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# Application of Operations Research in Financial Risk Management

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## ABSTRACT

***Financial risk management has moved from a specialist function to a core part of financial strategy, and operations research (OR) supplies much of its mathematical backbone through optimization, probability modelling, simulation and algorithmic decision support. Existing reviews, however, are organized around a single risk category or industry sector rather than around OR as a methodology, and most stop before the 2024–2026 surge in AI-integrated work. This paper reviews the literature linking OR and financial risk management and complements it with a bibliometric analysis of 260 Scopus documents (227 articles and 33 reviews) published between 2010 and 2026, retrieved with the search string "Risk Management AND Investments AND Analytics" and screened using the PRISMA framework. Performance analysis, keyword co-occurrence and a Callon centrality–density thematic map were produced using Biblioshiny, VOSviewer, Excel and Tableau. The results show a rapidly expanding field, with an annual growth rate of 24.66% and 65.8% of documents published in the last three years. Growth is led by technology rather than by finance-specific themes: machine learning and Industry 4.0 are the motor themes, technology vocabulary accounts for 59.2% of keyword occurrences on the map, and no finance-specific cluster occupies the motor quadrant. The scholarly landscape is also fragmented, with 190 of 218 sources publishing a single document and no author contributing more than three. The paper closes with a future research agenda that calls for structured comparisons of machine-learning models against Value-at-Risk and Conditional Value-at-Risk benchmarks, greater emphasis on explainable AI, sustained interdisciplinary research groups and renewed attention to the OR foundations of risk measurement.***

**Keywords:** *Operations Research, Financial Risk Management, Bibliometric Analysis, Value-at-Risk, Machine Learning, Thematic Mapping, Scopus*

## 1. INTRODUCTION

Non-bank financial institutions currently record non-performing asset ratios of six to eight per cent, almost double the three to four per cent seen at traditional banks (Mohan & Maniraj, 2026). The gap is stark. It suggests that a large amount of money is lost every year because dangers were seen coming but were not acted on fast enough. Every percentage point in that range represents value that was lost because a risk was foreseeable but not managed in time. This is why financial risk control has moved from a niche

function to a core part of financial strategy, and why the money that can be preserved by measuring and handling risk better is so large.

Recent studies of financial risk-warning programmes have examined data from many firms over five years. They show that machine learning can raise fraud-detection accuracy to about 96 per cent, cut default rates by twenty per cent and increase returns by twelve per cent. In one case, the system identified transactions worth nearly ten million US dollars in just six months, and it also reduced false alarms by fifteen per cent (Ma, 2025). The same data that exposes the problem also shows how much value is recovered when financial risks are monitored more carefully.

Continuous monitoring is what makes risk management a hard task. Banks and other large financial firms operate in an environment where market fluctuations, liquidity shortages, geopolitical shocks and credit problems occur at the same time, which makes them impossible to predict perfectly. A small error in pricing a risk or a delayed warning can cause losses larger than the cost of the tools that could have prevented them. Institutions today have more data and more computing power than ever before, so the uncertainty they face is no longer a matter of missing information. The real goal is not to find a problem after it has occurred, but to build systems that measure uncertainty continuously, detect trouble before it arrives and present that information in a form that supports quick decisions. This is the background against which this paper works, and it motivates a closer look at how decision-support tools fit into financial risk management.

Operations research (OR) provides a suitable decision framework for this context. It was developed to structure problems with limited resources, many alternatives and complex outcome variables, which are the defining features of financial risk assessment. Financial risk management involves deciding what level of risk is acceptable and how capital should be allocated, and these are central questions in portfolio optimization, hedging and related activities. The optimization methods of OR can answer such questions in a way that is accurate, testable and reliable, which trial-and-error approaches cannot match. Optimization allows the best solution to be found for a difficult problem with several goals and constraints, which is essential when capital, risk and profitability must be weighed together. Linear, integer, mixed-integer and multi-objective optimization, together with robust, stochastic and risk-constrained optimization, have each shown advantages for particular tasks in financial risk management.

OR also draws on stochastic and probabilistic methods. These make it possible to model uncertainty in cash flows, asset price behaviour or default through a defined set of random variables, which a purely deterministic approach often ignores. Simulation models built on these methods can project the expected future of financial performance under many scenarios. Option valuation, a further pillar of OR, allows the pay-off and cost of options to be quantified, and such cost-benefit assessment is critical to the sustainability of organizations. Management decisions on portfolio optimization, hedging and similar practices can therefore be evidence-based as well as realistic. Finally, OR covers a wide range of techniques, from queueing theory and network optimization to dynamic programming. These have been applied to credit-scoring models, software systems and transaction-processing optimization, and to identifying the most suitable prioritized actions in a given risk-management setting. They also help risk managers move from descriptive analytics, which summarizes what has happened, to predictive analytics, which sits at the centre of decision-making. The analytical rigour of OR, which rests on mathematical methods and evidence-based decision aids, is widely used in the statistical side of financial risk management, although it is not yet a standard framework in that field. OR acts as the optimization engine of risk management, and the two are interdependent.

The motivation of this paper is to address the gap between the measurement of risk and the use of OR-based decision processes. In recent years, most research effort has gone into improving the predictive performance of machine learning and deep learning models that estimate the probability of default, fraud and other risks. A less developed aspect is how the outputs of these predictive models can be turned into optimal decisions under limited resources. This matters because risk evaluation on its own is not sufficient; it must form part of the decision-making process. The value that optimization methods can add is especially important in light of the statistics quoted above, and it can benefit financial institutions that cannot fully implement complex mathematical models because of limited resources.

A second motivation is the opportunity to connect a traditional discipline, OR, with relatively young fields such as data science and financial risk management. OR practitioners can add value in financial risk management, while financial risk management researchers can help test new approaches and verify their validity. A third motivation is the opportunity to promote sustainable finance, a key priority, since well-applied OR can help protect the financial system against cascading failures. In response, this paper analyses the existing literature on OR and financial risk management, identifies emerging trends and sets out future research directions.

