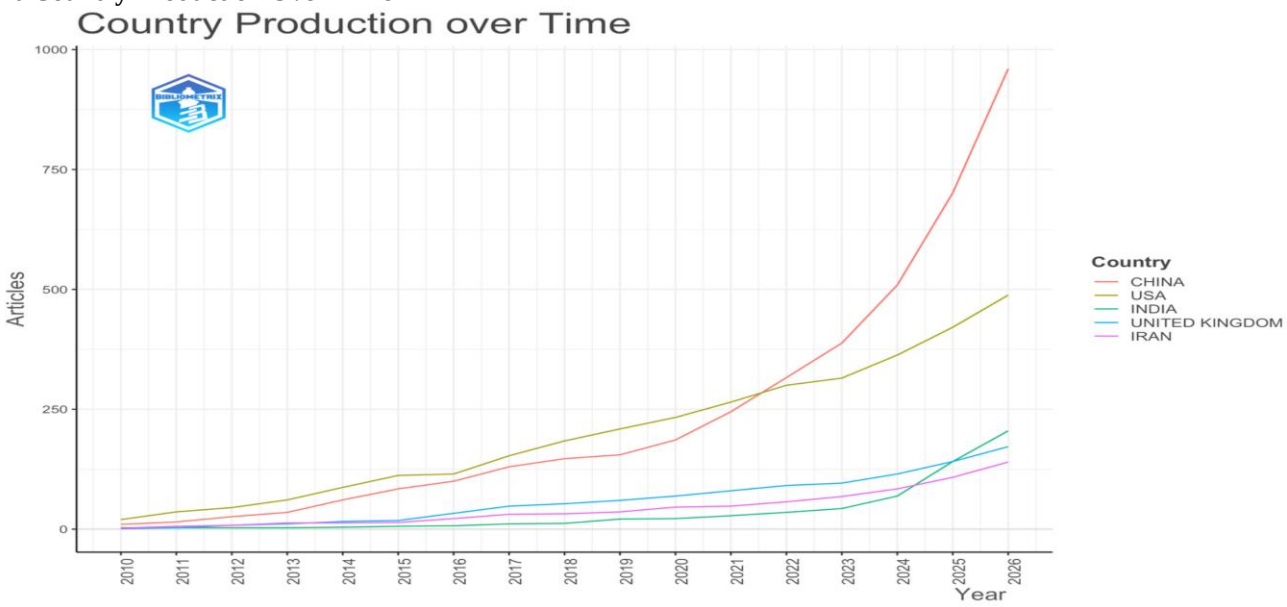


Figure 10. Country production over time.

