

# THE EVOLUTION OF FINTECH-DRIVEN RISK MANAGEMENT- A BIBLIOMETRIC STUDY

Sonia Kundra, Daljit Singh

E-Mail Id: soniakundra@gnducajal.org, daljitusfs.rsh@gndu.ac.in

Guru Nanak Dev University College, Jalandhar, Punjab, India

**Abstract** - This bibliometric study analyses 435 English-language articles from Scopus and Web of Science to map the evolution of Fintech in risk management. Research output surged significantly, with the USA (13 articles) and China (15 articles) emerging as dominant contributors. Key themes include Financial Technology & Credit Scoring, Artificial Intelligence in Peer-to-Peer Lending, and Machine Learning & Credit Risk. Leong, Carmen (TC=171) and Bartlett, Robert (TC=152) are the most influential authors, while the Journal of Financial Economics (TC=181, ABDC A\*) and International Journal of Information Management (TC=171, ABDC A\*) lead in scholarly impact. Local citation analysis highlights foundational works like Gomber et al. (2018, LC=27) and Bartlett (2022, LC=7). The findings reveal a shift toward AI/ML-driven solutions for credit risk, fraud detection, and operational risk, underscoring Fintech's transformative role in enhancing financial stability and inclusion. Emerging gaps in liquidity and market risk applications warrant further exploration.

**Keywords:** Fintech, Risk Management, Bibliometric Analysis, Credit Scoring, Fraud Detection.

## 1. INTRODUCTION

Over the past two decades, the financial services industry has witnessed a fundamental transformation fuelled by the rise of Financial Technology (FinTech). Characterized by the integration of innovative digital technologies such as artificial intelligence (AI), blockchain, big data analytics, and cloud computing FinTech has revolutionized how financial services are delivered, consumed, and regulated (Arner et al., 2015; Gomber et al., 2018). One of the most critical areas impacted by this evolution is risk management, where FinTech solutions have introduced new paradigms in risk identification, assessment, mitigation, and compliance. The fusion of advanced computational tools with finance has shifted traditional risk management from retrospective and manual processes to real-time, data-driven, and predictive approaches (Gai et al., 2018).

Traditionally, financial institutions managed risk through a combination of expert judgment, statistical models, and regulatory mandates. While effective to an extent, these legacy systems often failed to capture emerging and complex risks, such as cyber threats, systemic financial shocks, and interconnected market vulnerabilities. In contrast, FinTech tools allow institutions to harness vast amounts of structured and unstructured data, enabling granular insights into customer behaviour, creditworthiness, market dynamics, and operational anomalies (Puschmann, 2017). For instance, machine learning algorithms can detect fraud in real-time, blockchain can enhance transparency and reduce counterparty risks, and big data analytics can predict default probabilities with higher precision than traditional credit scoring models (Zavolokina et al., 2016).

The COVID-19 pandemic further accelerated the adoption of FinTech in risk management by exposing the fragility of conventional systems and underscoring the need for resilient, automated, and adaptive risk frameworks. Regulatory bodies, too, began to acknowledge the dual nature of FinTech as both a solution to and a source of risk. Consequently, new regulatory technologies (RegTech) emerged to ensure compliance in a digitized financial ecosystem, thereby reinforcing the role of FinTech in enterprise risk governance (Anagnostopoulos, 2018).

To address this gap, bibliometric analysis provides a powerful methodology. Unlike traditional literature reviews, bibliometric analysis employs quantitative techniques to evaluate the academic output, citation patterns, co-authorship networks, influential publications, thematic trends, and intellectual structures of a given research field (Donthu et al., 2021). By systematically analysing metadata from large academic databases such as Scopus or Web of Science, bibliometric methods reveal the dynamics of scientific production, including the emergence of new research frontiers and the diffusion of key concepts.

This study, therefore, aims to conduct a comprehensive bibliometric analysis of scholarly publications on the intersection of FinTech and risk management. By examining trends in publication volume, co-citation networks, keyword co-occurrences, and thematic clusters, the paper seeks to answer key questions: How has research output evolved over time? Which countries and institutions are leading the field? What are the dominant themes and emerging topics? In doing so, the paper contributes not only to academic knowledge but also to practical understanding for regulators, financial institutions, and technology developers seeking to navigate the evolving risk landscape in the digital age.

