

Applications of Operations Research in Financial Risk Management: A Bibliometric Review

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ABSTRACT

This bibliometric review examines the application of operations research in financial risk management, tracing the field's growth, structure, and emerging directions. A total of 423 peer-reviewed articles retrieved from ScienceDirect using seven targeted Boolean keyword searches were screened, spanning the period 2010–2026, and were analyzed using Biblioshiny (Bibliometrix) and VOSviewer to identify publication trends, keyword co-occurrence, and thematic clusters. The results reveal that research output has grown at an accelerating, near-exponential rate, with more than half of the sampled articles published in the last three years alone. The literature clusters around five core streams: credit risk modelling, systemic and network-based risk, portfolio and Value-at-Risk/Conditional-VaR optimization, artificial intelligence and machine learning in risk analytics, and climate/ESG-linked risk. Keyword co-occurrence analysis shows us that systemic risk as the most central and frequently connected node, linking nearly all the other themes and indicating that the field functions as a single, unified body of research rather than a set of fragmented sub-disciplines. A persistent tension between predictive accuracy and model interpretability emerges as a defining challenge, particularly as machine learning and graph-based methods increasingly converge with traditional credit and network risk frameworks. Building on these findings, the study outlines a forward-looking research agenda centered on artificial intelligence, graph neural networks, quantum computing, blockchain and distributed ledger technology, climate risk integration, and regulatory technology. Overall, the findings offer a structured view of the current state of operations research in financial risk management and highlight where deeper integration across methods and topics is most needed.

Keywords: Financial Risk Management; Operations Research; Bibliometric Analysis; Systemic Risk; Credit Risk; Portfolio Optimization; Artificial Intelligence; Climate Risk.

1. INTRODUCTION

Financial risk management is at the heart of the modern economy. The process of how banks evaluate risk or how firms navigate downfalls or how governments plan their budgets are all guided by the tools used to understand risk (Hammoudeh & McAleer, 2015). The financial crisis of 2007-2009 demonstrated what exactly happens when such tools malfunction. People thought that risk concentrations would be spread out, but they turned out to be very connected. Problems spread through the banking system at a speed that had never been seen before (Paltalidis et al., 2015). The same lesson was again learned from both, COVID-19 (Borri & Giorgio, 2022) as well as the geopolitical and trade-related turmoil happening in the present day, where financial instability is no longer considered an accounting inconsistency, but instead a feature of the interconnected system that emerges from the pursuit of efficiency by institutions (Chowdhry, 2026).

Operations research is deeply embedded in this subject. The connection extends to the origins of modern portfolio theory, which was fundamentally an optimization problem. Viewed broadly, virtually every major tool in operations research has been applied to financial risk management: mathematical programming is employed to construct portfolios under real-world constraints; simulation and stochastic control are used for pricing risk and minimizing losses; network models trace how shocks propagate between institutions; and, more recently, machine learning has been applied for prediction and pattern recognition. These approaches, once treated as distinct, are now being combined to address the same research questions from different methodological perspectives.

The motivation for this study comes from the rapid changes in the field occurring since 2020. A series of shocks, including the pandemic, geopolitical conflict, and trade-related turmoil, have led to the convergence of several modelling approaches. Artificial intelligence has transformed from a supporting technique to a major topic of interest, both as a tool for managing risk and a source of it. FinTech companies are now considered contributors to systemic risk, rather than neutral intermediaries. Climate change and quantum computing have entered the fray. A few reviews have been made on individual topics, including the interplay between climate risk and systemic risk (Pacelli et al., 2025), and FinTech and financial stability (Rani & Dochania, 2026), but none have attempted to characterize the operations-research side of financial risk management in its entirety.

This gap matters for two reasons. First, the field of financial risk management is dispersed across research communities that rarely engage with one another, employ different data sources, and evaluate models by different standards. As a result, institution-level risk and system-level risk are seldom studied together. Second, there is an ongoing tension between predictive precision and interpretability. Earlier credit-risk frameworks prioritised transparency so that outputs could be readily justified (Lanzarini, 2017), whereas the models that currently yield the strongest predictive performance are also the most difficult to interpret (Korangi et al., 2023). Recent efforts to enhance transparency have not fully resolved this problem. Consequently, until the field's organisation, growth trajectory, and blurring disciplinary boundaries are better understood, these underlying challenges will remain difficult to accurately diagnose or address.