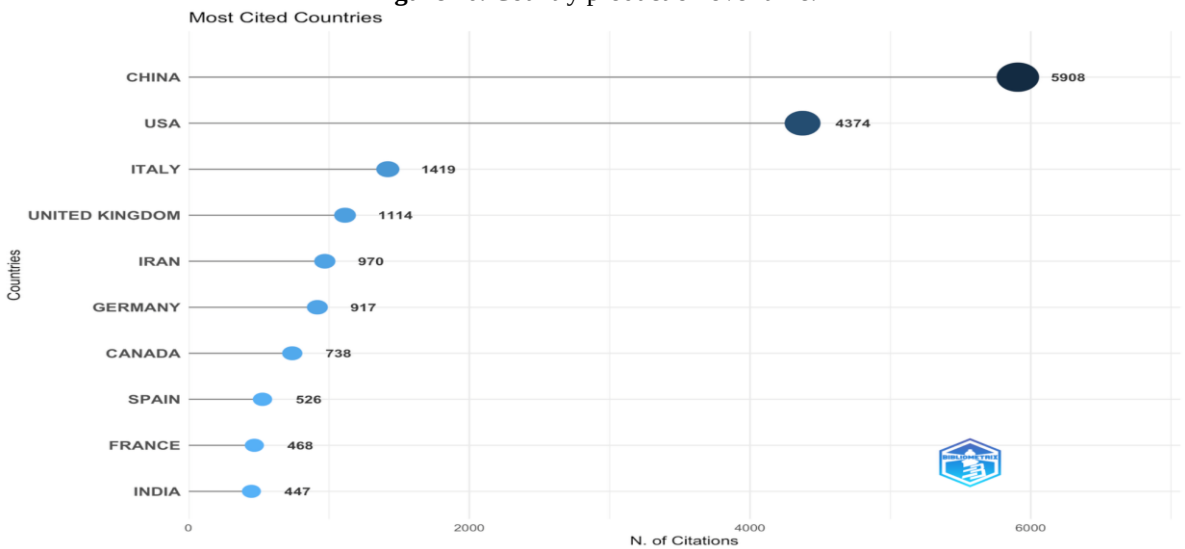


Figure 11. Country citation profile

Country synthesis

Dividing each country's citations by its corresponding-author articles gives a simple measure of citation efficiency (Table 9). On this measure, the ranking changes sharply. Italy and the United States lead with about 30 citations per article, twice China's 14.8. The United Kingdom and Germany follow at around 19. India produces the third-largest volume of work

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but averages 8.8 citations per article, the lowest of the countries compared.

Table 9. Citation efficiency: citations per corresponding-author article.

Rank	Country	Citations	Articles	Citations per article
1	ITALY	1419	48	29.56
2	USA	4374	148	29.55
3	UNITED KINGDOM	1114	58	19.21
4	GERMANY	917	48	19.10
5	CANADA	738	44	16.77
6	SPAIN	526	33	15.94
7	CHINA	5908	398	14.84
8	IRAN	970	76	12.76
9	INDIA	447	51	8.76

France, ninth on total citations, is left out because its corresponding-author article count falls outside the top ten. Two points follow from the table. Volume and visibility are not the same thing, and the most prolific countries are not the most influential per article. For India in particular, the gap is an opportunity. More international co-authorship and publication in higher-visibility outlets could widen the reach of a research base that is already large.

5.2.11 Most Frequent Keywords

Table 10. Ten most frequent words.

Rank	Word	Occurrences
1	investments	786
2	risk management	527
3	optimization	424
4	risk assessment	368
5	portfolio optimization	267
6	decision making	243
7	financial markets	209
8	financial data processing	177
9	commerce	172
10	investment	160

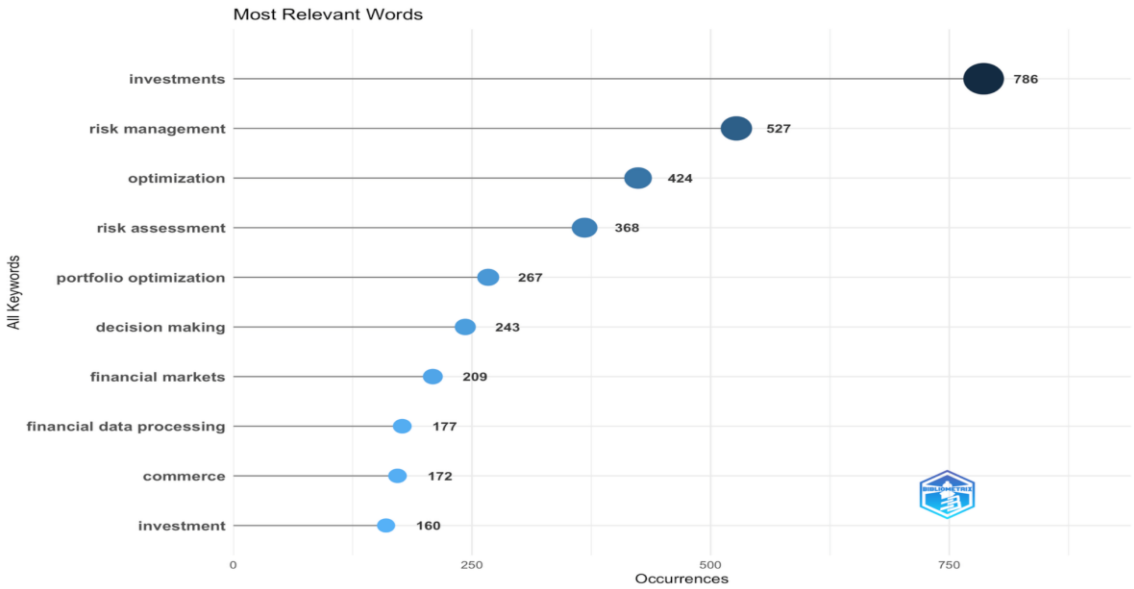


Figure 12. Most relevant words.

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Investments is the most frequent keyword by a clear margin, with 786 occurrences, followed by risk management (527) and optimization (424). The singular form, investment, is counted separately another 160 times, so the true lead of the concept is larger still. Together, the top terms describe the field in miniature: investment decisions, framed as optimization problems, made under risk. Terms such as financial data processing and commerce are database index terms rather than author choices, but they show how strongly the work leans toward data-driven, market-facing applications.