## 2. BACKGROUND OF FINTECH AND RISK MANAGEMENT

The landscape of risk management in the financial sector has undergone significant transformation with the advent of financial technology (fintech), which is increasingly recognized as a vital tool for enhancing the efficacy and responsiveness of risk mitigation frameworks (Thakor, 2020). Fintech, defined as the integration of digital technologies such as artificial intelligence (AI), big data analytics, blockchain, and mobile platforms into financial services, offers novel mechanisms for identifying, assessing, and managing risks in a dynamic environment (Puschmann, 2017). Traditional risk management approaches often rely on historical data and manual processes, which may limit their adaptability, timeliness, and precision in the face of increasingly volatile and interconnected financial markets. In contrast, fintech applications enable financial institutions to leverage vast volumes of real-time data and sophisticated algorithms to detect emerging risks, predict default probabilities with greater accuracy, and automate compliance and reporting functions, thereby reducing operational and credit risks (Gomber et al., 2018).

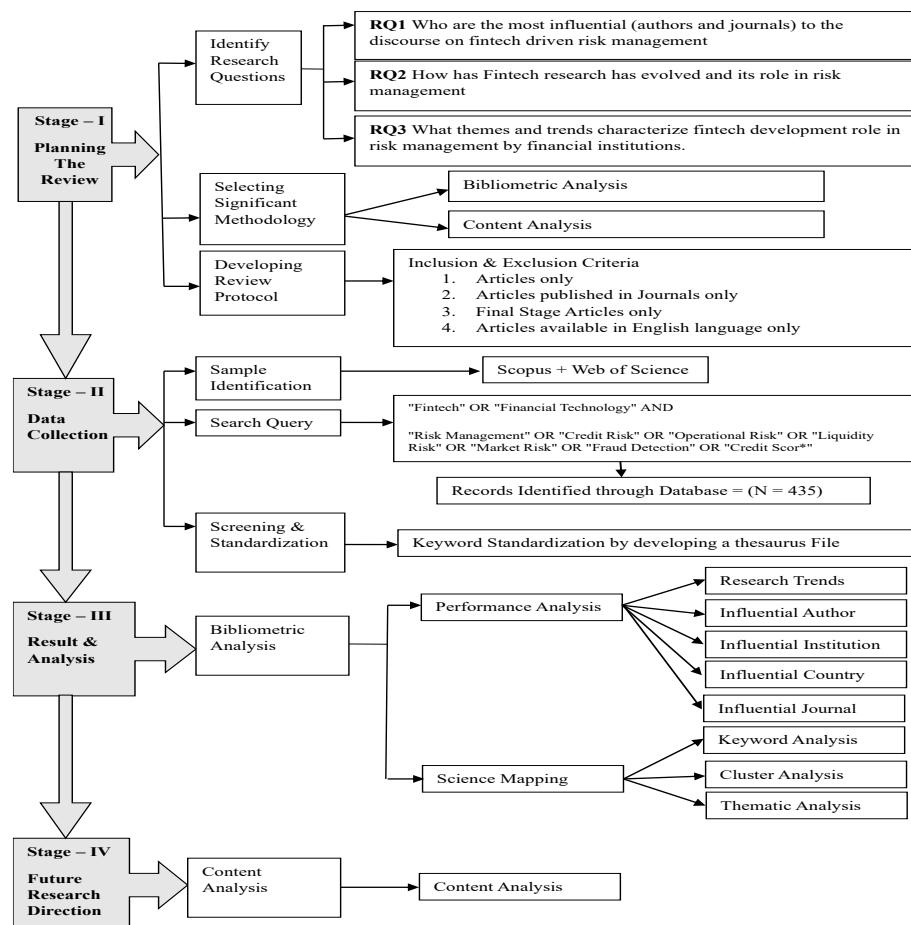


Fig. 2.1 Methodological Flowchart

## 3. RESEARCH QUESTIONS

This study will address the following questions: -

- Who are the most influential authors and journals to the discourse of fintech driven risk management.
- How has Fintech research has evolved and its role in risk management.
- What themes and trends characterize fintech development role in risk management by financial institutions.

## 4. RESEARCH METHODS

To ensure comprehensive coverage of the interdisciplinary components Fintech and Risk Management the study's search methodology incorporated associated keywords. These terms ('Fintech' OR 'Financial Technology' for Fintech; 'Risk Management' OR 'Credit Risk' OR 'Operational Risk' OR 'Liquidity Risk' OR 'Market Risk' OR 'Fraud Detection' OR 'Credit Scor\*' for Risk Management) were derived from an analysis of significant prior publications. The combined search strings utilized for Scopus and Web of Science are presented in Table 4.1.