## 2. LITERATURE REVIEW

Financial risk management draws heavily on tools originally developed within OR. This section defines the key terms used throughout, traces the conceptual link between OR and financial risk management, reviews existing bibliometric work in this space, outlines the thematic position of risk management in the field, sets out the resulting research gaps and states the research questions addressed by this study.

### 2.1 Key Definitions

**Table -1: Key definitions used in the study**

| Term | Definition | Source |
|---|---|---|
| Financial Risk Management | The set of institutional processes used to identify, evaluate and control an organization's exposure to potential monetary losses arising from market fluctuations, counterparty default or internal failures. | Acharya et al. (2021) |
| Value-at-Risk (VaR) | A widely used quantitative technique estimating the maximum expected loss on a financial position or portfolio over a defined time horizon at a given confidence level; treated as a central measure in financial risk management. | Sorwar & Barone-Adesi (2010); Gebizlioğlu et al. (2011) |
| Conditional Value-at-Risk (CVaR) | A coherent risk measure extending VaR by estimating the expected magnitude of loss in the tail of the distribution beyond the VaR threshold; increasingly favoured for capturing extreme-loss scenarios. | Luo (2020) |
| Credit Risk | The risk that a borrower or counterparty fails to meet contractual obligations; treated as a critical, heavily regulated component of bank capital adequacy. | Allen et al. (2015) |
| Financial Risk Assessment (FRA) | The process, internal to financial institutions, of evaluating a borrower's or company's creditworthiness ahead of a lending or investment decision. | Acharya et al. (2021) |

### 2.2 The Connection Between Operations Research and Financial Risk Management

OR supplies much of the mathematical backbone of financial risk management: optimization, probability modelling and algorithmic decision support turn the abstract goal of "managing risk" into something that can be computed, tested and compared. Value-at-Risk estimation illustrates this clearly. Sorwar & Barone-Adesi (2010) apply jump-GARCH processes to estimate VaR under volatility clustering, while Gebizlioğlu, Şenoğlu & Kantar (2011) compare VaR estimation methods for a two-parameter Weibull loss distribution, an approach drawn from actuarial theory rather than finance. Luo (2020) extends this to Conditional Value-at-Risk with a nonparametric kernel estimator for dependent data sequences, which is closer to how real financial time series behave.

On the credit side, Allen, Powell & Singh (2015) compare quantile regression, VaR and CVaR for estimating credit risk exposure, while Acharya et al. (2021) use an improved gradient boosting tree model to automate financial risk assessment, showing machine learning increasingly standing in for classical statistical techniques. Olson & Wu (2010) argue that the link is not incidental, applying OR tools such as optimization, decision trees and simulation directly to enterprise-level risk management. Together, this body of work positions OR not as a toolkit that finance borrows occasionally, but as the methodological foundation beneath nearly every major technique used to measure and manage financial risk today.

### 2.3 Prior Reviews and Bibliometric Studies

A search for existing review-type and bibliometric papers covering financial risk management, its sub-domains and related OR techniques turned up nine relevant studies (Table-2). Most are organized around a specific risk category or industry sector (banking, Islamic finance or enterprise risk) rather than around OR as a methodology. This leaves open exactly the gap that this study addresses.

**Table -2: Prior review and bibliometric studies**

| Author(s) & Year | Scope / Key Focus |
|---|---|
| Syed, Bawazir & McMillan (2021) | Broad financial risk domain; credit risk the most trending topic; corporate governance and financial innovation flagged as emerging themes. |
| Jadwani, Parkhi & Mitra (2024) | Restricted to operational risk in banks; climate, information security, geopolitical and compliance risks flagged as future themes. |
| Nguyen (2024) | Banking risk broadly; six conceptual domains identified; geographic shift of research output toward Asia. |
| Alghamati, Azam & Khatibi (2024) | Narrow focus on risk management within Islamic financial institutions only. |
| Spulbar & Cinciulescu (2025) | Global financial risk strategies with an emerging-economies focus; derivatives, insurance and reserve mechanisms. |
| Gupta, Mishra & Behera (2024) | Financial vulnerability construct spanning socioeconomics, finance and management. |
| Bedi, Malhotra & Sharma (2023) | Corporate risk management broadly; not finance-specific. |
| Aryati, Khomsiyah & Harahap (2023) | Enterprise risk management (ERM) treated as a distinct construct. |
| Veiga & Gomes (2022) | AI/ML techniques applied narrowly to portfolio optimization only, not OR broadly. |

### 2.4 Thematic Positioning of Risk Management in the Field

A thematic map built from the study's co-occurrence network (189 of 260 documents assigned to a cluster) shows where risk management sits relative to the rest of the field. The two motor themes, machine learning and Industry 4.0, concern methods and digital capability rather than finance specifically, while big data and artificial intelligence form the basic themes: broadly applied but without a tight shared vocabulary of their own. Risk management itself sits almost exactly on the centrality median. It is a

boundary theme that is central to the corpus (paired closely with data analytics) but has not developed into a dense, well-integrated cluster in the way the technology-led themes have.

Technology vocabulary (machine learning, AI, big data and Industry 4.0 combined) accounts for 59.2% of keyword occurrences on the map, against 23.6% for portfolio management and risk management together, and no finance-specific cluster occupies the motor quadrant. Risk management is therefore referenced throughout the literature but remains comparatively underdeveloped as a coherent research theme of its own, with the field's growth currently driven more by technology and analytics than by finance-specific concepts. The full cluster-by-cluster breakdown, including portfolio management, sustainability and the supply-chain-resilience themes, is presented in Section 4.4.

### 2.5 Current Research Gaps

Three gaps stand out. First, a disciplinary gap: existing bibliometric reviews are organized around a risk category or industry sector rather than around OR as a methodology, so no study has mapped what OR itself contributes to financial risk management (Jadwani, Parkhi & Mitra, 2024; Alghamati, Azam & Khatibi, 2024). Second, a timing gap: most reviews stop short of the 2024–2026 surge in AI-integrated financial risk work, a window that this study's dataset covers directly. Third, a scope gap: many reviews stay within one narrow slice of financial risk, such as operational risk or portfolio optimization, while a comprehensive treatment spanning OR applications, VaR estimation, portfolio optimization, credit risk assessment and enterprise risk modelling within one bibliometric frame is still missing.