5.2.12 Words' Frequency Over Time

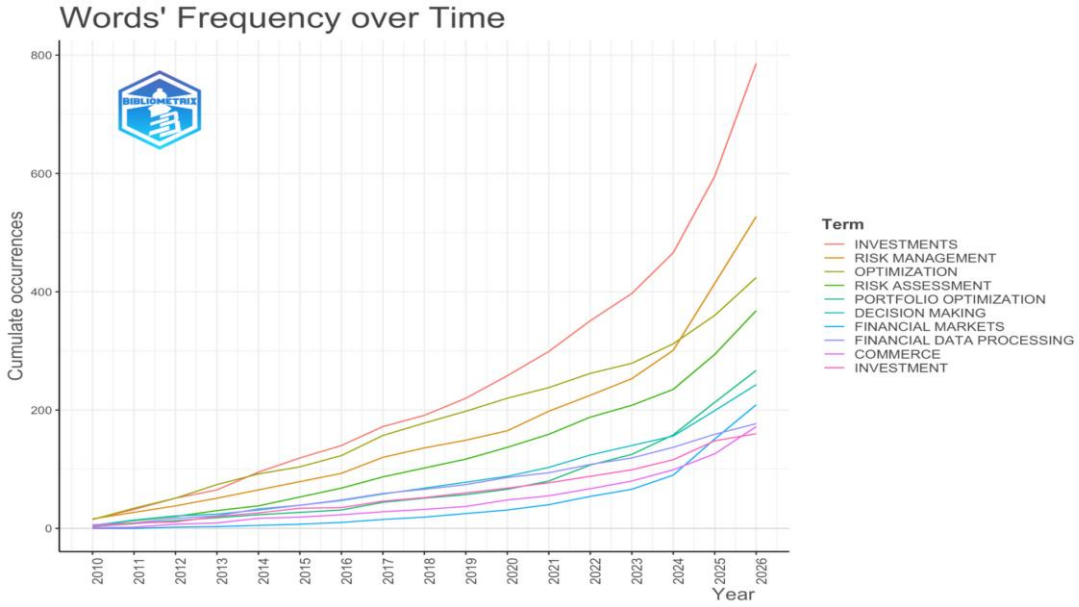


Figure 13. Words' frequency over time.

Investments has stayed the most frequent term throughout and has climbed steeply in recent years. The more interesting movement is further down. Risk management, third for most of the period, overtook optimization in 2024. This suggests the field's centre of gravity is shifting. Earlier work treated optimization as the object of study; more recent work treats risk management as the goal and optimization as one of several tools for reaching it.

