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Trends and Patterns in Artificial Intelligence Applications for Financial Technology: A Global Bibliometric Analysis (2000–2025)

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ABSTRACT
This study provides a comprehensive bibliometric mapping of artificial intelligence (AI) research in financial technology (FinTech) from 2000 to 2025, based on 958 Scopus-indexed publications. The research uses performance analysis and science-mapping methodologies to examine publishing patterns, citation impact, and topic progression.The findings suggest an increased development of AI–FinTech research from 2018, culminating in a large rise by 2024. Three important study areas emerge: cybersecurity and machine-learning-driven systems, digital finance and technical innovation, and decision-support systems with risk analysis. Despite this rapid expansion, persistent gaps remain in regulatory technological frameworks, ethical AI governance, and sustainability integration.By systematically structuring the intellectual landscape of AI–FinTech research, this study contributes to management systems and strategic operations by informing risk governance design, cybersecurity management, regulatory compliance optimization, and data-driven operational decision-making in digital transformation initiatives.

1. INTRODUCTION

Combining artificial intelligence (AI) with financial technology (FinTech) is one of the most important new ideas transforming how business is done worldwide. AI has completely revolutionized how financial operations function in the last twenty years It has revolutionized everything, from algorithmic trading and figuring out credit risks to discovering fraud, automating customer contacts, and making sure that regulations are followed (Chen & Robinson, 2019; Gomber et al., 2017). Thanks to new advancements in machine learning, natural language processing, and predictive analytics, banks and other financial institutions may now be able to work better, make better judgments, and deliver tailored financial services to clients on a scale that has never been seen before Researchers are highly interested in the widespread application of AI-powered FinTech solutions, which has led to a huge surge in research articles, especially after 2018 This rise means more than simply advancement in science; it shows how important AI has become for digital transformation, corporate governance, and keeping financial institutions stable. A lot of research has been done on how AI may be used in banking, but the work already done is still scattered across numerous fields, technologies, and real-world applications. Bibliometric studies provide a systematic approach to synthesize large amounts of literature by mapping intellectual structures, identifying key contributors, and tracing thematic development over time (Donthu et al., 2021). However, early bibliometric evaluations in the AI–FinTech sector frequently focus on individual technologies, such as blockchain or robo-advisory services, and provide limited integration with broader managerial, regulatory, and organizational perspectives. Against this context, the present study conducts a complete bibliometric analysis of AI–FinTech research published between 2000 and 2025. Drawing on Scopus-indexed journal articles and review papers, this study aims to: (1) analyze the evolution and growth patterns of AI–FinTech publications; (2) identify the most productive and influential authors, institutions, and countries; (3) map the dominant research themes and emerging trends; (4) examine international collaboration networks; and (5) highlight research gaps and future research opportunities. This research endeavor addresses the subsequent inquiries:

(1) In what ways has the landscape of AI-FinTech research evolved from 2000 to 2025, in terms of publication volume and thematic focus?
(2) Who are the key contributors and institutions that have significantly influenced this research domain?
(3) What thematic clusters and emergent motifs delineate the application of AI within financial technology?
(4) What mechanisms facilitate the evolution of international collaboration and knowledge networks in this sector?
(5) What prospective research trajectories emerge from the existing AI-FinTech academic discourse?

This study enhances the academic discourse by integrating AI-FinTech literature with management frameworks, strategic processes, and financial governance via bibliometric analysis and a management-centric perspective, offering critical insights for scholars, practitioners, and policymakers on the intricate relationship between artificial intelligence and finance.

2. RESEARCH METHODS

2.1. Research Design

This study employs a bibliometric research design to systematically examine global scholarly trends in the application of artificial intelligence to financial technology from 2000 to 2025. The methodological framework follows the structured bibliometric methodology established by Donthu et al.(2021), which is widely employed in management, information systems, and multidisciplinary research to study publishing dynamics, intellectual structures, and thematic progression

2.2. Data Source

Bibliometric data were obtained from the Scopus database, selected for its broad coverage of high-quality peer-reviewed journals and robust citation indexing capabilities (Baas et al., 2020; Martín-martín et al., 2021). Scopus is particularly ideal for interdisciplinary research such as AI– FinTech, which covers computer science, business, economics, and social sciences

2.3. Search Strategy and Selection Criteria

A systematic literature search was conducted in the Scopus database using the following search string:

TITLE-ABS-KEY (artificial AND intelligence AND financial AND technology) AND PUBYEAR > 1999 AND PUBYEAR < 2026 AND (LIMIT-TO (SUBJAREA, "BUSI") OR LIMIT-TO (SUBJAREA, "ECON") OR LIMIT-TO (SUBJAREA, "COMP") OR LIMIT-TO (SUBJAREA, "SOCI")) AND (LIMIT-TO (LANGUAGE, "English")) AND (LIMIT-TO (OA, "all")) AND (LIMIT-TO (DOCTYPE, "ar") OR LIMIT-TO (DOCTYPE, "re"))

The search was conducted on December 5, 2025, yielding an initial set of 1,784 records. After applying filters pertaining to subject areas, language, document type, and open-access availability, 1,020 records were identified as appropriate for further screening

Rationale for Open-Access and Subject-Area Selection

This study restricts the dataset to All Open Access (OA) publications to enhance transparency, replicability, and methodological rigor. Restricting the analysis to open-access literature guarantees comprehensive accessibility for verification, content validation, and subsequent bibliometric replication, which is crucial in fast-paced interdisciplinary domains like AI–FinTech; moreover, this accessibility enhances the dissemination of insights among scholars, industry professionals, regulators, and policymakers. Furthermore, the analysis focuses on four Scopus subject areas Business, Management and Accounting (BUSI); Economics, Econometrics and Finance (ECON); Computer Science (COMP); and Social Sciences (SOCI) to retain a multidisciplinary yet theoretically coherent scope. These areas jointly include the technical underpinnings of artificial intelligence, the financial and economic processes behind FinTech innovation, and the administrative, organizational, and social ramifications of AI- driven financial systems. Restricting the topic areas helps lessen disciplinary noise from peripheral fields while maintaining the core strategic, operational, and governance elements important to AI–FinTech research.

2.4. PRISMA Flow and Dataset Harmonization

This study followed a PRISMA-based screening procedure to ensure transparency, consistency, and replicability in the dataset selection process. The initial search conducted in the Scopus database yielded 1,784 records. After applying predefined filters for subject areas, language (English), document type (articles and reviews), and open-access status, 1,020 records remained and were retained for eligibility assessment. Given the dynamic nature of open-access classification in the Scopus database, where publication access status may change over time, a dataset harmonization step was performed to ensure consistency between the search date, data extraction phase, and bibliometric analysis. During this harmonization procedure, 62 entries were deleted due to discrepancies in open- access categorization across access classes (Gold, Green, Hybrid Gold, and Bronze). As a result, the final dataset comprised 958 papers, which were later employed for the bibliometric study. The PRISMA framework promotes methodological transparency by clearly documenting each step of the literature selection process, hence enhancing repeatability and allowing future researchers to confirm or expand this study. This structured approach is particularly critical in rapidly evolving interdisciplinary fields such as AI–FinTech, where clear documentation of inclusion and exclusion criteria ensures that bibliometric findings accurately represent the scholarly landscape rather than reflecting arbitrary or inconsistent selection procedures.