To explore all these dynamics, the paper has the following parts:

Section 2 - Literature Review, reviews all the previous work across five main pillars: credit risk, systemic/network risk, portfolio and VaR optimization, AI in risk analytics, and climate risk. Section 3 - Research Methodology, explains how the data was actually collected from ScienceDirect for the years 2010 to 2026 that resulted in our final set of 423 papers.

Section 4 - Data Analysis, presents what exactly this data shows like the growth in the field is speeding up rather than staying steady, the different research themes carry very different weight, and one keyword, systemic risk, connects to almost every other topic in the field, suggesting this is one connected body of research rather than several separate ones.

Based on the sections outlined above, the study pursues five goals: to measure how large this field is and how fast it is growing; to identify its main research themes and compare their size and maturity; to map how the literature is

intellectually structured, and whether it is unified or fragmented; to pinpoint where methods are converging and where tension remains, especially between predictive accuracy and interpretability; and to set out a research agenda for the next five to ten years. Through these goals we come to Section 5 which elaborates on the future research agenda covering artificial intelligence, graph-based approaches, quantum computing, blockchain, climate risk, and regulatory technology. And finally, Section 6 concludes the paper by returning to the five goals, discussing the implications of our findings for researchers, practitioners, regulators and policymakers, and society more broadly, and acknowledging the limitations of this study.

2. LITERATURE REVIEW

2.1 Historical and theoretical Background

Operations Research's application in financial risk gained prominence following the 2008 crisis. Prior to the crisis OR's application in this industry was siloed, each institution determined its own risk independently, with VAR models being the best example (Al Janabi, 2021). This overlooked the fact that each institution's risk is interdependent on its peers and the system as a whole (Abedifar et al., 2017). That shift from an institution-centric to a system-level perspective drove operations research toward the network and systemic-risk models this review covers.

2.2 Credit Risk Modelling

Credit risk concerns the likelihood that a borrower will fulfil repayment obligations and represents the largest thematic stream covered in this review. It is done by using discriminant analysis and logistic regression and solely based on financial ratios, however the industry has now moved towards data mining and machine learning. As the predictive model gets more complex and sophisticated, it also becomes harder for the average human to interpret and explain. (Khemakhem & Boujelbene, 2018) explain how folding in non-financial variables, not just ratios, improves how well default can be predicted. However, (Lanzarini, 2017) worked more towards the interpretability side and focused on simplifying the rules for humans to be able to follow well.

2.3 Systemic Risk and Network-Based Modelling

Systemic Risk doesn't just explain if this one bank is risky, it explains the overall inter-connectedness of the industry and how one bank and its Non-performing Assets affects the rest of the system. (Abedifar et al., 2017) explain that hybrid Islamic/ conventional banks were in fact less resilient since they are more interconnected in the banking system contrary to the belief that in finance diversification leads to lower risk. (Paltalidis et al., 2015) confirmed this pattern, tracing how interconnected banks helped transmit contagion during the European sovereign-debt crisis.

2.4 Portfolio and VaR/CVaR optimization

Similar to Markowitz's original model, Classical portfolio theory assumes that markets will function without friction. This means that assets can be bought and sold instantly with no extra cost. However, in reality this is not the case. Selling a large position takes time and has a certain cost attached to it, especially during a crisis time period when there is panic selling. (Al Janabi, 2021) addresses this by building liquidity directly into the risk model itself, through what is known as liquidity-adjusted Value-at-Risk (LVaR). This means the time and cost of unwinding a position becomes part of the risk calculation, not an afterthought added later. For banks specifically, these portfolio and VaR-based models are not just theoretical; they determine how much capital a bank must hold as a buffer against the risk in its own loan and asset portfolio, directly connecting portfolio theory to real-world bank regulation.