5.2.13 Thematic Map

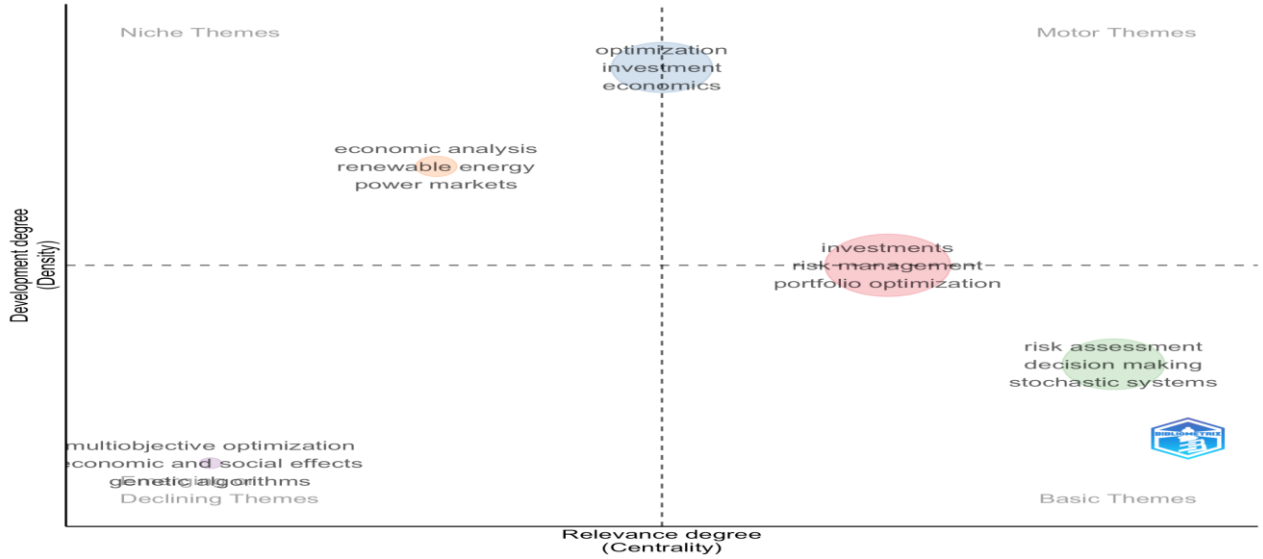


Figure 14. Thematic map based on centrality and density.

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The thematic map places each keyword cluster by centrality, meaning its relevance to the wider field, and density, meaning how far it has been developed internally. Motor themes sit top right and are both central and well developed. Niche themes sit top left: well developed but peripheral. Basic themes sit bottom right: central but less developed. The bottom-left quadrant holds themes that are either emerging or declining.

Optimization, investment and economics form the motor of the field. They are the themes the rest of the literature builds on and keeps returning to.

Investments, risk management and portfolio optimization fall in the basic quadrant, alongside a second cluster of risk assessment, decision making and stochastic systems. Their position is easy to misread. These are not exhausted topics. They are foundations: used across the whole field, but usually taken as given rather than developed for their own sake.

The niche quadrant holds economic analysis, renewable energy and power markets. This is a specialised and mature line of work, consistent with the strong showing of energy journals in section 5.2.4.

The bottom-left quadrant contains multiobjective optimization, economic and social effects, and genetic algorithms. Read alongside the literature review, which records rapid recent growth in multi-objective and metaheuristic methods, these are best understood as emerging rather than declining themes.

5.2.14 Keyword Co-occurrence Network

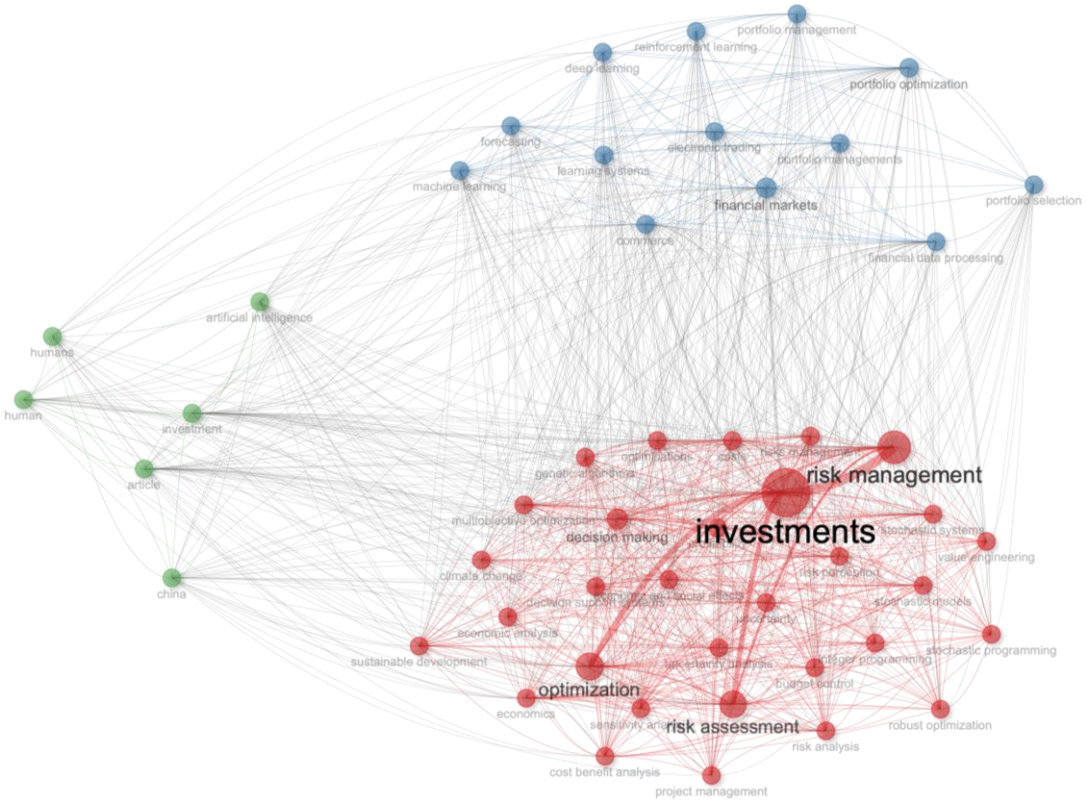


Figure 15. Keyword co-occurrence network.