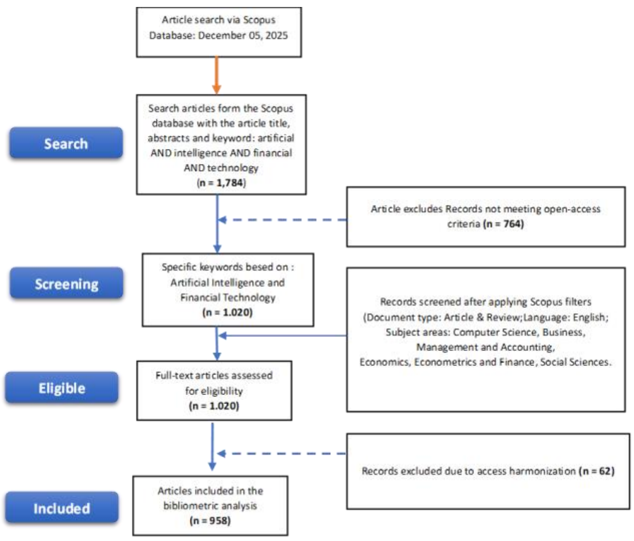

Figure 1. PRISMA Flow Diagram of the AI–FinTech Literature Selection Process
Note: Adapted from the PRISMA 2020 statement (Page et al., 2021)
Source: Authors' analysis based on Scopus database

2.5. Bibliometric Analysis Framework

Bibliometric investigations were conducted using the Biblioshiny interface, following a systematic analytical methodology derived from Donthu et al. (2021). The framework contained four interrelated components intended to capture both the quantitative performance and the conceptual structure of AI–FinTech research.

First, Productivity Analysis analyzed publication output and h-index metrics to identify the most prolific authors, companies, and nations advancing AI–FinTech scholarship. This analysis provides insights into the distribution of research productivity and the regional concentration of academic contributions.

Second, citation impact analysis evaluated the research significance of major publications, authors, and journals using citation frequency and co-citation relationships. This technique reveals the intellectual origins of the discipline, identifies key publications, and illustrates knowledge transfer patterns across the AI–FinTech research landscape.

Third, the Collaboration Network Analysis studied co-authorship links between writers, organizations, and nations. Network visualization techniques were applied to stress collaboration patterns, research clusters, and the degree of globalization, displaying how information is generated and disseminated via cooperative efforts.

Finally, Thematic Structure Analysis conducted keyword co-occurrence and temporal trend analyses to identify important research themes and their evolution over time. In addition, Latent Dirichlet Allocation (LDA) topic modeling was applied to uncover latent themes in the literature.

This unsupervised machine learning methodology extends standard bibliometric techniques by identifying deeper semantic links and correlations across research streams that may not be immediately visible via keyword analysis alone.

2.6. Data Visualization and Validation

Bibliometric results were depicted using network maps, thematic progression diagrams, and collaboration graphs designed by Biblioshiny (Kirby, 2023). These infographics make it easier for individuals to see how authors, businesses, governments, and research areas are all connected in the AI-FinTech sector. We used quantitative bibliometric data to strengthen the analysis. Triangulated with a qualitative evaluation of highly cited works, guaranteeing coherence between statistical trends and substantial scientific contributions. People who know a lot about artificial intelligence, financial technology, and bibliometric analysis also reviewed the data to ensure it was accurate, reliable, and easy to understand.

3. RESULTS AND DISCUSSION

3.1. Publication Trends in AI–FinTech Research

3.1.1. Annual Growth of Publications

The temporal evolution of publication volume in artificial intelligence applications for financial technology from 2000 to 2025 shows a pronounced, nonlinear growth trajectory. From 2004 to 2017, just nine articles were recorded, indicating low scientific effort. This time implies that AI–FinTech research was still at a basic level, primarily exploratory and technologically scattered. A structural shift happened in 2018, indicating the beginning of increased scholarly attention. The publication output has expanded dramatically, rising from 11 studies in 2018 to 20 in 2019, 39 in 2020, and 58 in 2021. The rise intensified in 2022, reaching 131 publications, followed by 125 publications in 2023 and a peak of 237 articles in 2024. Overall, the information suggests a compound annual growth rate of 66.8% from 2018 to 2024, well above the typical academic growth rate of 3–5%. This rapid spike reflects multiple converging factors, including advances in deep learning architectures, greater availability of large-scale financial data, and accelerated digital transformation in financial services during the COVID-19 pandemic.

The persistent growth— representing a more than twenty-fold rise since 2018—suggests that AI–FinTech has transitioned from a niche academic subject to a major interdisciplinary topic. Preliminary 2025 forecasts show continuing improvement, with no evident symptoms of saturation

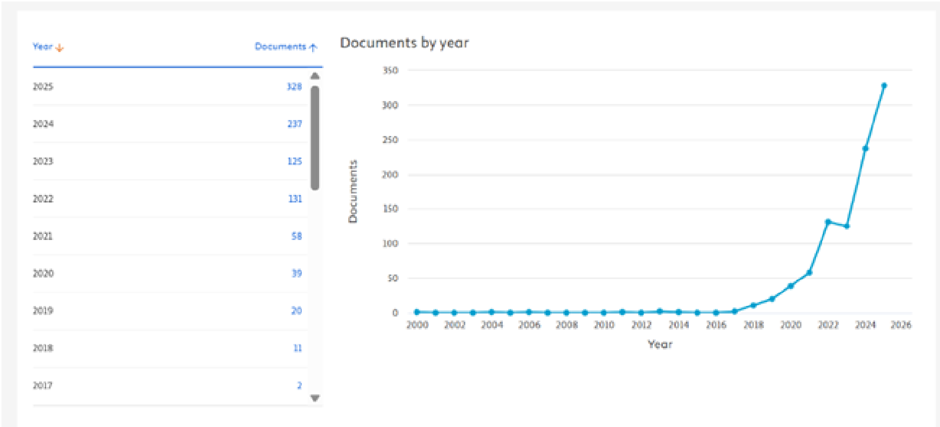

Figure 1: Quantity of Research Publications on " artificial intelligence AND financial technology"
Source: Scopus

3.2. Document Classification and Knowledge Consolidation

The distribution of document types reveals the dominant modes of scholarly communication within AI–FinTech research. Research articles account for 817 publications (85.3%), reflecting strong empirical engagement and methodological experimentation. Review articles comprise 141 publications (14.7%), indicating growing efforts to synthesize fragmented findings and consolidate theoretical foundations. This distribution is representative of a fast maturing area, where empirical innovation dominates while systematic reviews play a crucial role in structuring acquired knowledge. The balance between original studies and reviews suggests that AI–FinTech research is moving beyond exploratory phases toward cumulative and theory-informed development.

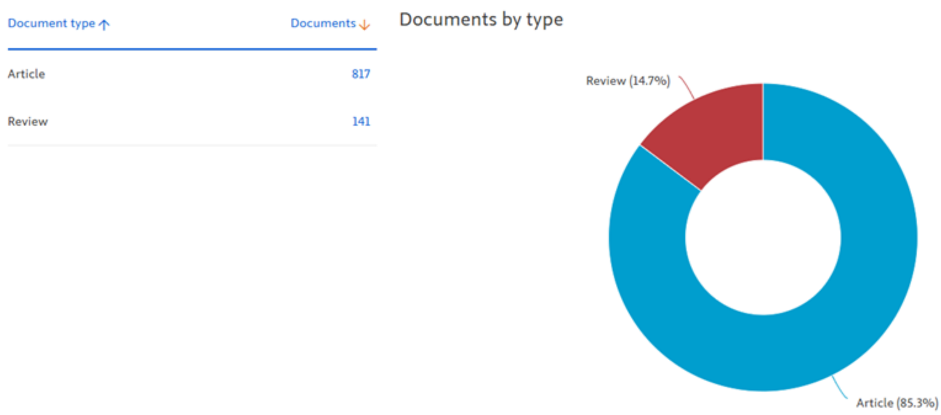

Figure 2: Distribution of Publications by Document Type

3.3. Productivity Patterns
3.3.1. Author Productivity

Analysis of author productivity suggests a highly scattered research ecosystem. The most prolific authors contributed only 4 publications each, while the remaining top contributors contributed 3 publications each. Collectively, the ten most productive authors account for only 3.4% of the total corpus. This dispersion implies the absence of dominant individuals or research groups and reflects the interdisciplinary and open character of AI–FinTech research. Contributions arise from several academic disciplines, including information systems, finance, computer science, and management. Such diversity allows methodological plurality and cross-domain knowledge integration.