**Table-4.1 Article inclusion and exclusion criteria**

	Scopus	Web of Science
Search Date: 18-07-2025 "Fintech" OR "Financial Technology" AND "Risk Management" OR "Credit Risk" OR "Operational Risk" OR "Liquidity Risk" OR "Market Risk" OR "Fraud Detection" OR "Credit Scoring"	920	260
Article	471	243
Journal	471	-
Final	444	-
English	434	-
Total Articles	434 + 243 = 677	
Duplicate Removed	242	
Final	435	

**Source:** Compiled by author

#### 4.1 Data Collection

This study employed a methodological approach to identify the final 435 publications listed in Table 1. Using keywords ('Fintech' OR 'Financial Technology') AND ('Risk Management' OR 'Credit Risk' OR 'Operational Risk' OR 'Liquidity Risk' OR 'Market Risk' OR 'Fraud Detection' OR 'Credit Scoring'), the search was restricted to English-language articles across disciplines shown in Table 1. Recognizing that data from Scopus and Web of Science can contain inaccuracies due to flawed bibliometric records (Donthu et al., 2021), using unrefined data risks significant misinterpretation. Consequently, the study implemented rigorous data cleaning procedures. Following recommendations by (Zupic & Čater, 2015) and (Donthu et al., 2021) this involved verifying bibliographic/bibliometric data and ensuring accurate visualization and interpretation of results.

#### 4.2 Technique for Analysis

Bibliometric analysis employs quantitative methods to examine textual data (Goyal & Kumar, 2021). This technique extracts novel insights from literature, supplementing research endeavours. To achieve this, it requires establishing thematic bibliographies, identifying research trends, and evaluating seminal works that map the field's landscape. Researchers apply methodologies—including authorship, citation, bibliographic coupling, co-citation, and co-word analysis to process bibliographic data (Donthu et al., 2021).

### 5. FINDINGS

#### 5.1 Performance Analysis

Figure 5.1 illustrates publication trends in fintech risk management research. While Arnold J et al. (2004) initiated this research domain, early studies predominantly addressed internet/e-banking rather than fintech. A notable surge began in 2020, with annual publication rates accelerating significantly since 2021. 2024 represents the current productivity peak, and based on current trends, research in this domain is expected to grow significantly in the coming years.


**Fig. 5.1 Publication Trend**

##### 5.1.1 Most influential authors, organisations and countries for fintech and risk management.

Table 5.1 identifies key influencers in fintech risk management research. Authors Leong (171 citations) and Bartlett (152 citations) lead with single high-impact publications. Similarly, Copenhagen Business School and

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Zhejiang's Research Centre for Information Technology, Economics & Social Development each received 171 citations from one document. At the per the most influential country, the USA (356 citations, 13 publications) and China (310 citations, 15 publications) dominate in the field of fintech and risk management domain.

**Table-5.1 Most Influential Author, Institutions and Countries**

TC	Authors	TP	TC	Organization	TP	TC	Country	TP
171	Leong	1	171	Copenhagen Business Sch	1	356	USA	13
152	Bartlett Robert	1	171	Res Ctr Informat Technol & Econ & Social Dev Zhej	1	310	China	15
91	Sutherland	1	171	University New South Wales	1	171	Australia	1
77	Bernards	1	171	University Sydney	1	171	Denmark	1
65	Benami	1	171	Zhejiang Gongshang Univ	1	72	Italy	2

**Source:** Compiled by author **Note:** - TC=Total Citations; TP=Total Publications

### 5.1.2 Most influential Journal for fintech and risk management.

Table 5.2 identifies the most influential sources in fintech risk management research. The Journal of Financial Economics leads with 181 citations from 3 publications, followed by the International Journal of Information Management (171 citations/1 publication). These journals, alongside the Journal of Accounting & Economics and Management Science, rank among the most productive. Elsevier publishes the majority of these sources. Author-level analysis reveals Gomber P. (2018) as the most locally influential, with 27 local citations against 1,180 global citations (LC/GC ratio: 2.29).