A related methodological tension runs through the broader literature. Many quantitative risk models rely on simplifying assumptions about market behaviour, transaction costs and the stability of model parameters. These assumptions make the mathematics tractable but can limit how well the models hold up in real, messier financial markets. Addressing these gaps is a large part of the motivation for the present study.

### 2.6 Research Questions

The following research questions define the scope of this review and of the bibliometric analysis that follows it.

**RQ1:** What are the major applications, techniques and limitations of OR methods within financial risk management, and how can those limitations be addressed in future work?

**RQ2:** Who are the influential authors, institutions and research themes within the literature connecting OR and financial risk management?

**RQ3:** What are the emerging and currently underdeveloped research themes in OR applications for financial risk management, and what directions should future research explore?

## 3. RESEARCH METHODOLOGY

Many researchers have used Systematic Literature Review (SLR) techniques to understand trends in a research area. An SLR helps to build on prior knowledge and to synthesize previous outcomes in order to identify gaps for future research (Paul & Criado, 2020). This study uses one such technique to identify and analyse research trends in the application of OR to financial risk management in academic and business research.

### 3.1 Article Selection, Inclusion and Exclusion Criteria

The data for this study were obtained from Elsevier's Scopus database using a keyword search. This method allowed the authors to systematically extract a starting dataset and to define a relevant sample space for bibliometric analysis. The inclusion and exclusion of records were guided by the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) statement. PRISMA is a systematic process that helps researchers document their review procedure, the rationale behind it and the decisions made throughout (Page et al., 2021). It comprises four established steps (Identification, Screening, Eligibility and Inclusion), which together ensure efficiency and consistency in documenting the research methodology.

The search string used to extract data from Scopus was "Risk Management AND Investments AND Analytics". This search, conducted on 10 September 2026, returned 722 documents. In the Identification step of PRISMA, all 722 documents were included in the sample space.

A time-span filter was then applied. Although publications on the topic date back to 1999, the number of papers published in the earlier years was minimal. To ensure an adequate and relevant time span for analysis, records published between 2010 and 2027 were retained and papers published before 2010 were excluded. This filter excluded 8 papers, leaving 714 documents.

Next, document types other than articles and reviews were excluded, including conference papers, book chapters, conference reviews, books, editorials, notes, errata, retracted publications and short surveys. This restricted the sample space to peer-reviewed articles and reviews suited to bibliometric analysis. This filter excluded 441 papers, narrowing the sample space to 273 documents.

The retrieved papers had been published in a range of languages. To maintain consistency in the analysis, non-English papers were excluded and only English-language publications were retained, given their wider global readership. This removed 10 papers, leaving 263 documents.

Finally, a source-type filter was applied. The source types identified included journals along with other categories. Only journal publications were retained, given their peer-reviewed and academically rigorous nature, and the remaining source types were excluded. This filter excluded a further 3 papers, resulting in a final sample space of 260 documents for the bibliometric analysis.

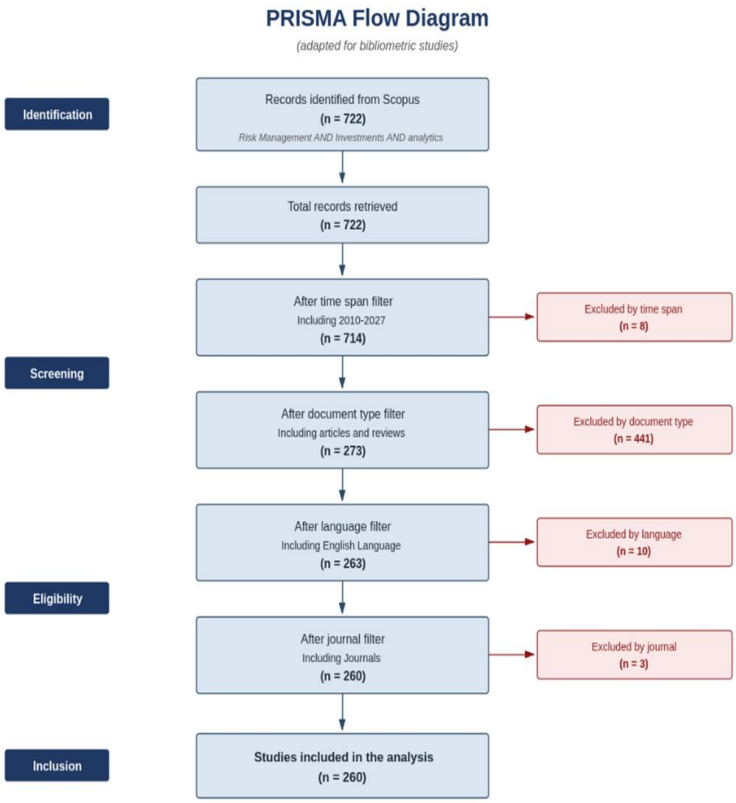



**Figure -1: PRISMA flow diagram of the record selection process**

The PRISMA flow diagram in Figure-1 documents all inclusion and exclusion criteria used to refine the sample space, as described above. It was generated using Biblioshiny, a web interface within the bibliometrix package in RStudio (Aria & Cuccurullo, 2017), and was constructed in accordance with the PRISMA 2020 statement (Page et al., 2021). The complete flow of records through the identification, screening, eligibility and inclusion stages is presented in Figure-1.

### 3.2 Bibliometric Analysis

Bibliometric reviews analyse a large body of published research using statistical tools, allowing researchers to identify trends and citation or co-citation patterns for a particular theme by year, country, author, journal, method, theory and research problem (Paul & Criado, 2020). Various software tools supported the data collection, analysis and referencing in this study. Data were retrieved from the Scopus database using the search string "Risk Management AND Investments AND Analytics", applied across the title, abstract and keyword fields. Following the initial search, filters were applied to narrow the dataset to records relevant to the scope of this review.