2.5 Artificial Intelligence and Machine Learning in Risk Analytics

Previously, credit risk and systemic risk for borrowers were analysed separately during the lending process. However, now with the help of AI and Machine learning one can analyse both side by side and merge the two ways of thinking. (Zandi et al., 2025) depicted this using the help of graph neural network a type of machine learning model built specifically to understand connections between nodes in a network which was discussed earlier in the systemic for borrowers to during the lending process risk part. Here it is used for the purpose of understanding if an individual will default on their loan. So now a machine learning model can predict both an individual borrower's risk of defaulting and how that will affect the overall system. Others like (Korangi et al., 2023) help predict the same for a corporate borrower's default and (Sigrist & Leuenberger, 2023) have gone beyond individual borrowers to predicting an entire loan portfolio.

2.6 Climate, ESG and Sustainability-Linked Risk

Now there is even a link between a firm's social activities or ESG and the financial risk factor it may have. Hence ESG is now being analyzed as a financial risk factor and not just for ethical concerns or reputation. The better the ESG, the lower the credit risk perceived by the institution lending to it (Veltri et al., 2023). This is also the newest and fastest-growing stream of the five covered here —(Pacelli et al., 2025), in their bibliometric review, found publication counts on climate and systemic risk rising sharply since around 2020.

2.7 Gaps and Emerging tensions

Even after five streams to analyze there still exists gaps. First being how credit risk and portfolio models are only tested using historical data so their performance in an unforeseen crisis is difficult to predict. Second, even though there is high demand for ESG based analysis and its usage is growing a lot, there is still little to no advanced network or AI model used for this. The third and the main concern will always be how the analysis can either be explainable (Lanzarini, 2017) or highly accurate (Korangi et al., 2023) (Zandi et al., 2025). Going forward, the next breakthrough in this field should not merely be a more powerful model, but one that bridges the gap between explainability and predictive accuracy rather than sacrificing one for the other.

3. RESEARCH METHODOLOGY

3.1 Research Design and Sample Selection

A bibliometric literature review was conducted to identify patterns in risk management research with respect to publishers, topics, and the evolution of the field over time.

Risk management was chosen as the focus of this study because it is a mature and well-established field within finance and banking, with a large and continuously growing body of academic literature, making it well suited to a bibliometric approach that requires a substantial volume of publications to produce meaningful patterns and trends.

We have obtained our data from ScienceDirect which is one of the most comprehensive bases of peer reviewed literature in finance, economics, and management sciences. The search period was from 2010 to 2026 to have a detailed understanding about the evolution of risk management. Search field was title, abstract or author specified keywords and type of articles were research articles. Initially we made a mistake in our search strategy by searching "risk management" which was a very broad term and gave us numerous articles which were irrelevant. Manual processing of all these papers would take a lot of time and would be difficult to screen. Hence, we decided to switch our search strategy to a set of seven targeted keywords given below.

Keyword 1	"systemic risk" AND (finance OR banking) AND (model OR simulation)
Keyword 2	"counterparty risk" AND (finance OR banking) AND (model OR optimization)
Keyword 3	"default risk" AND (finance OR banking) AND (model OR optimization)
Keyword 4	"credit risk" AND (bank OR banking OR finance) AND (optimization OR stochastic)
Keyword 5	("market risk" OR "portfolio risk" OR "value at risk") AND finance AND (optimization OR stochastic)
Keyword 6	("financial risk" OR "bank risk" OR "liquidity risk") AND (bank OR banking) AND (optimization OR simulation)
Keyword 7	"investment risk" AND (finance OR investment) AND (optimization OR stochastic)

Figure 1: Keywords used for obtaining the desired research articles

This resulted in a set of research articles diverse enough to cover various subcategories within risk management but specific enough to avoid unrelated articles. This is a common practice in bibliometric analysis where targeted search strings provide better results than one generic search string. After applying these keywords in ScienceDirect, we received 857 records. We further screened them by eliminating duplicates, articles in other languages, and articles which were not related to the field of finance. This reduced the database to 423 articles which are used throughout this analysis. The details of elimination at each step of selection are presented in the PRISMA diagram below.