### 5.1.3 Most Influential Articles on Fintech Development Research in Risk Management

Table 5.2 identifies Gomber P.'s (2018) study "On the Fintech Revolution: Interpreting the Forces of Innovation, Disruption, and Transformation in Financial Services" as the top-cited reference in fintech risk management research, with 27 local citations and 1,180 global citations (LC/GC ratio = 2.29). The work establishes that the Fintech Revolution stems from sustained technological innovation, entrepreneurial ventures, and customer-centric service evolution, driving industry-wide disruption. It further identifies critical challenges including regulatory adaptation, value appropriation strategies, and inter-firm cooperation.

**Table-5.2 Most Influential Journal in Terms of Global Citations**

TC	Source	TP	ABDC	ABS	Publisher	Impact Factor	Cite Score
181	Journal of Financial Economics	3	A*	4*	Elsevier	12	22
171	International Journal of Information Management	1	A*	2	Elsevier	27	54.9
128	Journal of Accounting & Economics	3	C	2	Taylor & Francis	6.8	8.8
77	Review of International Political Economy	1	A	3	Taylor & Francis	3.7	9.2
75	Management Science	3	A*	4*	I.O.R. & T.M.S.	4.9	7.9
65	Applied Economic Perspectives & Policy	1	B	2	Wiley-Blackwell	3.4	11.5
52	European Journal of Operational Research	1	A*	4	Elsevier	6	13.2

**Source:** Compiled by author, **Note:** - TC=Total Citations; TP=Total Publications; ABDC= Australian Business Dean Council 2022 ranking; ABS= Chartered Association of Business School Academic Journal Guide

**Table-5.3 Most Influential Journal in terms of Local Citations**

LC	Author	Paper Title	Year	GC	LC/GC Ratio (%)	NLC	NGC

27	(Gomber 2017)	On The Fintech Revolution: Interpreting the Forces of Innovation, Disruption, And Transformation in Financial Services	2018	1180	2.29	9.53	9.45
7	(Bartlett 2022)	Consumer-Lending Discrimination in the Fintech Era	2022	181	3.87	22.24	8.40
7	(Ashta & Herrmann, 2021)	Artificial Intelligence and Fintech: An Overview of Opportunities and Risks for Banking, Investments, And Microfinance	2021	201	3.48	10.82	5.94

**Source:** Compiled by author, **Note:** - TC=Total Citations; TP=Total Publications; LC=Local Citations; GC=Global; NLC= Net Local Citations; NGC=Net Global Citations.

#### 5.1.4 Top reference for fintech development research in risk management.

Table 5 identifies the most cited works in fintech risk management research. The highest-impact article ((Leong et al., 2017; 171 citations) examines China's Fenqi e-commerce platform, which uses an ecosystem model integrating lending, spending, and earning services with alternative credit data to serve underserved students. This approach enhances financial inclusion while promoting sustainable, responsible finance. The second-ranked study (Bartlett et al., 2022; 152 citations) reveals fintech lenders reduce discriminatory loan pricing by 40% versus traditional lenders, though pricing disparities persist. Crucially, fintech lenders show no discrimination loan approvals, with overall pricing discrimination declining from 2009–2015.