The co-occurrence network links keywords that appear in the same articles. Node size reflects frequency, and the thickness of a link reflects how often two terms appear together. Investments, risk management and optimization are the largest and best-connected nodes.

The network also separates into two main communities. One centres on investment decisions under uncertainty, with terms such as risk assessment, decision making, stochastic models, multiobjective optimization and sustainable development. The other centres on financial markets, with portfolio optimization, forecasting, machine learning, deep learning and reinforcement learning. The two communities meet mainly through a few hub terms, optimization above all. That thin bridge between classical operations research and machine learning is the gap section VI returns to.

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5.2.15Density Visualization

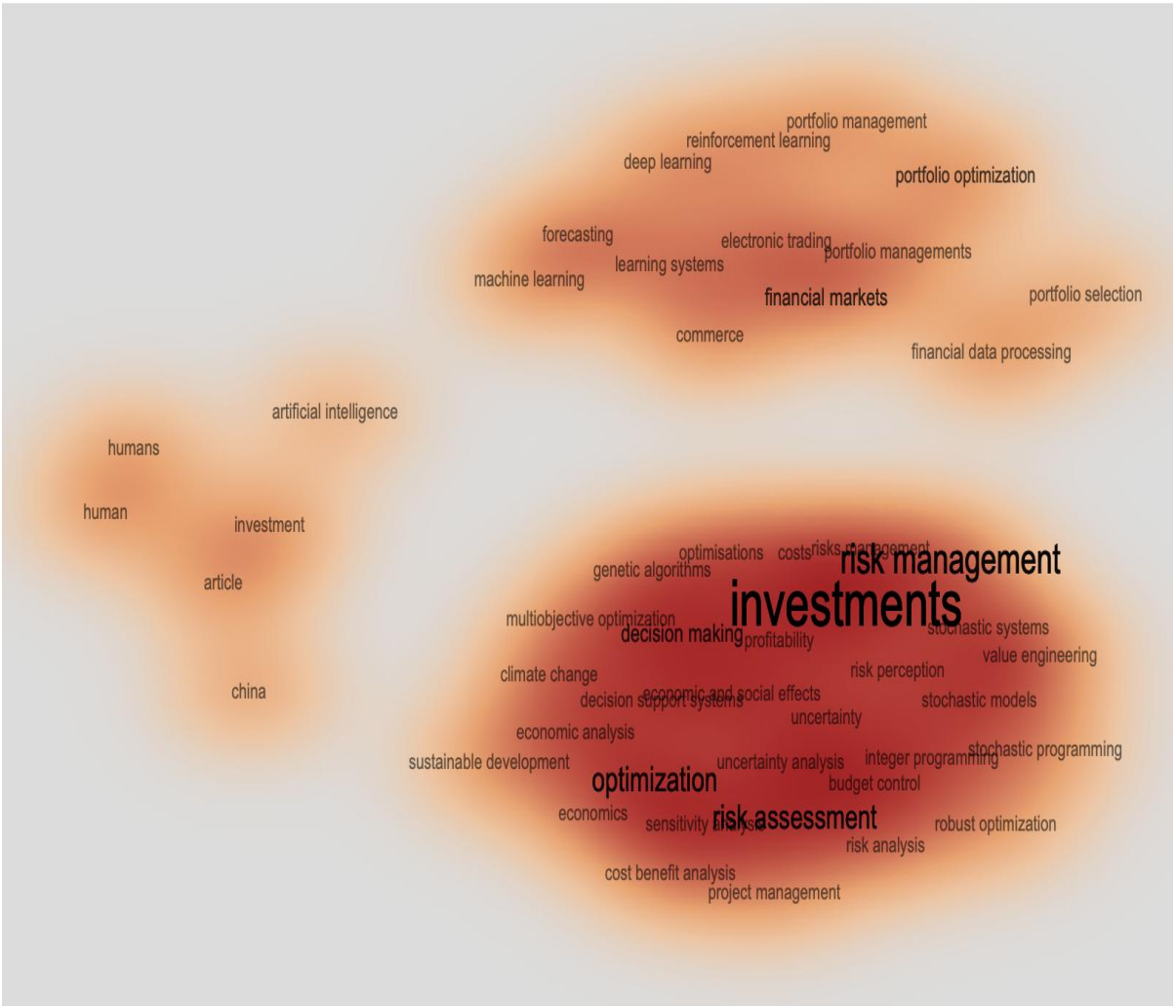


Figure 16. Density map

The density map tells the same story from another angle. The hottest zone sits around investments and risk management, the core of the field. A second, cooler zone forms around financial markets, machine learning and portfolio selection, and a small separate island holds general terms such as artificial intelligence. The space between the zones is the interesting part. It marks where computational finance and classical risk optimization have yet to fully meet.

5.3 Integrated Interpretation

Taken together, the results describe a field in rapid expansion. Output has grown at about 14% a year, and almost half of all articles appeared in the last three years. The pace accelerated sharply from 2024, in step with the wider adoption of machine learning in finance.

The field is also unusually dispersed. Its 1,674 articles are spread across 794 journals in operations research, artificial intelligence, energy and sustainability, and no single outlet holds even 3% of the total. Geographically, China leads on volume, while the United States and Italy lead on impact per article. India is already a major producer, but its work is not yet cited in proportion to its size.

Conceptually, the literature is held together by investment, risk and optimization, yet it is dividing into two communities. One is a classical community focused on decisions under uncertainty; the other is a computational community focused on markets and learning. The links between them are still thin. That gap, together with the rise of multiobjective and evolutionary methods, shapes the research agenda set out in the next section.

VI. FUTURE RESEARCH AGENDA

6.1 From Findings to Future Direction

The agenda builds on the bibliometric results in Section V, which cover 1,674 Scopus articles published between 2010 and 2026 on the use of Operations Research (OR) methods to

manage financial risk. The methods discussed include optimisation, data envelopment analysis (DEA), multi-criteria decision-making (MCDM), machine learning (ML) and simulation. The field is growing fast and is no longer a minor corner of OR: annual output rose from 39 articles in 2010 to 321 in 2026.