After filtering, the remaining papers were exported from Scopus in two formats. An RIS file was imported into Mendeley Desktop, a reference manager, for citation management. Separately, the papers were exported in BibTeX (.bib) format, which was required for further bibliometric analysis. The BibTeX file was imported into Biblioshiny, accessed through the bibliometrix package in RStudio, which was used to generate descriptive statistics, thematic maps and the PRISMA flow diagram. Biblioshiny also converted the data into an Excel-supported (.xlsx) file, which was used for further analysis in Microsoft Excel. The data were additionally analysed using VOSviewer (Van Eck & Waltman, 2010) and Tableau, employing thematic mapping and co-occurrence analysis to observe relationships between the searched keywords. Citations for key papers discussed throughout this review were inserted using the Mendeley Cite plugin for Microsoft Word, ensuring consistency and accuracy across the reference list.

## 4. DATA ANALYSIS

### 4.1 Main Information About the Dataset

The final dataset includes 260 documents published between 2010 and 2026 in 218 sources. The records were extracted from Scopus and comprise 227 articles and 33 reviews. These papers have collected an average of 14.83 citations per document over a span of 17 years. The 967 authors average 3.82 co-authors per document. Only 33 documents (12.7%) are single-authored, written by 32 authors. International co-authorship stands at 28.85%, covering 75 documents. Authors supplied 1,137 keywords in total, or 4.37 per document. The documents are also recent, with an average age of 2.78 years.

### 4.2 Annual Scientific Production

To trace the growth of research on financial risk management, the annual production of articles was compared across the 17 years covered, as shown in Figure-2. Production rose from 2 documents in 2010 to 68 in 2026, with a peak of 77 documents in 2025. The annual growth rate of 24.66% represents an expanding research field. Financial risk management is an emerging topic attracting increasing scholarly attention.

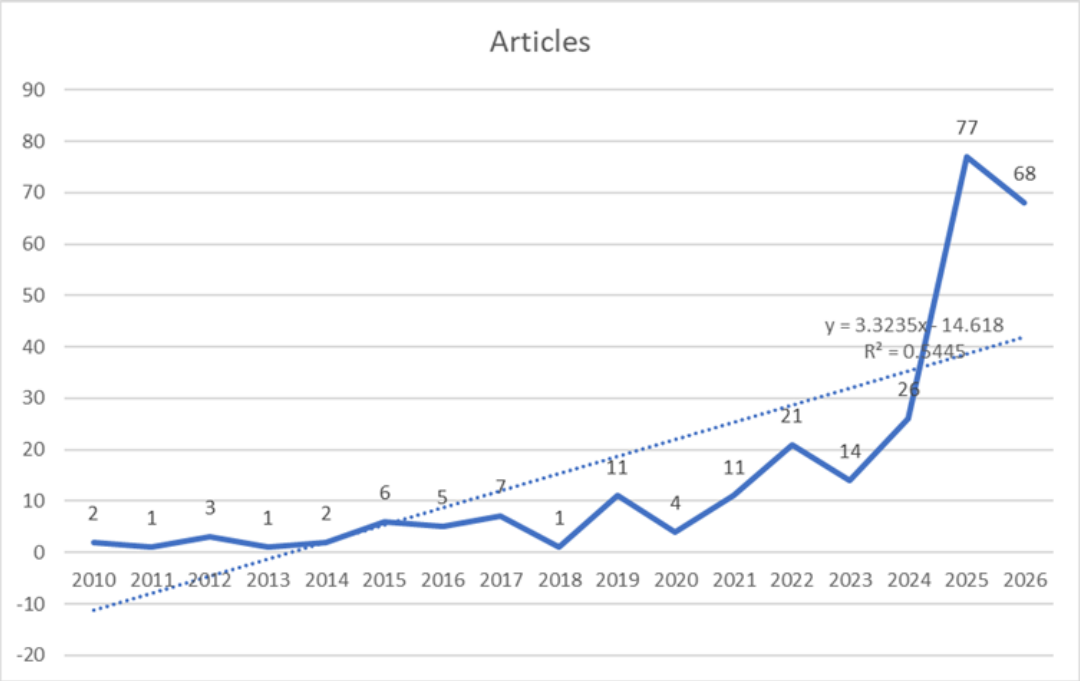



**Figure -2: Annual scientific production, 2010–2026**

Three phases stand out in Figure-2. From 2010 to 2018 the topic was marginal, with 28 documents (10.8% of the corpus), an average of 3.1 a year and a low of 1 in 2018. From 2019 to 2023 output stayed between 4 and 21 documents a year, 61 in total (23.5%), with a peak of 21 in 2022. The dip to 4 documents in 2020 coincides with the pandemic year, and the corpus contains a pandemic-related strand (Spieske & Birkel, 2021). From 2024 the field accelerated: 171 documents (65.8%) were published in three years, with output tripling from 26 in 2024 to 77 in 2025. The fall from 77 to 68 between 2025 and 2026 is not a slowdown, because the 2026 count covers just over eight months.

Taken together, the 24.66% annual growth rate, the tripling of output between 2024 and 2025 and the 65.8% of documents published in the last three years show that financial risk management research is expanding quickly and that the field is shaped mainly by recent work.

### 4.3 Most Relevant Sources

The 260 documents are spread across 218 sources, or 0.84 sources per document. Of these, 190 sources (87.2%) contributed one document, 21 contributed two, four contributed three, one contributed four and two contributed six. Only seven sources reached three or more documents, and together they account for 28 documents (10.8%). Table-3 lists these seven most relevant sources.

**Table -3: Most relevant sources**

| Sources | Articles |
|---|---|
| IEEE Access | 6 |
| Sustainability (Switzerland) | 6 |
| Journal of Securities Operations and Custody | 4 |
| Computers and Industrial Engineering | 3 |
| International Journal of Advanced Computer Science and Applications | 3 |
| Journal of Portfolio Management | 3 |
| Multidisciplinary Reviews | 3 |

IEEE Access and Sustainability (Switzerland) lead with six documents each. All six IEEE Access papers are applied and recent (2024 to 2026): Jeribi et al. (2024) build a deep learning framework for portfolio prediction, Kheneifar & Amiri (2025) model loan default in maritime finance and Alhameed (2026) addresses stress testing with synthetic finance data. Sustainability (Switzerland) has papers from 2019 to 2026, including Moro Visconti & Morea (2019) on big data in healthcare project financing. It also carries ESG and sustainability-risk work (Luke, 2022).