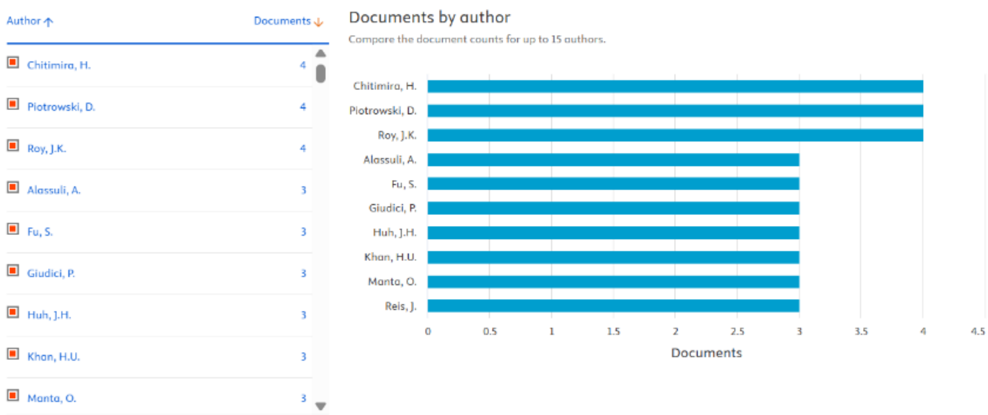

Figure 3. Distribution of Publications by Most Productive Authors
Source: Scopus

3.3.2. Institutional Contributions

At the institutional level, productivity is similarly dispersed. The leading institutions contributed between 9 and 11 papers apiece, accounting for less than 9% of total output. Notably, considerable participation arises from Eastern Europe and the Middle East, complementing institutions from Asia and Oceania. This pattern suggests that AI–FinTech research is not monopolized by traditional research powerhouses but increasingly driven by institutions in emerging and developing economies, where financial inclusion challenges and digital finance adoption provide fertile research contexts.

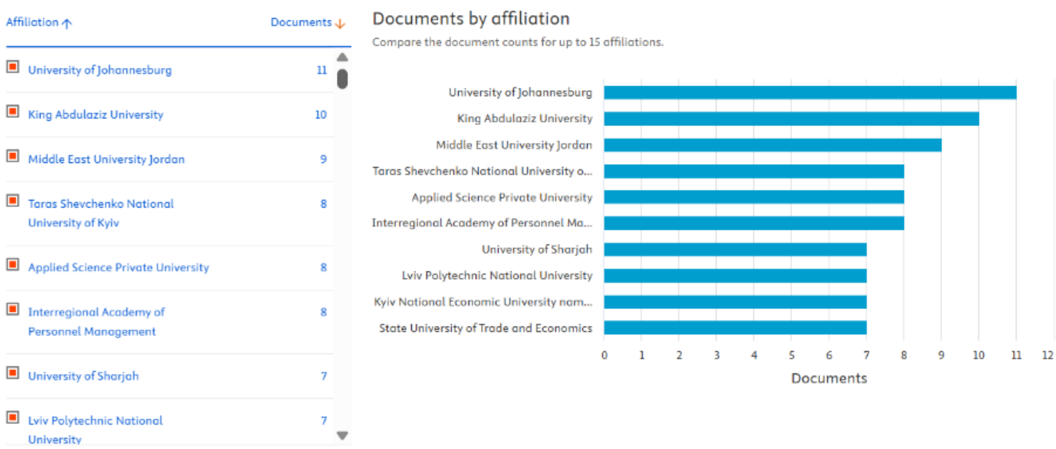

Figure 4. Preeminent Productive Institutions
Source: Scopus

3.3.3. National Productivity

A country-level study demonstrates significant concentration alongside global participation. China, India, and the United States lead publication production, followed by the United Kingdom, Saudi Arabia, and Ukraine. Emerging economies, including Malaysia, Jordan, and Indonesia, also demonstrate considerable research engagement. The regional distribution demonstrates that AI–

FinTech research is closely linked to places undergoing quick financial digitalization, regulatory transformation, and platform-based financial innovation.

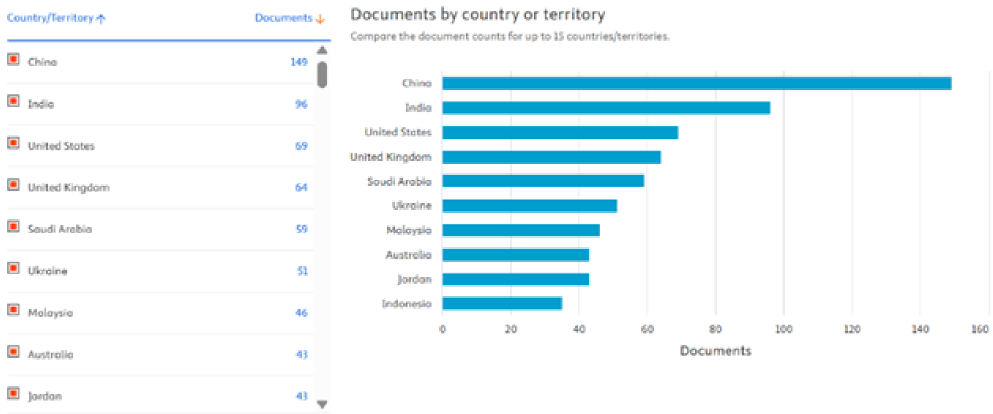

Figure 5. Catalog of the Most Productive Nations
Source: Scopus

3.4. Citation Impact and Intellectual Foundations
3.4.1. Highly Cited Publications

Citation analysis finds a group of significant papers that comprise the intellectual backbone of Artificial Intelligence–Financial Technology (AI–FinTech) research. Highly cited research often focuses on fraud detection, anomaly detection, privacy-preserving machine learning, and digital transformation methodologies. This research highlights applied AI approaches while simultaneously addressing organizational, regulatory, and behavioral factors. Their prevalence suggests that significant AI–FinTech research tends to connect technological innovation with managerial relevance and governance issues.

As shown in Table 1, the 10 most commonly cited papers collectively represent the field's key research interests. The most cited publication by Ghazal et al. (2021), with 459 citations, examines how machine learning can be used in smart systems for the Internet of Things. It emphasizes the importance of data-driven intelligence in complex digital contexts. This is followed by Habeeb et al. (2019) and Hilal et al. (2022), which focus on real-time anomaly detection and financial fraud analytics. These statistics reveal that the early main contributions focused on operational risk, system resilience, and security issues arising from financial digitalization.

The temporal distribution of highly cited publications shows that the most relevant research was published between 2019 and 2023, with 2022 as a peak year for influential outputs. Beyond technical advancements, several important studies stretch into organizational transformation, privacy governance, and strategy adaptation, demonstrating that high-impact AI–FinTech research increasingly incorporates technological, managerial, and regulatory challenges. Collectively, these studies establish fundamental paradigms that continue to guide further AI–FinTech research.