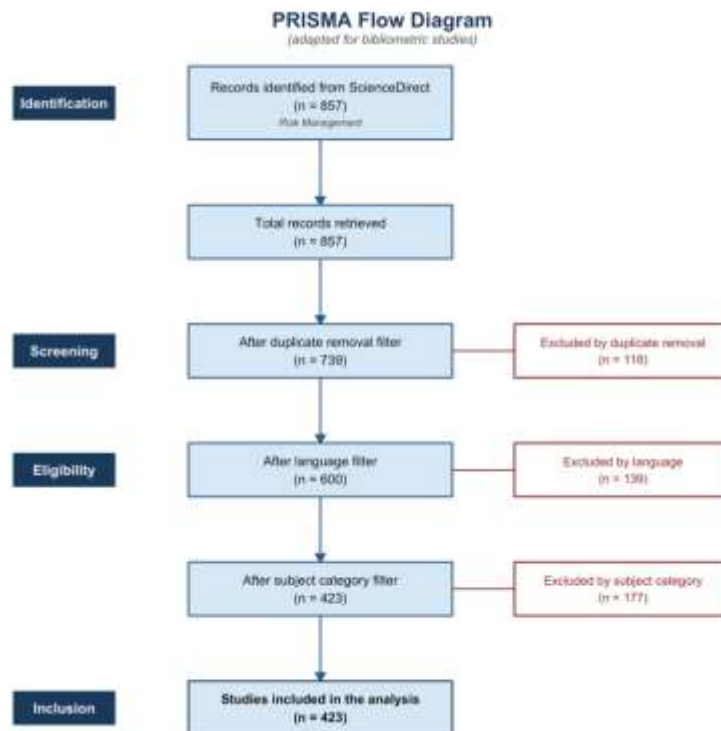


Figure 2: PRISMA chart of the Screening Process

3.2 Bibliometric Analysis

Bibliometric review takes an extensive amount of literature as a body of data for analysis and searches for patterns within it such as prominent authors, changes in publication output and how topics cluster. A bibliometric review was therefore selected because risk management spans banking, corporate finance, insurance, and mathematical modelling. In this study, bibliometric review is applied to risk management research articles to see how the field has grown and is organized internally. Bibliometric analysis first tracks publication output over the period 2010–2026 to see whether risk management research activity has increased or decreased and whether there are turning points. Then, it examines which authors, journals and institutions appear frequently and have had the greatest influence on risk management. Bibliometric analysis third maps the origin of risk management research to determine whether output is concentrated in a regions or countries. Bibliometric analysis fourth uses keyword co-occurrence and thematic mapping to reveal the research themes.

The purpose of performing this analysis is to move beyond an understanding of risk management research and to create a data-driven view of the field. This view tracks how risk management research output has changed over time identifies the authors, journals and topics that currently define risk management and highlights gaps or directions that are worth exploring in the future. All the processing was performed in RStudio. We used the Bibliometrix package and its Biblioshiny interface to import the data run the analysis and produce outputs such, as trend charts, thematic maps and network diagrams that comprise the results of this study. Mendeley was used to organize the reference list remove entries and export the collection in a format that Biblioshiny can read. Excel and VosViewer was used as well for further analysis.

4. DATA ANALYSIS

4.1 Introduction

For this bibliometric analysis, we used a ScienceDirect export containing 423 records on financial risk management. The dataset covers 2010–2026. Biblioshiny, RStudio, Excel, and VOSviewer were used for the analysis.

4.2 Annual Scientific Production

The annual publication series shown in the chart covers 2015 to 2026.

From 2015 to 2019, the number of papers published was relatively low and inconsistent, with the lowest count being 11 papers in 2019. This inconsistency suggests that research attention in this area was not yet stable.

There was a slight increase from 2020 to 2023 to publications numbering 25 and 26 (with the exception of 33 in 2021). Growth was gradual and not a high spike.

From 2023 to 2024, the number of papers almost doubled to 50. It then increased by 25 papers in 2025 and by a further 19 papers in 2026.