The Journal of Securities Operations and Custody ranks third with four documents, all from 2022 onwards. It covers the operational side of investing, as in Izzo et al. (2025) on the digital transformation of wealth managers. The Journal of Portfolio Management published three documents in 2024 and 2025, among them Jaffri et al. (2025) on transformer models for financial text, Plass & Robinson (2025) on physical climate risk in the built environment and Guijarro-Ordonez et al. (2024) on risk analysis with dynamic factors.

Overall, the sources publishing financial risk management research are highly dispersed: 190 of the 218 sources contributed a single document, and the seven leading sources account for only 10.8% of the corpus. The leading venues fall into three groups. Engineering and computing journals (IEEE Access, Computers and Industrial Engineering, and the International Journal of Advanced Computer Science and Applications) hold 12 of the 28 documents in the table (42.9%). Open-access multidisciplinary

outlets (Sustainability and Multidisciplinary Reviews) hold 9 (32.1%). Investment-practice journals (the Journal of Securities Operations and Custody and the Journal of Portfolio Management) hold 7 (25.0%).

### 4.4 Thematic Map

Figure-3 shows the thematic map of the corpus. It is built from a co-occurrence network of 119 keywords, which has been partitioned into nine clusters. Each cluster is placed by its Callon centrality, the strength of its links to other clusters, and its Callon density, the strength of the links among its own terms (Callon et al., 1991; Cobo et al., 2011, 2012). The dashed lines mark the medians: 1.05 for centrality and 54.17 for density. Risk management lies on the centrality median and "ai" on the density median. Table-4 reports the centrality and density of each cluster together with the documents assigned to it. Of the 260 documents, 189 were assigned to a cluster and 71 (27.3%) were not, so document statistics in this section refer to the 189 assigned records.

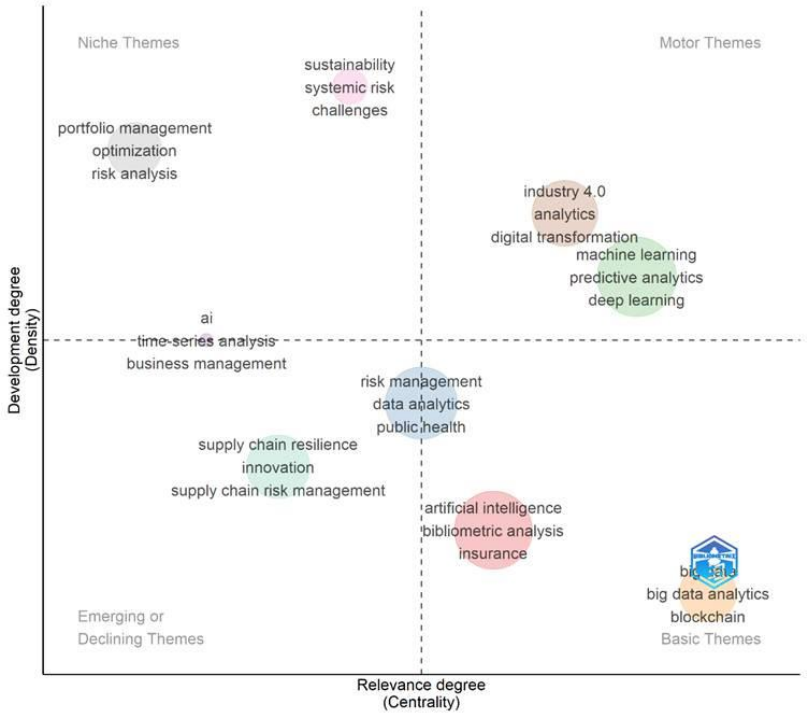



**Figure -3: Thematic map of the corpus**

**Table -4: Clusters in the thematic map**

| Cluster | Quadrant | Centrality | Density | Keyword freq. | Docs | Number of terms |
|---|---|---|---|---|---|---|
| Machine learning | Motor | 1.94 | 58.27 | 79 | 31 | 16 |
| Industry 4.0 | Motor | 1.55 | 61.82 | 56 | 24 | 14 |
| Big data | Basic | 2.14 | 45.38 | 45 | 18 | 11 |
| Artificial intelligence | Basic | 1.42 | 50.17 | 76 | 34 | 19 |
| Portfolio management | Niche | 0.27 | 64.07 | 42 | 21 | 14 |
| Sustainability | Niche | 0.54 | 70.68 | 26 | 13 | 9 |
| Supply chain resilience | Emerging / declining | 0.50 | 53.13 | 53 | 21 | 16 |
| ai | Emerging / declining | 0.35 | 54.17 | 15 | 5 | 4 |
| Risk management | Boundary | 1.05 | 53.63 | 66 | 22 | 16 |

#### *4.4.1 Motor Themes*

Machine learning (centrality 1.94, density 58.27) is the largest cluster by keyword frequency, with 79 occurrences across 16 terms. Its leading terms are machine learning (20 occurrences), predictive analytics (16), deep learning (8) and fintech (7), followed by algorithmic trading, cryptocurrencies, gradient boosting and explainable machine learning. The assigned documents concentrate on prediction: Jeribi et al. (2024) on portfolio forecasting, Hansen & Borch (2022) on alternative data and sentiment analysis in machine-learning-driven finance, and Mahmoud & Surwanti (2026) on AI in investment decision-making. It is also the youngest of the large themes: of its 31 documents, 23 (74.2%) date from 2025 or 2026.

Industry 4.0 (1.55, 61.82) has 56 occurrences across 14 terms, led by industry 4.0 (9), analytics (8), digital transformation (8) and resilience (6). Analytics enters here through the operations of firms. Browder et al. (2024) show how digital transformation promotes organizational resilience, and Wu et al. (2025) examine how digital intelligence strengthens supply chain resilience. Of its 24 documents, 15 (62.5%) are from 2025 or 2026. Its high density shows a tight shared vocabulary. Together, the two motor themes show that the best-developed parts of the field concern methods and digital capability: machine learning for prediction and digital transformation for resilience.