Table 1. Ten Most Frequently Cited Articles **Table 1. Ten Most Frequently Cited Articles**

No	Authors	Title	Citations	Ref
1	Ghazal et al.	IoT for smart cities: Machine learning approaches in smart healthcare—A review	459	(Ghazal et al., 2021)
2	Habeeb et al.	Real-time big data processing for anomaly detection: A Survey	424	(Habeeb Riyaz et al., 2019)
3	Hilal et al.	Financial Fraud: A Review of Anomaly Detection Techniques and Recent Advances	423	(Hilal et al., 2022)
4	Liu et al.	When Machine Learning Meets Privacy: A Survey and Outlook	421	(Liu et al., 2022)
5	Brunetti et al.	Digital transformation challenges: strategies emerging from a multi-stakeholder approach	361	(Brunetti et al., 2021)
6	Allioui et al.	Exploring the Full Potentials of IoT for Better Financial Growth and Stability	360	(Allioui et al., 2023)
7	Achouch et al.	On Predictive Maintenance in Industry 4.0: Overview, Models, and Challenges	350	(Achouch et al., 2022)
8	Flavián et al.	Intention to use analytical artificial intelligence (AI) in services – the effect of technology readiness and awareness	308	(Flavián et al., 2022)
9	Volberda et al.	Strategizing in a digital world: Overcoming cognitive barriers, reconfiguring routines and introducing new organizational forms	305	(H.W. Volberda, 2021)
10	Cubric	Drivers, barriers and social considerations for AI adoption in business and management: A tertiary study	290	(Cubric, 2020)

Source: Scopus

3.4.2. Author and Journal Impact

The local H-index analysis provides insights into the distribution of scholarly influence among authors within the AI–FinTech research corpus. As illustrated in Figure 6, Chen Y. and Kumar A. exhibit the highest local impact with an H-index of 5, followed by Li X. and Zhou H. with an H-index of 4. Several additional authors maintain H-index values of 3, indicating moderate yet consistent influence within this research domain.

The relatively narrow H-index range and the absence of extreme outliers suggest a highly distributed and non-hierarchical scholarly landscape. This pattern illustrates the interdisciplinary and evolving nature of AI–FinTech research, where influence is diffused across multiple contributors rather than concentrated in a small number of dominant experts. Such a form is characteristic of quickly growing research domains that encourage varied methodological approaches and cross-disciplinary collaboration.

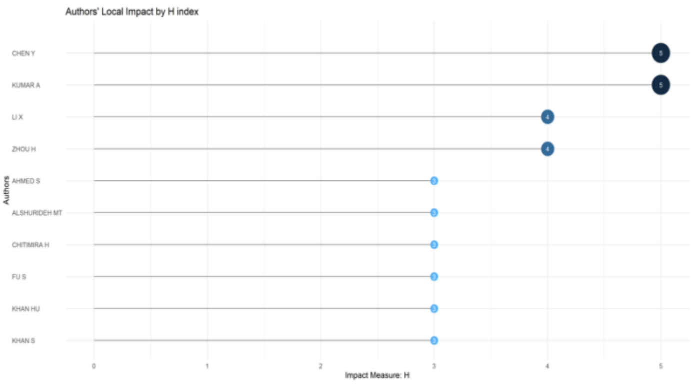

Figure 6. Authors with the Highest Local H-index in AI–FinTech Research
Source: Scopus & Biblioshiny

At the journal level, citation analysis demonstrates the dominance of open-access and multidisciplinary publication sources. Journals published by MDPI, IEEE, Elsevier, ACM, and Emerald account for a large fraction of total citations, with Sustainability (Switzerland) and IEEE Access leading in cumulative citation counts. The International Journal of Information Management, on the other hand, has a very high impact per publication, even though it publishes fewer papers. There are so many open-access publications that making citations easier is a key element of making them more. visible and helping scholars, professionals, and policymakers learn more.

Table 2. Ten Premier Journals Addressing AI and FinTech

Journal	Publisher	Articles	Citations
Sustainability (Switzerland)	MDPI	30	1,194
IEEE Access	IEEE	29	1,013
International Journal of Information Management	Elsevier Ltd	2	560
Future Internet	MDPI	4	539
Expert Systems with Applications	Elsevier Ltd	3	535
Applied Sciences (Switzerland)	MDPI	9	504
Sensors	MDPI	7	457
ACM Computing Surveys	ACM	1	421
TQM Journal	Emerald	1	361
Journal of Service Management	Emerald	1	308

Source: Scopus

3.5. Collaboration Structures

3.5.1. Author Collaboration Networks

The co-authorship network analysis reveals multiple research clusters collaborating within the AI–FinTech research domain. As illustrated in Figure 7, the collaboration structure consists of three major clusters, each centered on Liu Y., Zhou H., and Chen Y., who serve as key bridging scholars. Liu Y. anchors the largest cluster, connecting nine collaborators, including Wu Y., Chen Z., and Chen M., thereby facilitating extensive knowledge exchange across research subfields. Zhou H. leads a second cluster comprising six members, including Fu S., Zhou J., and Li H., while Chen Y. coordinates a smaller cluster that serves as an intermediary between otherwise disconnected network segments. These authors play a pivotal role in linking technical AI research with financial and managerial applications, reinforcing their importance as intellectual connectors within the field. Beyond these core clusters, several smaller and more specialized partnerships—such as Khan S. with Khan H.U., Kumar A. with Kumar S., and Huh J.H. with Seo Y.S.—exhibit limited connectivity to the broader network. This structure reflects a hybrid collaboration model in which central actors enable cross-domain integration, while peripheral groups concentrate on niche research agendas, including fraud detection, risk analytics, and algorithmic decision-making. From a management systems perspective, this pattern suggests that innovation in AI–FinTech emerges through both integrative collaboration and focused specialization. For financial institutions and FinTech developers, the findings imply that effective innovation strategies should combine cross-functional collaboration with domain-specific expertise. For regulators and policymakers, the ; the need to engage multiple ı neworks and governance mecha: ors.

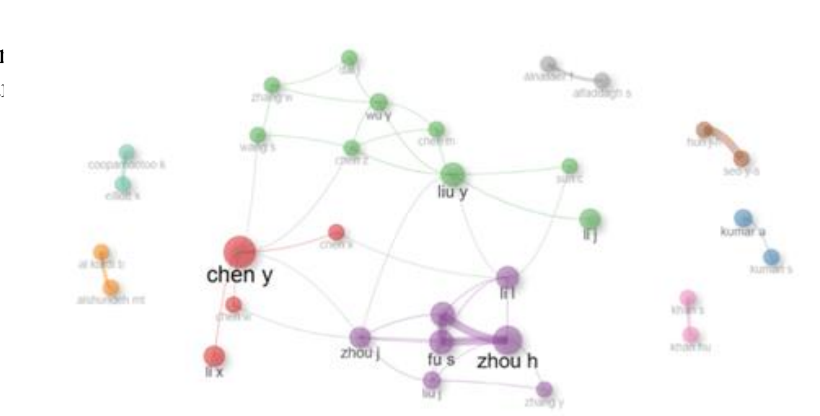

Figure 7. Collaboration Map among Authors
Source: Scopus & Biblioshiny

3.5.2. International Collaboration

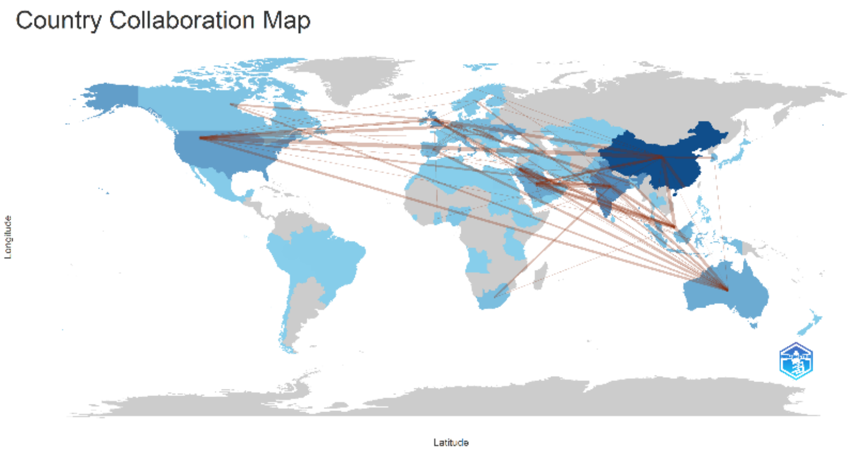

Figure 8. Map Depicting International Research Collaboration
Source: Scopus & BiblioshinySource: Scopus & Biblioshiny