Not all topics benefit equally from fast growth. Older topics go deeper, while newer ones remain thin. Investment and portfolio problems came first, because returns and risk are easy to measure and the mean-variance tradition gave OR researchers a ready starting point. Newer problems, such as risk in decentralised finance and regulators' demand for models that people can understand, have had less time to develop. The gaps below draw on the same keyword evidence as Section V, so they reflect patterns in the data rather than general opinion.

6.2 Key Terminology

Term	**Meaning in this review**
Operations Research (OR)	Mathematical methods for making decisions, such as optimisation and simulation
Data Envelopment Analysis (DEA)	Measures how efficiently units turn inputs into outputs
MCDM	Multi-criteria decision-making: ranking options against several criteria at once
Explainable AI (XAI)	Tools that show people why an AI model made a decision
Hybrid OR-AI model	A model that joins OR techniques with machine learning
Metaheuristic Optimization	Search methods, such as particle swarm and genetic algorithm, for problems too complex to solve exactly
Financial distress prediction	Forecasting whether a firm will run into financial trouble or go bankrupt
Supply chain finance	Financing between buyers, suppliers and lenders along a supply chain
Decentralised finance (DeFi)	Financial services that run on blockchains and smart contracts, with no central party
Systemic risk	The risk that one failure spreads and threatens the wider financial system

6.3 What the Data Shows

The keyword evidence in Section V points to three layers. The core is dominated by investments (786 occurrences), risk management (527), optimization (424), risk assessment (368) and portfolio optimization (267). Together they show a field centred on investment and portfolio decisions under risk. A second layer contains the basic and niche themes of the thematic map, such as decision making, stochastic systems, renewable energy and power markets. These are established but more specialised. The third layer holds the emerging themes: multiobjective optimization, genetic algorithms and economic and social effects, along with the machine learning, deep learning and reinforcement learning terms that make up the newer computational community in the co-occurrence network. These are the youngest parts of the field and offer the clearest avenues for future work.

Three gaps follow from these patterns.

Gap 1: Models are difficult to interpret. Numerous research works utilize multiple ML or deep learning models and evaluate them mainly through their accuracy. However, lenders have to explain the reasons of loan denial, while the bank must give the justification of why a borrower is categorized as risky. A precise model becomes useless if it cannot be understood by those who use it.