#### *4.4.2 Basic Themes*

Big data (2.14, 45.38) has the highest centrality and the lowest density on the map. Its 45 occurrences are spread over big data (9), big data analytics (7), blockchain (6), internet of things (5), cloud computing (4) and financial performance (4). Its documents are older than those of the other technology clusters: only 8 (44.4%) date from 2025 or 2026, against 74.2% for machine learning. Lăzăroiu et al. (2023) combine AI algorithms, cloud computing and blockchain in fintech management, Saleh et al. (2023) link big data analytics to financial reporting quality, and Turek et al. (2023) relate Industry 4.0 technologies to sustainability risk management. The cluster works as shared infrastructure for other themes, and newer papers increasingly describe the same practices in machine learning or AI terms.

Artificial intelligence (1.42, 50.17) is the largest cluster by documents (34, of which 25 or 73.5% are from 2025 or 2026). The term is the most frequent keyword in the corpus, with 23 occurrences against 21 for risk management and 20 for machine learning. Documents range from Dutta et al. (2019) on insurer asset-liability management to Jagrič et al. (2026) on AI-based sustainability risk and Naseem & Rizwan (2025) on food safety.

#### *4.4.3 Niche Themes*

Portfolio management (0.27, 64.07) has the lowest centrality on the map and a coherent technical vocabulary: portfolio management (7), decision support, optimization, risk analysis and risk assessment (4 each), and stress testing (2). Its documents include Al Janabi (2022) on optimization and portfolio analytics under liquidity constraints and Sarmas et al. (2022) on a data-driven tool for assessing energy efficiency investments.

Sustainability (0.54, 70.68) has the highest density on the map, with sustainability (9), systemic risk (3), and financial contagion and infrastructure asset management (2 each). Luke (2022) on ESG investment and Goforth et al. (2022) on network analytics for systemic risk show a compact group of papers that rarely connects to other clusters.

#### *4.4.4 Emerging, Declining and Boundary Themes*

Supply chain resilience (0.50, 53.13) falls in the lower-left quadrant, just under the density median. Terms such as COVID-19 and crisis management suggest a shock-driven origin, and non-performing loans and financial stability mark where the theme touches finance.

The “ai” cluster (0.35, 54.17) is the smallest, with four terms, 15 occurrences and five documents, all from 2025 or 2026. They are forecasting papers, such as Jadhav et al. (2026) on LSTM-ARIMA ensembles and Karthick et al. (2026) on hybrid CNN-LSTM models. It is partly a labelling effect, because it holds the abbreviation of a concept that the artificial intelligence cluster holds in full.

Risk management (1.05, 53.63), the theme closest to the topic itself, lies on the centrality median. It pairs risk management (21 occurrences) with data analytics (12) and terms such as compliance, information technology, public health and investment. Its 22 documents mix healthcare informatics, led by Simpao et al. (2014), with financial services work such as Andriosopoulos et al. (2019) on data analytics in financial services and Kalina et al. (2022) on corporate security risk management.

#### *4.4.5 Findings from the Thematic Map*

Two conclusions can be drawn from the thematic map. First, technology vocabulary dominates: the machine learning, artificial intelligence, “ai”, big data and Industry 4.0 clusters hold 271 of the 458 keyword occurrences on the map (59.2%), against 108 (23.6%) for portfolio management and risk management. Second, finance-specific terms such as fintech, algorithmic trading, stress testing and insurance sit inside technology-led clusters or in the niche themes, and no finance cluster occupies the motor quadrant.

Taken together, the thematic map shows that financial risk management research is organized around technology rather than around finance. The motor themes, machine learning and Industry 4.0, concern methods and digital capability. The basic themes, big data and artificial intelligence, supply tools that are applied across many areas without forming a tight vocabulary of their own. In conclusion, financial risk management is a rapidly growing field, with 65.8% of its literature published in the last three years, and this growth is led by technology and analytics rather than by finance-specific themes.

## 5. FUTURE RESEARCH AGENDA

The bibliometric dataset spans 2010 to 2026 and shows a field that was marginal for most of the period and then accelerated sharply from 2024, when annual output rose from 26 documents to 77 in 2025. This section converts the patterns in the data into a research agenda: not only a list of gaps, but a roadmap that future researchers, including students, can follow. The problems that the data reveal are set out first, before the next steps are planned.

### 5.1 Problems Identified in the Bibliometric Data

**1. A fragmented publishing environment.** The 260 documents are published in 218 different sources, and the seven leading sources account for only 10.8% of the corpus. This scatter is typical of a small number of “core” journals surrounded by a much larger number of “periphery” journals (Bradford, 1934). It reflects the lack of a recognised flagship journal that could provide an intellectual home for researchers and students in the field.

**2. Very low author concentration.** The field shows the typical inverse-square productivity profile of a developing and relatively unconsolidated community (Lotka, 1926): 967 authors have produced 260 documents, and no author has more than three. This implies a lack of long-term research-team formation, as there are hardly any stable teams to support deep and cumulative research programmes.

**3. AI and machine learning remain loosely connected to classical risk theory.** In the keyword co-occurrence network, the AI and machine learning clusters are linked to the statistical risk-measurement clusters by two connecting hub nodes instead of by dense, direct links (Van Eck & Waltman, 2010). The AI science of risk is therefore being conducted alongside, and not as an integral part of, the quantitative core of the field.

**4. Basic concepts of risk measurement are becoming less visible.** Value-at-Risk and expected shortfall do not appear among the leading terms of any cluster on the thematic map, which is dominated by AI-related vocabulary (Callon, Courtial & Laville, 1991; Cobo et al., 2011). This is a real concern: as long-standing risk metrics fade from view, new AI models can be built without adequate validation against established risk theory.