**Table-5.4 Most Influential Articles on Fintech Research in Risk Management**

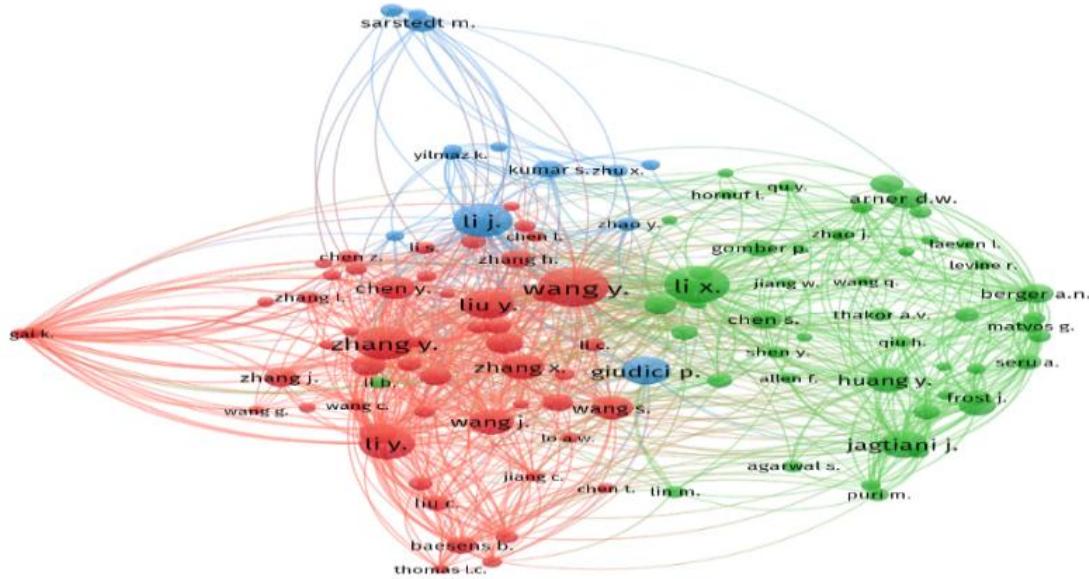
Author	Title	TC
(Leong 2017)	Nurturing A Fintech Ecosystem: The Case of a Youth Microloan Startup in China	171
(Bartlett et al., 2022)	Consumer-Lending Discrimination in The Fintech Era	152
(Sutherland, 2018)	Does Credit Reporting Lead to A Decline in Relationship Lending? Evidence From Information Sharing Technology	91
(Bernards, 2019)	The Poverty of Fintech? Psychometrics, Credit Infrastructures, And the Limits of Financialization	77
(Benami & Carter, 2021)	Can Digital Technologies Reshape Rural Microfinance? Implications For Savings, Credit, & Insurance	65
(Kriebel & Stitz, 2022)	Credit Default Prediction from User-Generated Text in Peer-To-Peer Lending Using Deep Learning	52
(Ahelegbey et al., 2019)	Latent Factor Models for Credit Scoring in P2P Systems	46
(Balyuk, 2023)	Fintech Lending and Bank Credit Access for Consumers	42
(Chen et al., 2022)	Finance And Firm Volatility: Evidence from Small Business Lending in China	33
(Costello et al., 2020)	Machine Plus Man: A Field Experiment on The Role of Discretion in Augmenting AI-Based Lending Models	31

**Source:** Compiled by author, TC=Total Citations

#### 5.2 Science Mapping

##### 5.2.1 Knowledge foundations of fintech development research in risk management through co-citation analysis

The semantic relationships among co-cited references, as identified through co-citation analysis, represent the foundational knowledge of a research field (Donthu et al., 2021). Figure 3 illustrates the co-citation network map, highlighting references that have been cited at least twenty times within the reviewed literature. The orange node, comprising authors such as Wang Y, Liu Y, Zhang Y, Wang J, and Li Y, indicates a concentrated citation pattern within a specific domain of fintech research focused on risk management. Similarly, the green node including Li X, Cheng S, Berger A.N., Wang R, Jagtiani I, and Huang Y reflects frequent citations of another key area in fintech risk management studies. The sky-blue node, associated with Li J, Sarstedt M, and Guidici P, also shows a significant cluster of highly cited works contributing to the same thematic focus in fintech-related risk management research.



**Fig. 5.2 Co-citation analysis of fintech development and risk management**

**Note:** Each node in the co-citation map represents a cited reference and a thematic cluster of references sharing a similar research focus. The size of a node corresponds to the frequency of local citations larger nodes indicate a higher number of times the reference has been cited within the dataset. Connections between nodes depict co-citation relationships, with the thickness of each link reflecting the strength of these connections thicker links signify a higher degree of co-citation intensity among the references.

### 5.2.2 Thematic and influence structure analysis through bibliographic coupling.

Table 5.5 delineates the thematic clusters of fintech risk management research through bibliographic coupling analysis. The three predominant research domains emerging from this analysis are: Financial Technology & Credit Scoring, Artificial Intelligence & Peer-to-Peer Lending, and Machine Learning & Credit Risks. Each cluster's seminal articles are identified within the table, collectively encompassing the core conceptual facets of fintech risk management scholarship. This tripartite structure demonstrates how current research converges around technological applications in credit assessment, AI-driven lending platforms, and computational risk modelling.