International collaboration networks in AI–FinTech research demonstrate a high level of global integration. As illustrated in Figure 8, China emerges as the predominant collaboration hub, maintaining extensive research partnerships with the United States, the United Kingdom, Australia, and several Asian and Middle Eastern countries, including Saudi Arabia, Singapore, and Malaysia. India also exhibits substantial collaborative intensity, particularly with China, the United States, the United Kingdom, and Australia, while the United States plays a pivotal role in trans-Pacific and trans-Atlantic knowledge exchange. These trends point to a strong and linked worldwide research network covering the regions of Asia, Europe, North American, and the Middle East. The observed geographical cooperation emphasizes the global relevance of AI-FinTech concerns, notably in areas such as cybersecurity, regulatory alignment, digital infrastructure improvement, and financial inclusion. Strong collaboration links between developed economies and emerging markets indicate that AI–FinTech research benefits from complementary knowledge flows, where advanced technological capabilities are combined with implementation insights from rapidly digitizing financial systems. From a management and systems perspective, this collaboration structure suggests that effective AI–FinTech innovation increasingly depends on cross-border coordination among researchers, financial institutions, and regulators. For financial institutions, global collaborative research initiatives facilitate the spread of optimal methodologies in risk management, fraud prevention, and governance of artificial intelligence. For legislators and regulatory bodies, the results highlight the necessity of international regulatory dialogue and collaborative frameworks to address the transnational risks emerging from AI-enhanced financial services.

3.6. Thematic Structure and Research Evolution

3.6.1. Keyword Analysis

Keyword co-occurrence analysis was conducted to identify the conceptual foundations and dominant research orientations within the AI–FinTech literature. As illustrated in Figure 9, the thematic structure of the field is strongly anchored in artificial intelligence–driven computational methods and digital financial innovation. The term “artificial intelligence” emerges as the most prominent keyword, with 336 occurrences, underscoring its central role as the core technological paradigm in FinTech research. "Machine learning" (80 times) and "finance" (73 times) come next This shows how often people utilize data-driven algorithms to make decisions about money, figure out danger, and make things run more smoothly. The fact that "fintech" (55 times) and "blockchain" (49 times) come up so often shows how AI is being used alongside digital financial systems and decentralized technology. There is a lot of research going on in predictive modeling, automated decision-support systems, and intelligent financial analytics, as shown by the high number of times the phrases "deep learning" (47 times) and "decision making" (45 times) are used. The fact that "internet of things" and "technology" are both mentioned 29 times each shows that AI, linked digital systems, and real-time data settings are becoming more common in financial services. Overall, the keyword distribution suggests that AI–FinTech research is structured around three interrelated pillars:

(1) algorithmic intelligence (AI, machine learning, deep learning);
(2) digital financial innovation (FinTech, blockchain);
(3) data-driven decision systems (decision making, IoT-enabled analytics).

This topic arrangement represents a mature field of study that increasingly integrates technical AI capabilities with managerial, operational, and systemic factors in financial services.

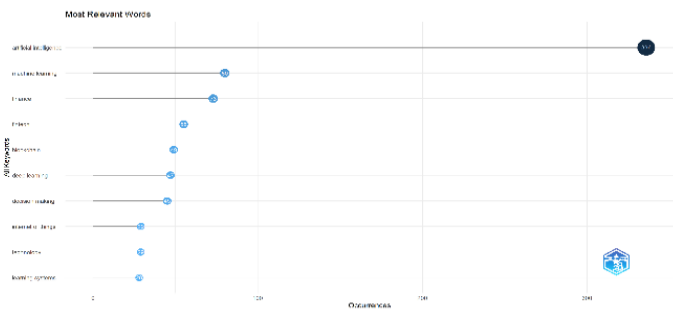

Figure 9. Most Relevant Keywords in AI–FinTech Research
Source: Scopus & Biblioshiny

3.6.2. Conceptual Structure of AI–FinTech Research

The conceptual structure analysis based on Multiple Correspondence Analysis (MCA) reveals three dominant and interrelated research clusters that collectively define the thematic landscape of AI–FinTech scholarship.

First, the cybersecurity and machine-learning-driven systems cluster concentrates on issues of network security, cybersecurity, anomaly detection, and learning-based algorithms. This problem shows why it's important to safeguard digital financial systems from cyberattacks while also using machine-learning models to make systems stronger, stop fraud, and keep an eye on risk in real time.

watching. Second, the digital finance and technical innovation cluster studies subjects like blockchain, cloud computing, automation, AI, and digital transformation. This group highlights the technological backbone of AI-FinTech by demonstrating how new digital platforms, decentralized systems, and growing computer infrastructure can drive innovation, improve how things are done, and enable new ways to deliver financial services.

Third, the decision support, risk management, and financial analytics cluster focuses on AI-powered tools for managers and analysts, including decision-making, forecasting, data mining, risk assessment, and financial management. This stream focuses on how AI can help financial organizations make better strategic and operational decisions by improving prediction accuracy and enabling data-driven insights.The spatial proximity and overlap among these clusters show that modern AI–FinTech research increasingly addresses integrated concerns, where cybersecurity resilience, technological innovation, and analytical decision support must be developed together. This convergence signals a shift from isolated technological solutions toward comprehensive AI-driven financial systems that connect technical robustness with management effectiveness and organizational strategy.

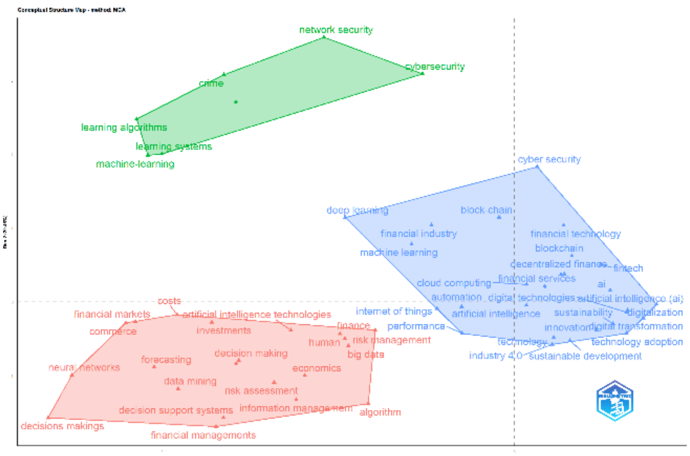

Figure 10. Conceptual Structure Map of AI–FinTech Research Based on Multiple Correspondence Analysis (MCA)
Source: Scopus & Biblioshiny

3.6.3. Evolution of Research Themes

The evolution of study themes in AI–FinTech from 2004 to 2024 displays a clear and orderly movement reflecting technical maturity and evolving research objectives. Figure 11 demonstrates that early studies mostly looked at important AI principles such neural networks, knowledge-based systems, intelligent solutions, and basic decision-support approaches. These themes show that AI algorithms are still in their early phases of research and testing in financial situations. As the area advanced, research interest went toward increasingly complex computational approaches, including agent-based simulation, cognitive computing, data mining, and decision support systems. This phase implies a move from theoretical investigation into scalable analytical models capable of supporting complicated financial decision-making processes.

In the last several years, a number of new concerns have grown more relevant Some of these are machine learning, the digital economy, financial transactions, the Internet of Things, productivity, and sustainability. The rise of concepts associated to sustainability suggests that AI-driven financial innovation is becoming more linked to wider concerns in the domains of environment, society, and governance (ESG). In general, this change in themes shows that AI-FinTech research has grown beyond just technical development to include a more complete view that combines technology progress with social and economic effects, ethical issues, and governance problems in digital financial ecosystems.