**5. Explainability lags behind technical progress.** Explainable machine learning appears only as a minor term in the machine learning cluster, while prediction-oriented terms dominate the vocabulary of the field (Donthu et al., 2021). The interpretability and trustworthiness of AI tools in financial institutions could therefore become a practical barrier to their adoption.

**6. There is no dedicated home for newer computational methods.** Growth since 2024 has been absorbed mainly by engineering and computing journals and open-access multidisciplinary outlets, which together hold 21 of the 28 documents in Table-3, rather than by a stable risk-management venue. There is no dedicated outlet for AI-based risk scholarship, and standards of quality and rigour in this sub-area are inconsistent (Zupic & Čater, 2015).

### 5.2 Proposed Research Directions

Given the problems above, the following areas are proposed as a research programme for the field.

**Compare machine-learning and classical risk models.** Structured, well-designed comparative studies should evaluate the performance of machine-learning risk models, such as XGBoost or deep reinforcement learning, with and without the existing VaR and CVaR models. This would directly address the integration gap identified in the co-occurrence network and give practitioners evidence-based direction instead of competing, separate toolkits.

**Emphasise explainable AI (XAI) for risk problems.** Explainable machine learning is only a minor term in the vocabulary of the field, so further research is needed on methods that make AI more interpretable for financial risk decisions. This would allow regulators and risk managers to rely on the output of AI instead of treating it as a black box.

**Encourage inter-institutional and interdisciplinary cooperation.** Because authorship is widely distributed, universities and funding agencies should actively create joint AI and finance research groups, in order to build long-term, sustainable research networks and not just one-off papers.

**Carry out meta-analyses of methodological migration.** A thorough meta-analysis of how machine-learning pipelines have been adapted through Monte Carlo simulation and feature selection would reveal the thematic-evolution patterns already evident in the data and establish the trend as a properly tested theory.

**Develop themes with perceived growth potential.** Themes such as supply chain resilience, systemic risk and sustainability currently occupy small and peripheral positions on the thematic map. Special issues, workshops or student research competitions dedicated to these niches could accelerate their development before they are absorbed by the general AI trend.

**Reinstate basic risk theory in AI studies.** Future papers that use AI models should deliberately reinstate traditional metrics as evaluation measures, so that methodological soundness is not sacrificed to the speed of technological advancement.

**Test whether the recent growth is sustainable.** The growth curve of the field still shows exponential rise and not maturity. Researchers should examine whether the increase is a sign of a true paradigm shift or a temporary AI hype bubble, using longer citation-window analyses once the 2024–2026 cohort of papers has had enough time to be cited.

### 5.3 Summary of the Research Agenda

Examination of the dataset shows that a hot research area does not always equal a healthy field. Financial risk management is growing in volume because of the arrival of machine learning and artificial intelligence, but its underlying structure shows scattered journals, thin author networks and a still loose connection between AI and classical theory. This makes the field exciting but not yet fully mature.

The dataset also shows that there is genuine room for new researchers, even at student level, to make a meaningful contribution simply by addressing the problems it exposes. If the seven directions proposed above are pursued, financial risk management could move from being a fast-growing niche to a well-integrated, methodologically sound discipline over the next decade.

## 6. CONCLUSION

This paper examined financial risk management through the lens of OR. It combined a review of the existing literature with a bibliometric study of 260 Scopus documents published between 2010 and 2026. Financial risk management is the set of processes used to identify, evaluate and control exposure to monetary loss from market movements, counterparty default or internal failure (Acharya et al., 2021). The results provide insight into how knowledge in this area has been formed, which methods and topics have contributed to its development and which areas lack exploration. They suggest that the field has grown exponentially and is now predominantly driven by data analytics and artificial intelligence, while its foundational theories have been understudied and require more attention. The academic structure of the field is also fragmented.

### 6.1 How the Data Were Collected

The documents were retrieved with the search string “Risk Management AND Investments AND Analytics”, run on 10 September 2026. They were screened through the four PRISMA stages: identification (722 records), screening by period and document type (714, then 273), eligibility by language (263) and inclusion by journal source (260). The final corpus holds 227 articles and 33 reviews. It was analysed using Biblioshiny, VOSviewer, Excel and Tableau, through performance indicators, a keyword co-occurrence network and a centrality–density thematic map. The conclusions below rest on this structured process and on a review of earlier bibliometric studies and of the main OR-based risk techniques.

### 6.2 What the Literature Says About the Subject

Risk management converts uncertainty into numbers that can be compared, constrained and manipulated. Value-at-Risk (VaR) summarizes the maximum expected loss over a period at a given confidence level. Conditional Value-at-Risk (CVaR) is a complementary measure that estimates the average loss given that the loss exceeds the VaR threshold, which is why it is gaining traction among practitioners who want to consider tail risks. Credit risk, a heavily regulated component of bank capital adequacy, is assessed through creditworthiness models. OR supplies the mathematical backbone for these tools through optimization, probability modelling and algorithmic decision support (Olson & Wu, 2010).

Studies of VaR under jump processes (Sorwar & Barone-Adesi, 2010), of CVaR under dependent data (Luo, 2020) and of competing credit-risk techniques (Allen et al., 2015) show that the choice of method can change how risky an exposure appears. A risk figure is therefore an estimate that depends on the technique used, and not a fixed fact. The main limitation of these quantitative models is that they are based on simplifying assumptions about market behaviour, transaction costs, estimation accuracy and parameter stability. These assumptions make the mathematics tractable but can undermine performance in more realistic, messier markets. Addressing this limitation requires testing the models against alternatives, stress-testing beyond recent experience and treating model risk as a risk category in its own right.

### 6.3 Technology Leads and Finance-Specific Theory Follows

The thematic map based on 119 keywords in nine clusters shows that machine learning and Industry 4.0 are the two motor themes. Both relate to methods and the digital capabilities of organizations. Artificial intelligence and big data are the two basic themes, which are extensively interconnected but only slightly developed in their own right. The keyword clusters of these technology fields account for 271 occurrences (59.2%), compared with 108 (23.6%) for portfolio management and risk management combined. Apart from technology, no area has a motor theme. Themes such as portfolio management and sustainability did not move beyond niche status. Supply chain resilience, which gained special attention because of the COVID-19 pandemic, belongs to the cluster of emerging or declining themes.