Gap 2: There is no combination of methods. DEA and MCDM are usually conducted in the sphere of operations and engineering, while ML has its research only in computer science, which implies their small convergence. Meanwhile, DEA estimates efficiency with known inputs and outputs, as opposed to ML that reveals the most important inputs. One interesting pipeline would be involving ML in risk factor selection through the use of DEA and MCDM. However, only few studies researched it.

Gap 3: Some domains are neglected. Most studies address investment and portfolio risk, followed by credit, market and energy applications. Supply chain finance, fintech-specific risk and systemic or macro-financial risk receive far less attention, even though they matter more each year. Data for these areas are less organised than market or credit data, so researchers often have to collect their own.

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6.4 Proposed Future Research Framework

Table 11. Possible research topics, set out as input, process and output

Input	Process	Output / Possible Research Topic
Gender differences in financial behaviour	Explainable AI + ML	Gender fairness in AI-based credit risk prediction
Country-specific economic indicators	Hybrid OR-AI model	Comparing financial risk prediction across countries
Fintech transaction data	Optimisation + ML	Managing risk on digital financial platforms
Blockchain and crypto-asset indicators	Simulation + optimisation	Modelling systemic risk in decentralised finance
Behavioural and financial variables	DEA + ML	Finding the factors that drive financial resilience
Supply chain financial data	Network optimisation	Managing counterparty risk in supply chain finance

Each of the three research areas below answers one gap.

Area 1: Explainable and trustworthy risk models. Future research should pair accurate models such as deep learning with tools that explain their decisions, so the models can be checked as well as trusted.

Financial institutions need this because they must follow regulations and justify their decisions. Researchers could also build models that are interpretable from the start, instead of explaining them after the fact.

Area 2: Hybrid OR-AI frameworks. Future studies should combine DEA, MCDM and optimisation with machine learning. Some studies already pair ML with one OR method. Few ask how the methods perform together, especially when a bank has to process very large numbers of transactions.

Area 3: Expansion to emerging financial domains. Future research should move beyond investment and credit risk to supply chain finance, fintech and blockchain risk, using simulation and optimisation. In crypto and decentralised finance, simulation can show how risk spreads and how digital assets fail. These systems have no central party, and smart contracts can sell assets automatically, so they behave differently from traditional markets. DEA could also compare how institutions or market segments cope with such shocks.

Research Questions

Area 1: Explainable and trustworthy models

- **RQ1:** Can deep learning risk models be paired with XAI tools without losing predictive accuracy?
- **RQ2:** Can models that are interpretable by design predict default and bankruptcy as well as black-box models?
- **RQ3:** Do AI-based credit models treat men and women fairly, and can XAI help find and reduce bias?

Area 2: Hybrid OR-AI frameworks

- **RQ4:** Does using ML to pick risk factors and DEA or MCDM to decide give better decisions than either method alone?
- **RQ5:** How can hybrid OR-AI models stay efficient on large transaction volumes?
- **RQ6:** How do country-specific economic indicators affect how well hybrid models predict risk across countries?

Area 3: Emerging financial domains

- **RQ7:** How can network optimisation help manage counterparty risk in supply chain finance?
- **RQ8:** How can simulation model the spread of risk and asset failure in decentralised finance?
- **RQ9:** Can DEA compare how well financial institutions or market segments withstand digitalasset shocks?

6.5 Concluding Remark

Operations research is now firmly established in financial risk management, especially in investment and portfolio decisions. Adding more models of the same kind will not move the field forward. Progress will come from models that are easier to understand, from closer collaboration between operations research and artificial intelligence, and from applying these methods to newer areas such as fintech and supply chain finance. This does not mean earlier work should be set aside. Existing portfolio and risk models are mature and effective. They now need to be made more transparent, linked with other methods and extended to new types of financial risk, so that regulators, researchers and institutions can use them with confidence.

VII. CONCLUSION AND LIMITATIONS

This study set out to map the research landscape at the intersection of operations research and financial risk management. Using a PRISMA-guided search of Scopus and a bibliometric analysis in Biblioshiny and VOSviewer, it examined 1,674 peer-reviewed articles published between 2010 and 2026. The results give a clear, consolidated picture of how the field has developed over the past fifteen years: who contributes to it, where it is published, and which themes drive it.

The field is growing quickly. Output has risen at 14.08% a year, and almost half of all articles appeared between 2024 and 2026. Growth was steady until 2022 and then accelerated sharply from 2024. This acceleration coincides with the wider adoption of artificial intelligence and machine learning in financial decision-making. Applied work reflects the same

shift, for example AI-powered predictive analytics frameworks for financial risk (Hossan et al., 2025).