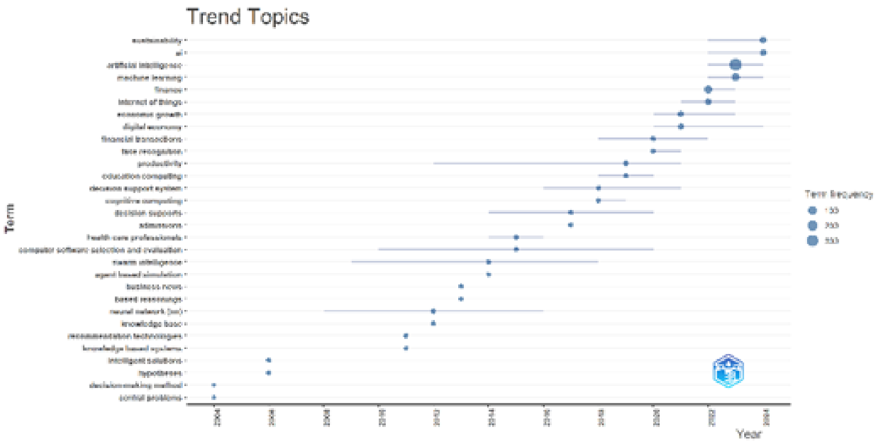

Figure 11. Developing Research Trends
Source: Scopus & Biblioshiny

3.7. Managerial and Systems Implications of AI–FinTech Research

While the preceding studies give a systematic bibliometric picture of publication trends, collaboration patterns, and subject evolution, their significance extends beyond descriptive mapping. The highlighted research clusters have significant managerial and systemic implications for financial institutions, regulators, and FinTech developers functioning in more digitalized financial environments.

Cluster 1: Cybersecurity and Machine-Learning-Driven Systems

Technical Insight:

The cybersecurity and machine-learning-driven systems cluster emphasizes on network security, cybersecurity, anomaly detection, and learning-based algorithms. Research in this subject covers the application of supervised and unsupervised machine learning algorithms for real-time fraud detection, behavioral analytics, and threat intelligence.

Management Implication:

From a management systems viewpoint, this cluster underscores the strategic relevance of incorporating AI-based fraud detection, anomaly monitoring, and risk analytics within core financial operations. The findings imply a fundamental shift from reactive, rule-based security controls toward proactive, AI-enabled risk governance architectures that anticipate threats before they materialize.

Organizational Action:

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Financial institutions should integrate AI-driven security measures into enterprise risk management (ERM) frameworks, internal control systems, and regulatory compliance processes. This needs cross-functional cooperation between IT security teams, risk management departments, and business divisions to ensure that AI-based monitoring solutions are aligned with strategic objectives while providing operational resilience.

Regulatory Consideration:

For regulators, insights from this research stream inspire the development of supervisory technologies (SupTech) that harness AI for real-time regulatory monitoring and surveillance. Regulatory authorities should invest in AI-enabled platforms capable of processing large-scale transaction data to detect systemic vulnerabilities, market manipulation, and developing dangers to financial stability.

Cluster 2: Digital Finance and Technological Innovation

Technical Insight:

The digital finance and technological innovation cluster comprises research on blockchain, financial technology platforms, cloud computing, automation, and digital transformation. This research stream explores how distributed ledger technologies, cloud-native architectures, and API-based ecosystems enable novel financial service delivery models.

Management Implication:

This cluster demonstrates the ongoing reconfiguration of financial business models driven by blockchain-enabled platforms, cloud computing infrastructure, automation technologies, and platform-based services. These technology developments demand significant organizational redesign in terms of operational procedures, IT governance structures, data management strategies, and inter-organizational coordination mechanisms.

Organizational Action:

Banks and other financial institutions need to adapt how they do business to support digital-first aims. This means using cloud-native infrastructure, API-driven integration, and microservices architectures. You need to spend more than simply money on technology to create this change You also need to change the culture of your company, set up flexible governance structures that balance risk management and innovation, and assist your employees improve their skills.

Regulatory Consideration:

For policymakers, the rapid proliferation of digital financial services emphasized in this cluster underlines the necessity for flexible regulatory frameworks that balance innovation, interoperability, consumer protection, and financial stability. Regulators should create technology-neutral policies that accommodate changing business models while creating clear accountability mechanisms and consumer safeguards.

Cluster 3: Decision Support, Risk Analytics, and Financial Management

Technical Insight:

The decision-support, risk analytics, and financial management cluster focuses on AI-enabled managerial and analytical applications, including predictive modeling, forecasting, data mining, risk assessment, and financial planning. Research in this subject studies how machine learning algorithms increase credit rating, portfolio optimization, liquidity management, and strategic planning.

Management Implication:

This group shows how important AI is for improving decision-making by managers through predictive modeling, forecasting, and advanced data analytics for both strategic and operational management. The findings demonstrate that more and more individuals are adopting AI-powered decision-support tools to make financial choices more quickly, correctly, and effectively.

The organization's actions:

Organizations should create decision-support systems that employ AI to analyze data in real time and prepare for the future Companies must find a balance between algorithmic efficiency and human examination if they want to continue making critical financial choices.

Regulatory Consideration:

But adopting AI-based decision-making systems also brings up fundamental problems with algorithmic transparency, accountability, and ethical governance, especially when it comes to big financial decisions that influence credit distribution, risk assessment, and consumer outcomes. Regulators need to define standards for algorithmic responsibility, benchmarks for AI models used in lending and risk assessment, and make sure that financial organizations keep an eye on significant decisions made by computers.

Integrated Perspective:

These three groups of things show that AI-FinTech research is slowly becoming one with management systems, strategic operations, and governance design. The analysis indicates a significant transition towards organizational integration, regulatory alignment, and systemic transformation, rather than only technological development.

This point of view shows how important AI-FinTech research is for both academic study and real-world use in today's financial institutions and regulatory systems. For technical skills, organizational processes, and governance frameworks to all operate together, all of these things need to change at the same time. This covers topics like the need for cybersecurity, new ways for businesses to make money online, and AI-powered decision-making. Banks and other financial institutions that wish to make this transition will need to establish thorough plans that involve buying new technology, managing changes inside the company, educating workers, and dealing with regulators before they have to.

Table 3. Management and Governance Implications by Research Cluster

Research Cluster	Key Technologies	Management Priority	Governance Challenge	Recommended Actions
Cybersecurity & Machine-Learning Systems	• Fraud detection algorithms	Proactive risk governance and real-time threat monitoring	• ERM integration	• Implement AI-based SupTech
	• Anomaly detection		• Real-time surveillance	• Upgrade internal controls
	• Behavioral analytics		• Cross-functional coordination	• Establish security operations centers
	• Threat intelligence			• Develop threat intelligence capabilities

Research Cluster	Key Technologies	Management Priority	Governance Challenge	Recommended Actions
Digital Finance & Technological Innovation	• Blockchain platforms	Business model transformation and digital-first strategies	• Interoperability standards	• Redesign IT governance frameworks
	• Cloud infrastructure		• Consumer protection	• Adopt cloud-native architectures
	• API ecosystems		• Data sovereignty	• Develop API management strategies
	• Automation technologies		• Platform governance	• Build ecosystem partnerships
Decision Support & Financial Analytics	• Predictive modeling	Strategic decision quality and data-driven operations	• Algorithmic transparency	• Establish AI ethics committees
	• Forecasting systems		• Model accountability	• Develop explainable AI frameworks
	• Portfolio optimization		• Bias mitigation	• Implement model risk management
	• Credit scoring algorithms		• Ethical AI governance	• Create human oversight mechanisms

Source: Synthesized from bibliometric analysis and thematic clustering

4. CONCLUSION AND FUTURE RESEARCH AGENDA

4.1. Key Findings

This analysis demonstrates that AI–FinTech research has shown strong, sustained growth since 2018, evolving from a nascent field into a mature interdisciplinary topic. From 2018 to 2024, the number of publications rose from 11 to 237, which implies a compound annual growth rate of 66.8%. This is substantially more than the normal growth rate for academic subjects. China, India, and the United States ranked as the most productive countries, while institutional contributions were extensively shared among rising and existing economies. Bibliometric mapping indicates three important issue clusters: cybersecurity and machine-learning systems, digital finance and technical innovation, and AI-based decision-support and risk analysis, supported by substantial worldwide collaboration networks. Citation analysis indicated fraud detection, privacy-preserving machine learning, and digital transformation techniques as the most influential research topics. The distributed nature of author and institutional productivity, combined with strong international collaboration, indicates an open, rapidly evolving scholarly domain characterized by cross-disciplinary engagement and global knowledge exchange.