The citation analysis confirms the trends identified by the clustering algorithm. The eight most cited papers, which account for 33.7% of all citations, include only one that relates directly to finance. The others address supply chain resilience, healthcare analytics, infrastructure and wildfire, sports technology and other topics. Analytics applied across different fields of human activity is therefore a major theme, and its impact extends beyond finance. The most cited paper in the corpus may not be explicitly related to finance at all.

### 6.4 A Fragmented Scholarly Landscape

The 260 documents are spread across 218 sources, and 190 of them (87.2%) published only one document. The seven sources with three or more documents hold just 10.8% of the corpus, and they come from engineering and computing journals (42.9% of the leading-source table), open-access multidisciplinary outlets (32.1%) and investment-practice journals (25.0%). Among 967 authors, none has more than three documents. Papers average 3.82 co-authors, 12.7% are single-authored and 28.85% involve international collaboration. Collaboration therefore happens within projects, but durable research groups and a recognised flagship venue have not yet formed.

The review-only analysis shows the same pattern: just two journals appear twice among the reviews, and 11 of the 33 reviews (a third) could not be placed in any single cluster. In that analysis, risk management, investments and predictive analytics form the most central and connected group but remain a basic theme, one that everyone cites but few have developed in depth.

### 6.5 The OR Foundation Is Real but Under-Recognised

The literature review showed that OR lies at the foundation of most risk-measurement approaches, but the bibliometric analysis revealed that this is rarely explicit. OR-specific terminology is found in the niche of portfolio management articles, whereas the dominant themes are labelled with machine learning and artificial intelligence. Previous bibliometric studies focused on a specific risk category or sector (banking, Islamic finance, corporate and enterprise risk) and did not explore the role of OR as a methodology, and their timelines ended before the 2024–2026 surge. This study partially fills these two gaps. It also highlights a related concern: that canonical, theory-driven approaches are being displaced by unproven innovations.

### 6.6 Answers to the Research Questions

For RQ1, the study found that OR methods are used for market risk, credit risk, portfolio optimization and enterprise risk, but the central limitation is reliance on idealizations, which future research can address through comparisons and simulations that explicitly incorporate model risk. For RQ2, the influence of OR is found across a variety of authors, institutions and journals, but the most impactful publications are data-centred and come from non-financial domains. For RQ3, the underdeveloped areas are the peripheral and niche topics (sustainability, systemic risk, supply chain risk, portfolio management and stress testing) and the intersection between data-driven methods and theoretical approaches.

### 6.7 Implications for Practice and Research

The findings have implications for three audiences: practitioners, researchers, and the institutions that host the field.

**For practitioners.** The literature review shows that risk measures such as VaR and CVaR are estimates, and that the choice of technique can affect how risky an exposure appears. Several techniques should therefore be employed in parallel, and a disagreement between them should be regarded as a sign of model risk. Many quantitative models also rely on simplifying assumptions about markets, transaction costs, estimation accuracy and parameter stability, and organizations should subject these to open scrutiny, as they may constrain how far a model can reflect real-world markets. The thematic map shows that machine learning and artificial intelligence now dominate the field but are only loosely tethered to classical risk theory. Practitioners adopting these tools should compare them against established measures such as VaR and CVaR, rather than treating them as entirely separate toolkits. They should also prioritize interpretability, so that regulators and risk managers can understand a model and not regard its output as a

black box. The corpus also contains work on sustainability, systemic risk and supply chain resilience, which suggests that risk management should look beyond traditional financial exposures.

**For researchers.** The thematic map shows no finance-specific cluster in the motor quadrant. The best-developed themes relate to methods and digital capability, and the core theme of risk management and investment analytics is widely referenced but not explored in depth. Researchers can add most value by linking novel methods to established risk theory. This means structured comparisons of machine learning models with VaR and CVaR benchmarks, and a return to traditional risk measures as assessment standards, so that technical speed does not come at the expense of methodological rigour. Explainability is another opportunity, as it appears only as a minor term alongside the large prediction-focused cluster. The niche and peripheral themes (sustainability, systemic risk, supply chain resilience and portfolio work) are coherent but disconnected from the main body of work, and there is scope for studies that connect them to it. Because OR is rarely visible as a labelled theme, studies that map OR techniques across the entire spectrum of financial risk management would fill a gap that earlier reviews, grouped by risk category or sector, have left. Finally, as most of the literature originated in the last three years, researchers should repeat this analysis with longer citation windows and across several time periods to establish whether this burst represents a durable shift or merely a transitory interest in artificial intelligence.

**For institutions, journals and funders.** The corpus is distributed across 218 sources, 190 of which published a single document, and no author has produced more than three. The field therefore lacks a home and long-standing research teams. Universities and funders could support consortia that bring together finance, OR and computing expertise, so that work is cumulative and not simply a series of one-off papers. Special issues, workshops and dedicated venues for AI-based risk research would ensure uniform quality control and give the underdeveloped themes opportunities to flourish.

### 6.8 Limitations

The findings should be read with several limitations. The data come from a single database and a single three-term search string, so related work using different terminology may be missed. The split between “artificial intelligence” and “ai” shows, for example, that the keyword mapping is subject to author labelling. Of the 260 documents, 71 (27.3%) were not assigned to any cluster, so cluster statistics refer to 189 records. The 2026 data are incomplete, recent papers have had little time to accumulate citations, and the thematic map is a single snapshot that cannot show whether low-density themes are increasing or decreasing.

### 6.9 Closing Remark

The field of financial risk management is growing rapidly, but growth does not equate to maturity. It involves very effective but not foolproof measurement techniques, a basis in OR that deserves more attention, and technology developments that outpace the theory and forums that should accompany them. The biggest breakthroughs will result from combining novel techniques with proven risk theories, testing them thoroughly and establishing common frameworks that turn a rapidly growing field into a discipline. Organizations that treat risk numbers as estimates, use a combination of techniques, govern their models and keep judgment at the centre will be best placed to manage risk.

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