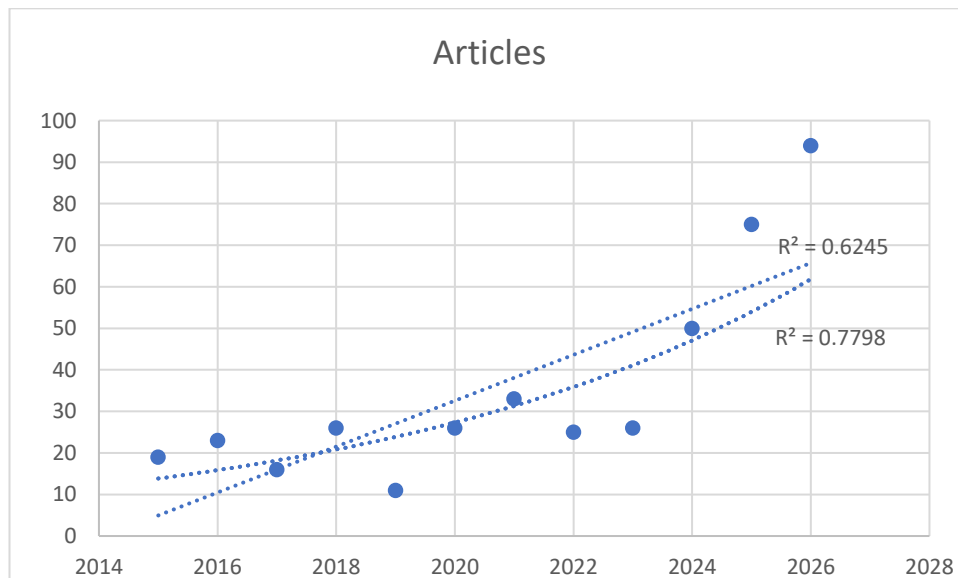


Figure 3: Annual Publication Trends with Linear and Exponential Trendlines

To determine which growth model best represents this pattern, both linear and exponential trendlines were applied to the data.

R^2 measures how well a fitted model explains variation in the observed data, with values closer to 1 indicating a stronger fit.

The exponential trendline fits the data slightly better than the linear trendline. The R^2 value is approximately 0.6327 for the exponential model and 0.6245 for the linear model.

This suggests that publication growth is better described by an exponential pattern than by a linear one.

The faster growth is probably due to more researchers currently using computers and machine learning in their study of credit risk, as well as increased interest in large financial risks and supply chain problems.

4.3 Cluster Analysis

The keywords were entered into VOSviewer to identify co-occurrence trends across the papers. Words that occur together frequently are grouped into the same cluster.

It is a common sub-theme in the area. Node size is indicative of overall frequency, with larger nodes signifying a term's frequency across the literature, and lines connecting nodes show which terms tend to co-occur. This results in a map of the clustering of topics based on their co-occurrence in the papers.