4.2. Theoretical Contributions

From a theoretical perspective, this study contributes by systematically structuring the intellectual landscape of AI–FinTech research and linking bibliometric patterns to the broader literature on digital transformation and management systems. By integrating performance analysis and science mapping, the study advances understanding of how AI-driven technologies reshape financial governance, organizational routines, and strategic decision-making. This study extends existing frameworks in digital transformation literature (H.W. Volberda, 2021) and financial innovation research (Chen & Robinson, 2019) by demonstrating how AI applications reshape not only technological capabilities but also organizational routines, governance structures, and strategic decision-making processes. Building on Volberda's (2021) framework of cognitive barriers and organizational reconfiguration in digital contexts, our findings reveal that AI–FinTech adoption requires simultaneous transformation across three interdependent dimensions: technical infrastructure, organizational processes, and governance mechanisms. The three identified clusters reveal distinct yet interconnected theoretical contributions: the cybersecurity cluster advances enterprise risk management theory by integrating real-time AI-based monitoring into core financial operations, transforming risk management from a periodic assessment function into a continuous, algorithmically-mediated organizational capability; the digital innovation cluster extends business model transformation theory through blockchain-enabled platforms and cloud-based infrastructures, challenging traditional assumptions about intermediation, trust mechanisms, and value creation in financial services; and the decision-support cluster enriches managerial decision-making theory by establishing predictive analytics as a fundamental organizational capability rather than a peripheral technical function, thereby redefining the relationship between human judgment and algorithmic intelligence in strategic contexts.

More crucially, our findings indicate the merging of three previously disparate research streams: cybersecurity, digital innovation, and decision analytics into an integrated AI–FinTech paradigm. This convergence indicates a theoretical shift from viewing AI solely as a technological tool to recognizing it as a strategic resource that requires coordinated management systems, risk governance, and regulatory alignment. The spatial proximity and thematic overlap among clusters, as evidenced in our Multiple Correspondence Analysis (Figure 10), indicate that contemporary AI–FinTech research increasingly addresses holistic challenges where technical robustness, organizational effectiveness, and regulatory compliance must be developed simultaneously rather than sequentially. This finding challenges linear technology adoption models and supports complexity theory perspectives that emphasize interdependencies, feedback loops, and emergent properties in socio-technical systems (Brynjolfsson, E., & McAfee, 2014). Our thematic analysis thus provides a conceptual foundation for future research on AI-enabled financial ecosystems, bridging technological determinism with organizational agency in digital transformation processes and offering a more nuanced understanding of how AI reshapes competitive dynamics, institutional logics, and power structures within financial services industries.

4.3. Practical Implications

The findings give actionable implications for numerous stakeholder groups negotiating the complicated convergence of artificial intelligence and financial services.

For Financial Institutions:

The prominence of cybersecurity and decision-support clusters underscores the strategic importance of integrating AI into enterprise risk management (ERM) frameworks and developing explainable AI governance structures. Financial firms should establish cross-functional AI governance committees at the board level, implement continuous real-time monitoring systems, and redesign operational procedures to meet AI-driven decision-making. The convergence of technical innovation with organizational transformation involves balanced investment in both technological infrastructure and human capital development, notably in increasing AI literacy among senior management and frontline people.

For Regulators and Policymakers:

The rapid dissemination of AI–FinTech applications revealed in this study needs adaptable regulatory frameworks capable of combining innovation with consumer protection and financial stability. Regulators should prioritize the development of supervisory technologies (SupTech) that leverage AI for real-time regulatory monitoring, create regulatory sandboxes to facilitate responsible innovation, and foster international regulatory cooperation to address cross-jurisdictional risks arising from globally integrated digital financial systems. The findings emphasize that effective AI governance requires collaborative engagement across multiple research communities and stakeholder groups rather than reliance on isolated regulatory interventions.

For FinTech Developers and Technology Providers:

Innovation strategies must balance technical advancement with ethical considerations and societal impact. The prominence of fraud detection and privacy-preserving machine learning in highly cited publications implies that prioritizing cybersecurity, data privacy, and algorithmic transparency assures sustainable and responsible FinTech development. Developers should follow privacy-by-design principles, create explainable AI architectures, and interact proactively with regulatory requirements across the innovation lifecycle rather than considering compliance as a post-hoc limitation.

4.4. Future Research Directions

Based on our bibliometric analysis and theme progression, we highlight five priority study areas that require deeper scholarly investigation:

1. Regulatory Technology (RegTech) and Supervisory Innovation

Future study should examine how AI can boost real-time regulatory compliance monitoring and reporting procedures within financial organizations. Key topics include: What governance approaches most effectively enable RegTech adoption in emerging nations with limited regulatory infrastructure? How do AI-powered RegTech solutions change the danger of systemic financial problems and the spread of crises? What organizational structures allow collaboration between compliance functions and technology development teams? Comparative studies across nations with various regulatory regimes would uncover viable approaches for balancing innovation with prudential regulation.

2. Ethical and Explainable AI in Financial Decision-Making

Ethical and Explainable AI in Financial Decision-Making The rising depend on AI for high-stakes financial decisions necessitates study on algorithmic transparency and accountability Critical research topics include: How can financial institutions create interpretable machine learning models that fulfill both anticipated performance objectives and regulatory explainability standards? How can responsibility be proved when automated evaluations create bad results for customers or contribute to biased lending patterns? Interdisciplinary study combining computer technology, organizational behavior, and legal understanding would progress this crucial subject.

3. Sustainable and Green FinTech

The rise of sustainability-related themes in recent publications shows greater congruence between AI-driven financial innovation and environmental, social, and governance (ESG) factors. Future study should investigate: How might AI enable ESG-integrated investment strategies and sustainable portfolio management? How does AI help make carbon credit trading platforms more open and less likely to be used for greenwashing? How does digital financial inclusion help to sustainable development objectives among marginalized populations? Longitudinal research measuring the environmental impact of AI technology in financial services would give factual underpinning for sustainable FinTech development.

4. AI Governance and Organizational Risk Management

As AI gets incorporated in key financial processes, research on governance structures and risk management frameworks becomes increasingly vital. Key research directions include: How should financial institutions form board-level AI oversight committees, and what competence should members possess? What cross-functional collaboration tools work best for AI governance while yet allowing for quick changes in operations? How can enterprises balance AI-driven innovation with risk management imperatives in highly regulated environments? Case study research investigating successful AI governance implementations across varied institutional contexts would give useful insights for practitioners.

5. Longitudinal Studies on AI Adoption Dynamics and Organizational Transformation

The bibliometric evidence of significant development implies that many financial organizations are currently navigating AI adoption processes. Longitudinal study is needed to understand: What organizational factors—including leadership commitment, workforce capabilities, and legacy system constraints—drive successful AI adoption trajectories over time? How does the application of AI impact how organizations function, how they make decisions, and how they compete? What are the long-term implications of AI integration on financial success, operational efficiency, and customer satisfaction? Mixed-method study incorporating quantitative performance data with qualitative organizational case studies would boost knowledge of AI-driven transformation processes.