**Table-5.5 Thematic Clusters of Fintech in Risk Management**

Themes	Title	TC
Financial Technology & Credit Scoring	Is The Relationship Between Financial Technology and Credit Risk Monotonic? Evidence From the BRICS Economies	12
	Stabilizing Leverage, Financial Technology Innovation, And Commercial Bank Risks: Evidence from China	11
	Latent Factor Models for Credit Scoring in P2P Systems	46
Artificial Intelligence & Peer to Peer Lending	Industry 4.0 In Finance: The Impact of Artificial Intelligence (AI) On Digital Financial Inclusion	330
	Artificial Intelligence and Fintech: An Overview of Opportunities and Risks for Banking, Investments, And Microfinance	201
	How Signaling and Search Costs Affect Information Asymmetry in P2P Lending: The Economics of Big Data	81
Machine Learning & Credit Risk	Explainable Machine Learning in Credit Risk Management	239
	Performance Evaluation of Machine Learning Methods for Credit Card Fraud Detection Using Smote and Adaboost	143
	Does Bank Fintech Reduce Credit Risk? Evidence From China	291

**Source:** Compiled by author; TC=Total Citations.

Cluster 1 is concerned with Financial Technology & Credit Scoring research. Tochukwu et. al., (2020) study investigates the nexus between financial technology (Fintech) adoption and bank credit risk across BRICS economies (1995–2018), revealing a nonlinear U-shaped relationship. Initial Fintech implementation correlates with reduced credit risk (measured by non-performing loans), driven by short-term efficiency gains and improved loan performance. However, beyond a critical adoption threshold, further technological penetration paradoxically elevates credit risk, potentially precipitating systemic banking crises over extended horizons.

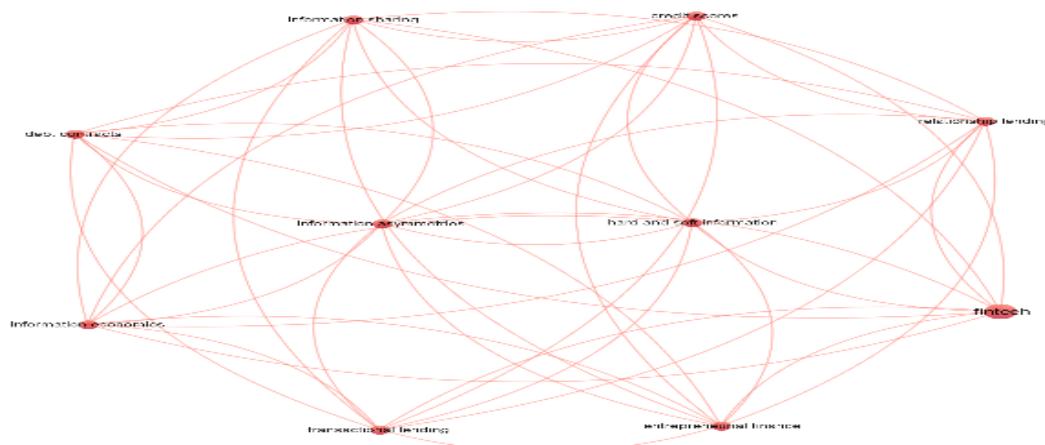
Cluster 2 includes Artificial Intelligence research on Peer-to-Peer Lending. David et. al., (2020) reveals AI significantly enhances digital financial inclusion by overcoming barriers facing vulnerable populations (women, youth, smallholder farmers). Traditional exclusion drivers' information asymmetry and perceived high risks are mitigated through AI's algorithmic assessment of heterogeneous datasets, enabling refined risk detection/management and lowering uncertainty for financial providers.

Cluster 3 include use of machine learning in credit risk research. Niklas et. al., (2020) This paper introduces an explainable AI framework for credit risk management that integrates correlation networks with Shapley value analysis, enabling borrower clustering based on similarity in financial risk drivers. When applied to 15,000 SMEs, the method outperforms traditional logistic regression in predictive accuracy while providing critical model interpretability essential for regulated financial contexts. The approach identifies distinct clusters of high-risk and low-risk borrowers, revealing actionable financial characteristics underlying credit decisions.

### 5.2.3 Thematic trends of fintech development research in risk management.

In order to develop intellectual foundations mapped through co-citation analysis and thematic clusters identified via bibliographic coupling, this study employs co-occurrence analysis to examine thematic evolution in fintech risk management research. Using author-provided keywords as analytical units, the methodology applies chronological filtering to trace conceptual trajectories and emerging foci within the domain. This temporal lens reveals how core themes including machine learning applications, regulatory technologies, and algorithmic credit scoring have dynamically developed across distinct research phases.