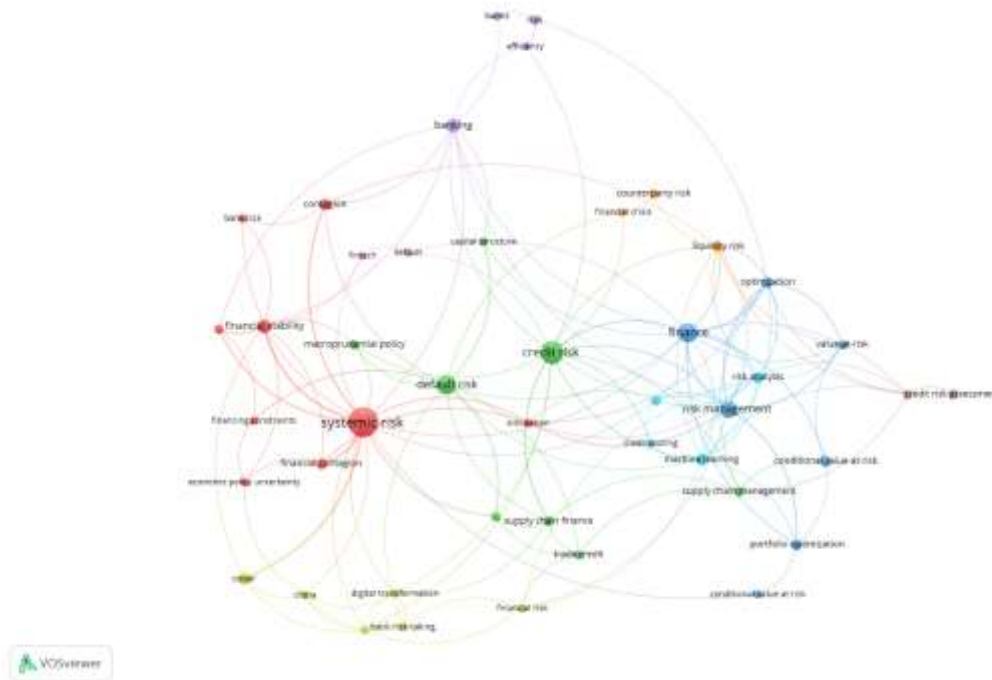


Figure 4: Keyword Co-occurrence Network Generated Using VOSviewer

“Systemic risk” is the largest and most central node on the map, linking to nearly all other clusters. It is bordered by several different groupings.

One focuses on credit and default risk, comprising credit risk, default risk, and supply chain finance. Another deals with applied risk management such as finance, risk management, risk analysis and portfolio optimization.

Smaller clusters cover banking basics and crisis related risk: counterparty risk and liquidity risk. There is also a more peripheral cluster involving China, digital transformation, and bank risk-taking. “Credit risk assessment” is largely isolated, with few connections to the rest of the network. There are no isolated sub-fields within this literature. It remains linked through systemic risk as the common point of reference.

4.4 Data Analysis Conclusion

Overall, the presented statistics indicate that the field is developing rapidly and has a strong structure. The exponential growth model fits the publication data slightly better than the linear model, suggesting some acceleration rather than growth at a constant rate.

This conclusion is also supported by the network analysis, which indicates that the development is not spread across various themes but is concentrated on one particular theme which is systemic risk.

An evident rise in the number of papers after 2024 most likely indicates a growing interest towards machine learning and credit-risk analysis, which are strongly related to the topic of systemic risk.

The 94 papers reported for 2026 represent part-year statistics and should therefore be treated as a minimum rather than a final count.

5. FUTURE RESEARCH AGENDA

The five thematic streams and four method families in Sections 2–3, plus the convergence patterns in Section 4, provide several clues about the likely directions of operations research for financial risk management in the next five to ten years. The dominant trend is that risk management research will shift its focus from disparate and occasionally idiosyncratic tools, from single VaR or credit-scoring models, toward more integrated, data-rich, and increasingly automated decision architectures. With this theme in mind, the seven prospects below suggest possible options for the future.

5.1 Artificial Intelligence as Both Tool and Object of Risk

The next big thing in operations research for financial risk management is artificial intelligence (AI), first as a danger and then as a solution. (Tanbour et al., 2025), using mixed methods in the Palestinian banking sector, find that embedding AI requires adjustments to organizational governance. (C. Zhang et al., 2026), using a statistical approach, find that AI adoption reduces bank risk via double-debiased treatment of its machine learning. (Wu, 2025) shows that hybrid multi-objective LSTM-based AI can help banks make their financial and service infrastructure more resilient to the risks of the AI itself. (W. Zhang et al., 2026) highlight potential dangers of AI in financial leasing, specifically its algorithmic bias. Thus, the “more AI” agenda for risk management is likely to be accompanied by studies of specific risks associated with its adoption.