6. Cross-Cutting Methodological Priorities

Beyond the five substantive study areas listed above, many methodological priorities require attention to increase the rigor and relevance of AI–FinTech scholarship:

Causal Inference and Quasi-Experimental Designs:

The majority of extant research employs descriptive or correlational methodologies. The next study should leverage natural experimentation, differences in results methods, regression discontinuity, and instrumental variable approaches to demonstrate causal correlations between AI adoption and organizational performance. Regulatory changes, technology shocks, or staggered implementation schedules provide opportunity for quasi-experimental research methodologies that boost internal validity.

Interdisciplinary and Multi-Method Integration:
The convergence of technical, organizational, and regulatory factors in AI–FinTech needs research that transcends academic boundaries. The engagement in collaborative efforts that amalgamate an extensive variety of professionals from disparate fields, which may include, although not exclusively limited to, the realms of computer science, economics, management studies, legal analysis, and sociological research, would unquestionably culminate in a significantly more thorough and intricate comprehension of multifaceted issues when compared to research endeavors that are strictly limited to the confines of a singular academic discipline. By employing a mixed-methods approach that integrates extensive quantitative analysis on a large scale with thorough qualitative case studies, ethnographic observations, or action research, researchers would significantly enhance their comprehension of the various obstacles associated with implementation, the intricate dynamics within organizations, and the critical human factors that influence the adoption of artificial intelligence technologies.

Industry-Academia Collaboration and Practice-Oriented Research:
The establishment of more robust and synergistic partnerships between academic researchers affiliated with universities and financial institutions operating in the marketplace would significantly enhance the relevance of research outputs while concurrently amplifying their practical applicability and impact in real-world settings. By forming collaborative research frameworks that provide scholars with access to proprietary datasets, operational systems, and the intricate processes that govern organizations—while simultaneously ensuring the safeguarding of confidentiality and addressing any competitive concerns—the research community would be empowered to conduct studies that are not only more realistic but also yield actionable insights that can be directly implemented within the industry. Design science

approaches that design and analyze AI governance artifacts, decision frameworks, or organizational practices in real-world situations would supplement traditional hypothesis-testing research.

Global South and Emerging Market Perspectives:
Current research disproportionately focuses on wealthy economies. Future research should explore AI–FinTech connections in emerging nations, where financial inclusion difficulties, regulatory capacity restraints, and infrastructural limitations yield various potential structures and risk profiles. Comparative investigation across institutional settings would elucidate how country innovation systems, regulatory traditions, and cultural variables effect AI–FinTech trajectories.

Concluding Remarks on Future Directions:
The research agenda stated above reflects both the maturity and the openness of AI–FinTech as an academic topic The topic has progressed beyond solely technical inquiries into holistic studies that concurrently evaluate technology capabilities, organizational procedures, regulatory frameworks, ethical difficulties, and social repercussions. Nevertheless,methodological gaps continue, empirical, and major theoretical. Addressing these gaps involves continual multidisciplinary collaboration, methodological innovation, and attention to research that is both scientifically rigorous and practically valuable.As AI technologies continue to progress and financial institutions become increasingly digitalized, the research prospects provided in this study will extend and diversify, assuring that AI–FinTech remains a lively and consequential topic of scholarly analysis.

4.5. Limitations and Methodological Considerations

This work admits some shortcomings that present possibilities for future research refinement and growth.

Data Source Limitations:

The scope of this analysis is constrained to Scopus-indexed literature, thereby perhaps omitting relevant research indexed in supplemental databases such as Web of Science, Google Scholar, IEEE Xplore, or Dimensions. Regional and discipline-specific journals with substantial contributions to AI–FinTech research may not be fully represented in Scopus. Furthermore, the omission of conference proceedings—particularly notable in computer science and information systems—may underrepresent early-stage technical advances and emerging research trends that have not yet evolved into complete journal publications.

Scope and Selection Constraints:

The open-access limitation, while boosting openness and replicability, may induce publishing bias by excluding high-impact subscription-based publications such as those published by top-tier academic associations. Although open-access publishing has risen dramatically, major finance and management journals with traditional subscription models may contain influential research not represented in this analysis. Furthermore, limiting the analysis to four Scopus subject areas (BUSI, ECON, COMP, SOCI) may overlook relevant interdisciplinary research in adjacent fields such as engineering, applied mathematics, behavioral psychology, or law and policy studies that also address AI–FinTech topics from specialized perspectives.

Methodological Extensions for Future Research:

Future bibliometric analysis could combine many databases simultaneously to enable cross-validation and full coverage assessment. Integrating patent databases would capture technical progress beyond academic publications, highlighting industrial R&D trends and commercial uses not represented in scholarly literature. Including grey literature such as industry white papers, central bank studies, regulatory guidance documents, and consulting company publications would provide insights into practitioner opinions and policy issues. Mixed-method tactics combining bibliometric analysis with expert interviews, organizational case studies, and content analysis of policy papers will improve understanding of AI adoption patterns, implementation challenges, and institutional responses to AI-driven financial transformation.

Geographic and Temporal Extensions:

Expanding the analysis to include non-English publications—particularly papers published in Chinese, Spanish, German, French, and other key languages—would provide a more internationally inclusive view on AI–FinTech scholarship. This is especially essential considering China's dominance in both AI development and FinTech innovation, where key domestic research may be released in Mandarin. Temporal expansions beyond 2025 will be crucial for capturing growing trends in generative AI applications, massive language models in financial services, quantum computing implications for financial encryption, and next-generation FinTech technologies currently in early research phases. Regular updates to bibliometric analyses would allow for dynamic tracking of field evolution and early detection of paradigm shifts in AI-Fintech research.

Reflexive Limitations and Boundary Conditions:

Beyond the methodological constraints described above, this study demonstrates intrinsic limitations in bibliometric methodologies more broadly. Bibliometric analysis is fantastic at discovering trends and mapping intellectual structures in vast collections of works, but it can't fully reveal the theoretical depth, practical value, or substantive substance of individual studies. Citation counts demonstrate how well-known and prominent a work is, but they don't always show how good the research is, how strict the techniques are, or how valuable it is in reality. Highly cited articles may achieve popularity by startling assertions, methodological advancements, or timely distribution rather than true additions to knowledge. Conversely, intensive research addressing narrow subjects or published in specialist venues may be under-cited despite its scholarly superiority. Furthermore, keyword-based analysis depends on author-selected terms that may not accurately represent research topic or may employ inconsistent wording across studies.

The thematic clusters found via Multiple Correspondence Analysis and topic modeling represent statistical patterns in term co-occurrence rather than theoretically grounded taxonomies created through expert consensus. Readers should therefore interpret our theme structure as a data-driven exploratory framework rather than a canonical or official classification approach. Additionally, bibliometric snapshots indicate a field's state at a specific instant but cannot foresee future trends with accuracy. The highlighted study trends and priorities reflect current scholarly interests and may alter fast in relation to technology advancements, regulatory actions, or macroeconomic shocks that redirect research emphasis. The findings given here should be viewed as historically contingent observations that highlight tendencies in past study rather than deterministic forecasts of future scholarship.

Finally, our study focuses primarily on academic publications, so neglecting critical insights offered by industry research, regulatory reports, patent filings, and practitioner discourse that considerably influence AI–FinTech innovation trajectories. A more full understanding of AI–FinTech progress would entail integration of academic research with industry intelligence, policy analysis, and market data—a synthesis that transcends beyond the bounds of bibliometric approach alone. Future investigation could benefit combine bibliometric mapping with other knowledge synthesis approaches to provide a more comprehensive perspective on AI–FinTech evolution.
Despite these limits, this work provides a comprehensive, transparent, and complete bibliometric analysis that promotes understanding of AI–FinTech research history, intellectual organization, and evolving goals. The methodological transparency afforded by PRISMA-based screening techniques, coupled with expert validation and triangulation across several analytical methodologies, raises confidence in the robustness of our findings while conceding the restricted nature of all empirical investigation.

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