The field is also collaborative and geographically concentrated. China leads clearly on both output, with 960 author appearances, and total citations, with 5,908. The United States follows, and India has emerged as the third-largest producer with 205 author appearances. Impact per article tells a different story, with the United States and Italy well ahead of the largest producers. The publication base is highly interdisciplinary. The European Journal of Operational Research is the leading journal, but the rest of the literature is spread across computer science, engineering, energy and applied mathematics outlets. Financial risk optimization is no longer only a finance or economics topic; it has become a cross-disciplinary computational problem. This matches earlier descriptions of the operations-finance interface as an emerging and interdisciplinary field (Wang et al., 2021).

The science mapping identifies the core vocabulary of the field. Investments, risk management and optimization are the central hubs of the keyword network. On the thematic map, optimization, investment and economics are the motor themes, both central and well developed. Risk assessment, portfolio optimization and decision making are basic themes: foundations that the whole field relies on, rather than exhausted topics. Multiobjective optimization, genetic algorithms and economic and social effects sit in the emerging quadrant and point to where the field is heading. Applied examples already exist, such as fuzzy portfolio models built on coherent risk measures (Yoshida, 2020) and multi-objective swarm optimization with CVaR for bond ETF allocation (Tang et al., 2026).

The literature review points to a clear methodological shift. Researchers are moving from static, Gaussian-based models toward dynamic approaches that use deep reinforcement learning, neural networks and robust stochastic programming to manage downside risk. Examples include deep reinforcement learning rebalancing models (Zhu et al., 2026) and machine learning combined with CVaR for portfolio construction (Kaur et al., 2026). Reviews in related areas describe a similar move from manual, qualitative practice toward data analytics (Cornwell et al., 2023). The shift is not one-directional, however. Sahu and Bhandari (2026) compared deep reinforcement learning with classical models across different levels of market efficiency, a reminder that newer methods do not simply replace older ones.

These findings carry implications for four groups.

First, for academic research, the study documents the shift from classical operations research toward AI-integrated methods in finance. It brings a fragmented, interdisciplinary literature together in a single thematic map, giving future researchers a baseline for studying how computational intelligence is merging with financial decision-making.

Second, for managers and practitioners, the results suggest that static risk models alone are no longer enough for fast, interconnected markets. A hybrid approach is more practical. Machine learning can forecast volatility and detect nonlinear patterns, and those forecasts can then feed into operations research models that make the final allocation decision. The literature already contains examples of this pipeline, such as deep learning forecasts of covariance matrices used ahead of portfolio allocation (Reis et al., 2026).

Third, for society more broadly, better risk optimization supports financial stability. Downside-focused models, such as those based on Conditional Value-at-Risk (CVaR) and semi-Tsallis entropy (Sharif et al., 2026; Sheng et al., 2026), can help institutions protect pension funds, retail savings and other long-term investments from severe market losses.

Finally, for regulators and policy-makers, the growing body of work linking optimization to geopolitical risk (Papathanasiou & Koutsokostas, 2026) and deep uncertainty suggests that oversight frameworks need to keep pace. Stochastic optimization has already been used to build reverse stress tests that identify the combination of risk factors that would push a bank to default (Montesi et al., 2020). Methods of this kind could inform stress-testing standards, capital buffers and model audits for banks, fintech lenders and peer-to-peer lending platforms (Zhu & Shneor, 2026).

The study also has limitations.

- **Time constraints:** The available time ruled out a full-text reading of all 1,674 articles. The analysis therefore relies on bibliographic metadata rather than a detailed review of each paper's methods.
- **Data coverage:** Only the Scopus database was used, so relevant work indexed only in Web of Science, Google Scholar or other databases is missing. The dataset is also limited to English-language publications. This excluded more than 80 papers written in Chinese and may understate China's contribution.
- **Technical depth:** As undergraduate management students, the authors could not evaluate the mathematical proofs, code and algorithm design in the more technical papers. The analysis focuses on overall trends and managerial implications rather than on auditing individual models.
- **Citation lag:** Articles published in 2025 and 2026 have had little time to be cited, so citation-based measures understate their eventual impact.

Despite these limitations, the study offers a consolidated, data-driven map of how operations research is being applied to financial risk management, and a clear starting point for the research agenda set out in Section VI.

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