5.2 Graph Neural Networks and the Convergence of Network and Credit Risk

As noted in Section 2.5, the network-based systemic risk stream and the machine learning–based credit risk stream (via graph neural networks for loan default) are coming together, and that convergence is likely to accelerate. The papers in both streams predominantly focus on either systemic risk (network-level) or default probability (node-level) using different data, methods, and measures, with only a few recent ones highlighting their joint consideration. As firms accumulate relational data on supply chains, common equity, and transaction networks, graph-based methods may increasingly be used to jointly model these items, transcending the risk modeling of single banks or other financial institutions. (Faryal et al., 2026) provide an example of this trend, highlighting FinTechs as new sources of systemic risk and employing time-frequency network modeling to demonstrate the contagion channels from these technology-based organizations to traditional banks—effectively expanding the scope of systemic risk analysis from banks to include technology firms.

5.3 Quantum Computing and Next-Generation Risk Measures

An emerging area for investigation is the use of quantum computing for financial risk, particularly for the quantum metrics of credit risk factors. (Q. Han & Song, 2026) highlight quantum measures for some credit risk indicators, noting that the optimization and simulation challenges associated with value at risk (VaR) and conditional VaR (CVaR), particularly at the level of the institution portfolio, could benefit from quantum approaches. Although quantum computing is likely several years away, the appearance of quantum-inspired studies of risk measures suggests the field’s interest in embracing this development.

5.4 Blockchain, Distributed Ledgers, and Credit Risk Transparency

The next technological frontier is blockchain and distributed ledger technology, which offer to enhance the transparency of credit and default processes. (Islam et al., 2026) demonstrate the impact of blockchain on the communication process of bank boards and credit risk management. (Sun et al., 2023) find that blockchain adoption reduces corporate bankruptcy risk (for Chinese listed firms) by mitigating information asymmetry between creditors and debtors. If these benefits extend to other firms, blockchain research can converge with studies of credit risk practices.

5.5 Climate Risk as a Permanent Feature of Risk Architecture

As discussed in Section 2.6, climate and sustainability risk is set to become a permanent feature of financial risk architecture rather than a transitory concern. At present, credit, market, and systemic risk streams predominantly use separate data to study climate risk, with only a handful of papers directly linking it to conventional VaR, credit scoring, or systemic risk measures, with climate risk being an add-on indicator. (Iyke, 2026) discusses climate risk in the context of asset pricing, institutional, and economic balance frameworks, arguing that it should be integrated directly into decision-making processes rather than used as an ancillary factor. (Wang et al., 2026) investigate the connection between climate data disclosure, systemic risk, and corporate green transformation using firm-level data, suggesting that climate risk levels can trigger transformations in firms' economic behavior. (Ghaemi Asl, 2026) provides another example of a risk-mapping methodology for conventional and Islamic sustainable markets, which incorporates technology spillover risk as a factor—effectively combining three themes discussed in this review—AI, network/spillover analysis, and environment/sustainability risk—into one paper.

5.6 Policy-Driven and Regional Diversification

Finally, policies and regional differences are likely to dominate this literature, with a substantial number of papers examining the effects of a given regulation or the differences between two regions. Few studies will have a truly global focus, and those that do will typically rely on data from just a handful of countries to represent the entire world. (Qiaogen et al., 2026) illustrate this trend by showing the effects of the innovative-development pilot-zone policy in China on the public company investment-financing maturity mismatch. This policy signal, related to the regulation of AI, effectively serves as a moderator of the financial risk management process. The tendency of the field to focus on a single region or country will diversify as the literature begins to incorporate more data and regulations from Latin America, Africa, and beyond, complementing the traditional dominance of China, India, and Southeast Asia. The shift from a primarily North America/Europe-centric perspective toward a more genuinely global approach may take years to manifest.

5.7 Regulatory Technology and the Supervisory Feedback Loop

One final note on a potential future trend is regulatory technology (RegTech), which sits at the intersection between truly innovative modeling and the supervisors who must understand it. As financial institutions begin to adopt more sophisticated AI-driven risk models (Section 5.1) and network-based systemic-risk measures (Section 5.2), regulators must be able to evaluate, stress-test, and potentially challenge them, making RegTech a natural outgrowth of the literature. (Wang et al., 2025) and (Guo, 2025) provide two examples of this trend, using big data infrastructure and neural-network based early-warning systems to perform their supervisory function. If the focus of the literature were to shift from individual institutions to the system-level (as discussed in Section 4.3), RegTech could emerge as a sixth risk management/metrics stream, using the same tools (optimization, networks, machine learning).