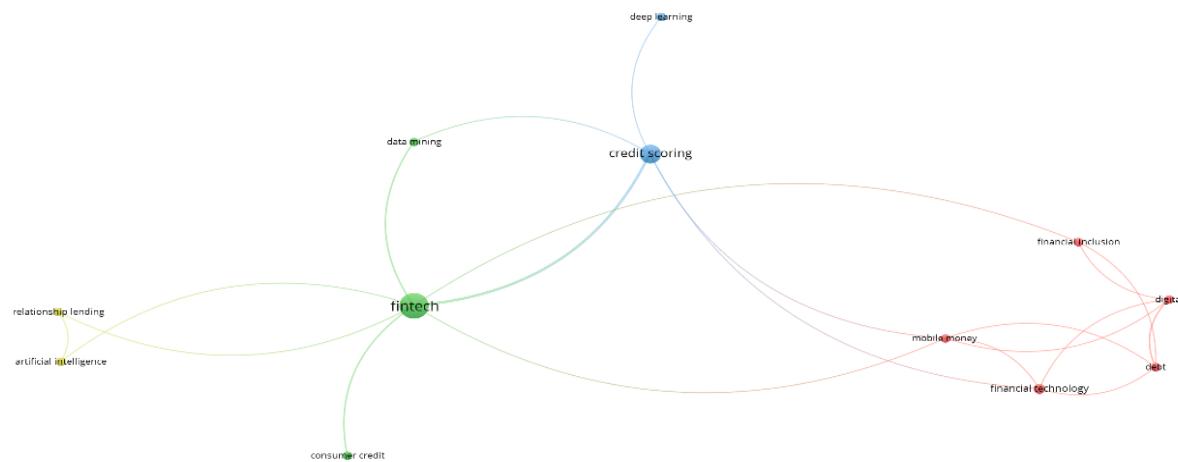
The study conducted on the theme on the theme of fintech development research in risk management between 2004 and 2019 was more focussed on fintech, information sharing and information asymmetry. It is the initial phase of fintech development in risk management which begins with information sharing and moves to information asymmetry.



**Fig. 5.3 Influential topics in the period of 2004 - 2019**

**Notes:** Orange node represents initial phase of development of topic with keywords, information sharing, information asymmetry and fintech.

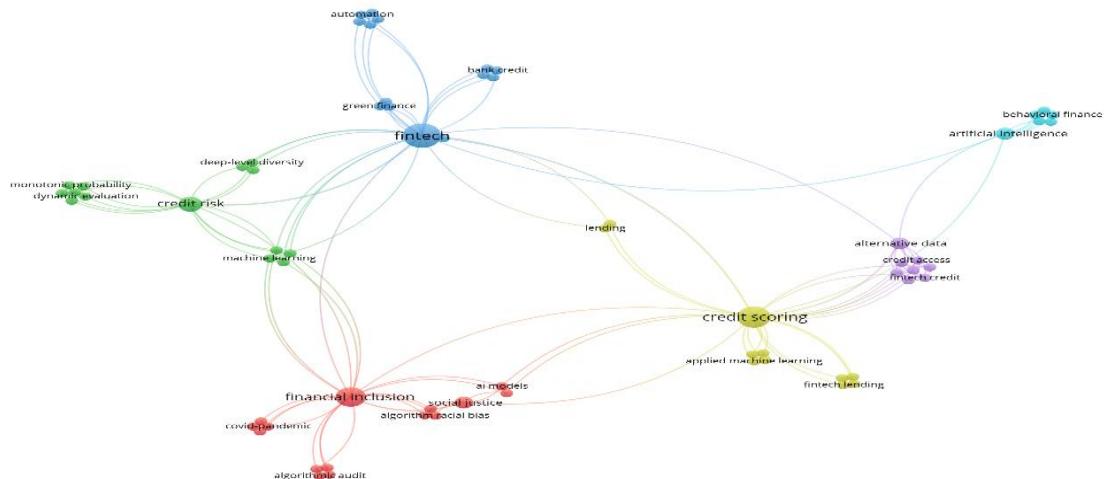
Co-occurrence analysis of fintech risk management literature (2020–2022) identifies four dominant thematic clusters: consumer credit (green node), deep learning and credit scoring (blue node), mobile money and financial inclusion (orange node), and artificial intelligence in relationship lending (yellow node). This diversification beyond foundational fintech concepts demonstrates significant thematic expansion within the field, reflecting its maturation into a multifaceted research domain during this period. The co-occurrence of these distinct yet interconnected themes underscore how fintech risk management has evolved to address complex financial ecosystems through varied technological lenses.