6. CONCLUSION

In summary, the aim of this study was to determine precisely what the operations-research literature on financial risk management encompasses, as well as how quickly it is expanding, how it is structured, and where it is headed. Our work was guided by these five objectives, and all of them have been achieved, although certain findings are more solid than others. The forward-looking projections are informed extrapolations rather than established facts.

Regarding growth, the pattern is unmistakable: the field is in fact expanding more rapidly with each passing year, rather than at a constant rate. Over half of the papers in our sample appeared within just the past three years, whereas the preceding five years account for a considerably smaller proportion.

In terms of content, five principal topic areas emerge, and they differ greatly in both size and maturity. Systemic risk and network-based modelling forms by far the largest group, exceeding the others by a wide margin (Abedifar et al., 2017). Credit risk modelling follows, and it encompasses the broadest array of methods (García et al., 2019). Portfolio and value-at-risk optimization is the most established area. Artificial intelligence and climate-related risk are the smallest groups, yet they are expanding at the fastest rate.

Now explaining how these areas connect with each other, systemic risk sits clearly at the centre, linked to almost every other topic rather than standing apart. This means that this field is best understood as one connected body of research with a clear core and not just a set of loosely related sub-fields. A major trend running across these areas is the merging of network analysis with machine learning, especially in newer models that predict default risk by combining borrower-level data with network structure (Zandi et al., 2025) (C. Han et al., 2026). At the same time, an unresolved tension remains between how accurate a model is and how easy it is to interpret.

These findings matter to several audiences. For researchers, the old habit of studying individual borrowers separately from network-wide risk no longer holds up because now the most interesting work blends the two, and the biggest gaps sit where topic areas overlap. Climate risk, for example, is rarely built into today's network and machine-learning models, despite a solid climate-risk literature of its own. Researchers should also pay closer attention to whether models hold up in a real crisis, not just whether they fit past data well.

For practitioners, several tools are already mature enough for real use: reinforcement learning for managing debt collection (Sivamayilvelan, 2024), computational methods for loan forecasting and customer segmentation, and hybrid models for assessing borrowers in peer-to-peer lending. Managers adopting these tools should remember that success depends on more than the technology itself as it also requires governance and organizational change (Tanbour et al., 2025).

Apart from that, the regulators face a similar challenge because the work on capital and liquidity rules (Chockalingam et al., 2018) along with the growing field of regulatory technology (Guo, 2025) both point out that the supervision itself is turning into a data and monitoring problem.

Additionally, the topic of social stakes is often disregarded. The stakes are more than just technical because these risk models are the ones that are ultimately responsible for determining who gets credit and under what conditions. A significant portion of the literature addresses small-business credit access (Taghizadeh-Hesary et al., 2021) and models that utilise alternative data sources (Roa et al., 2021). This body of work demonstrates that more sophisticated risk models do not automatically benefit all stakeholders: while they may expand credit access for previously excluded borrowers, they can equally restrict it under different parameterisations.

There are also some limitations that are worth flagging. The database that we used did not include the citation counts or the author affiliations, so the analysis of citation impact, institutional influence, or country level collaboration just wasn't possible. ScienceDirect was the only database used, which means that some regions and areas may not have been as well represented as others. Also, because the review was based on keywords and metadata instead of the full texts, we know what the field is working on but not which methods are actually performing the best in practice. Lastly,

the 2026 data were still incomplete when collected, so the most recent growth figures should be treated as a floor rather than a final count.

Nevertheless, the overall picture is still important despite all these limitations. Our review has highlighted that the field is not slowing down or even showing a fragmented pattern of growth. Instead, the trends of credit risk, market risk, network risk and climate risk are all meeting towards the common goal of advancing systemic risk analysis along with the integration of machine learning technologies which is becoming a shared language across the separate subfields. Going forward, the most important contribution that this field of financial risk management can make is not just a single better risk measure but it is going to be building integrated systems that are very accurate, explainable and can be actually used by both institutions and the regulators watching over them.

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