**Fig. 5.4 Influential topics in the period of 2020-2022**

**Notes:** Green node = fintech, data mining and consumer credit; Orange node = mobile money, financial inclusion; Blue node = deep learning, credit scoring; Yellow node = artificial intelligence, relationship lending

The study conducted from 2023 to 2025 on fintech development research in risk management is concentrated on the theme such as fintech and green finance (blue node), machine learning and credit risk (green node), AI models and algorithmic audit (orange node), fintech lending and credit scoring (yellow node), alternative data and fintech credit (plum node), artificial intelligence and behaviour finance (sky blue node).



**Fig. 5.5 Influential topics in the period of 2023 to 2025**

**Notes:** Blue node = fintech and green finance; Green finance = machine learning and credit risk; Orange node = AI models and algorithmic audit; Yellow node = fintech lending and credit scoring; Plum node = Fintech credit and credit access; Sky blue node = Artificial Intelligence and Behavioural finance.

## 6. FUTURE RESEARCH DIRECTION

A future study might look at how the most recent technology drivers in risk management to perform better in local and global markets. Between 2004 to 2019, the studies were focused on fintech, information sharing and information asymmetry in the area of fintech development and risk management. Between 2020 to 2022, the studies were focussed on fintech, data mining and consumer credit. Furthermore, the study 2023 to 2025 focused on fintech, financial inclusion, credit scoring and credit risk.

The use of fintech and credit scoring is the trending topic in recent studies. Advancing FinTech and AI applications in credit risk management necessitates targeted investigation across two critical domains. First, researchers must prioritize refining predictive modeling through optimal threshold identification, particularly

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given the nonlinear U-shaped relationship observed in BRICS economies where initial FinTech adoption reduces credit risk but excessive integration amplifies it. This requires examining heterogeneous drivers including divergent economic structures, financial systems, political climates, and institutional frameworks to establish context-specific saturation points. Second, to bridge AI's black-box limitations in regulated finance (as evidenced in P2P lending), Explainable AI (XAI) frameworks must be expanded to complex datasets.

Future research must critically examine FinTech's dual impact on market competition dynamics and consumer financial behavior, particularly how algorithmic lending innovations reshape traditional financial ecosystems. This necessitates comparative analysis of competitive pressure points (e.g., pricing models, service accessibility) and behavioral shifts (e.g., platform loyalty, decision heuristics) across borrower segments. Crucially, studies should quantify the differential implications for traditional institutions (burdened by legacy infrastructure) versus algorithmic lenders (leveraging scalable AI), enabling evidence-based regulatory frameworks that balance innovation with market stability.

## CONCLUSION

Bibliometric analysis offers valuable insights for guiding collection development, highlighting institutional research strengths, mapping citation patterns, and revealing prominent co-citation networks representing schools of thought. This study has explored and visualised the trends, thematic evolution, and influential works within fintech development research focused on risk management. Data were collected and analysed from the Scopus and Web of Science databases, which are among the most comprehensive bibliographic resources available. The study outlines the progression of research and thematic shifts across different time periods, providing a detailed account of the evolution of fintech-related risk management scholarship and suggesting future research directions. Researchers are encouraged to investigate emerging areas within this field to offer more nuanced insights for policymakers and practitioners. Through this approach, the study enhances the understanding of research trends, identifies potential future topics, and maps out the trajectory of fintech development research in risk management. However, it is important to note that the scope of this analysis was confined to data drawn exclusively from Scopus and Web of Science; future research could broaden its scope by including additional databases to gain an even more comprehensive perspective.

## IMPLICATIONS OF THE STUDY

This study offers multiple implications for marketers, entrepreneurs, investors, financial institutions, and academic researchers. It provides a comprehensive overview of existing research in this field, enabling stakeholders to gain deeper insights into the landscape of fintech and risk management scholarship. By identifying the most influential authors and understanding the factors that have contributed to their prominence, readers can consult these pivotal works to address current academic and industry challenges more effectively. Additionally, the study highlights gaps in the existing literature and outlines potential future research directions, which can guide scholars in designing meaningful future studies. Finally, the findings may also assist researchers in targeting reputable, high-impact journals for disseminating their work.

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