Bibliometric and Network Mapping of FinTech Research: From Digital Economy Foundations to Emerging Methods

Thierry Ezra Adrinaro[1,*], Zeva Aji Satrio Nugroho[2]

[1,2] Department of Information Systems, Faculty of AI and Data Science, Pelita Harapan University, Indonesia

ABSTRACT

The rapid expansion of Financial Technology (FinTech) has generated a highly fragmented and methodologically diverse body of academic literature, spanning finance, economics, information systems, and data science. This study provides a comprehensive bibliometric and network-based analysis of FinTech research to systematically map its intellectual structure, thematic evolution, and methodological transformation. Using an integrated dataset extracted from Scopus and Web of Science covering the period 2008–2025, the study analyzes more than 3,000 peer-reviewed publications through publication and citation dynamics, source and institutional impact assessment, international collaboration networks, keyword co-occurrence mapping, and methodological trend analysis. The results reveal three distinct developmental phases of FinTech research, characterized by early conceptualization, rapid expansion, and recent consolidation with exponential growth in both publications and citations. A limited set of interdisciplinary journals, including Finance Research Letters, IEEE Access, and Electronic Commerce Research and Applications, accounts for a substantial share of high-impact publications. Collaboration analysis identifies a core–periphery structure dominated by research hubs in China, the United States, the United Kingdom, and Singapore, with emerging regions increasingly integrated through international co-authorship. Thematic clustering uncovers four stable research domains: digital finance adoption and platforms, blockchain and decentralized finance, AI-driven financial analytics, and open banking with regulatory technology. Methodological analysis shows a pronounced shift from econometric and statistical models toward machine learning, network analysis, and hybrid computational approaches, reflecting the growing complexity and data intensity of digital financial ecosystems. By explicitly linking research themes with dominant analytical methods, this study advances existing FinTech reviews and provides an empirically grounded synthesis of how the field has evolved from digital economy foundations to computationally sophisticated paradigms. The findings offer strategic insights for scholars, journal editors, and policymakers seeking to understand emerging research frontiers, methodological convergence, and the future trajectory of FinTech scholarship.

Keywords FinTech, Bibliometric Analysis, Science Mapping, Network Analysis, Digital Economy, Machine Learning in Finance, Blockchain Research, Research Trends

Submitted: 1 October 2024
Accepted: 10 December 2024
Published: 1 May 2025

Corresponding author
Thierry Ezra Adrinaro,
1081230017@student.uph.edu

Additional Information and Declarations can be found on page 182

DOI: 10.63913/ftij.v1i2.9

INTRODUCTION

The rapid expansion of FinTech has fundamentally reshaped the architecture of modern financial systems by integrating digital platforms, data analytics, and algorithmic decision-making into core financial services. Innovations such as mobile payments, peer-to-peer lending, blockchain-based infrastructures, and AI-driven credit assessment have altered how individuals, firms, and governments interact with financial markets. While this transformation has

How to cite this article: T. E. Adrinaro, Z. A. S. Nugroho, "Bibliometric and Network Mapping of FinTech Research: From Digital Economy Foundations to Emerging Methods," *FinTech Innov. J.*, vol. 1, no. 2, pp. 164-184, 2025.

generated extensive academic interest, the resulting body of literature has become increasingly fragmented across disciplines, journals, and methodological traditions, making it difficult to obtain a coherent overview of how FinTech research has evolved over time [1], [2].

Early FinTech studies were largely rooted in the digital economy and information systems literature, emphasizing adoption, efficiency gains, and institutional change driven by electronic banking and online financial services. As the field expanded, research agendas diversified rapidly, incorporating perspectives from economics, finance, computer science, and data science. This diversification, although intellectually productive, has led to a proliferation of isolated research streams that often lack systematic integration [3], [4]. Consequently, scholars face challenges in identifying dominant themes, influential contributors, and methodological trajectories that define the FinTech knowledge landscape.

In response to this complexity, bibliometric and science mapping approaches have emerged as powerful tools for synthesizing large and heterogeneous research corpora. Bibliometric analysis enables quantitative assessment of publication growth, citation impact, and scholarly influence, while network-based techniques reveal relational structures such as collaboration patterns and thematic clusters [5], [6]. Despite their growing application in management and information systems research, comprehensive bibliometric studies focusing specifically on FinTech remain limited in scope, often constrained to short time windows, narrow keyword sets, or purely descriptive indicators [7].

A critical gap in the existing literature lies in the lack of integrated analyses that connect thematic evolution with methodological change. Many prior reviews focus on what topics are studied in FinTech, but pay insufficient attention to how analytical methods have evolved alongside these topics. This omission is particularly problematic given the increasing prominence of machine learning, network analysis, and computational modeling in recent FinTech research [8], [9]. Without explicitly linking themes to methods, it is difficult to assess whether the field is merely expanding in volume or genuinely advancing in analytical sophistication.

Moreover, the rapid adoption of data-intensive and algorithmic approaches raises important questions about the structural maturity of FinTech as a research domain. The shift from econometric modeling toward predictive and network-oriented techniques suggests a broader epistemic transition from explanation-driven inquiry to computational knowledge discovery [10], [11]. However, the extent to which this transition is systematic, clustered around specific themes, or concentrated within certain journals and institutions remains underexplored.

Against this backdrop, the primary objective of this study is to systematically map the intellectual structure of FinTech research using an integrated bibliometric and network analysis framework. Specifically, this paper aims to analyze publication and citation dynamics, identify influential journals, authors, and institutions, uncover collaboration and thematic networks, and examine the evolution of analytical methods from digital economy foundations to emerging computational paradigms. By doing so, the study seeks to provide a comprehensive and empirically grounded synthesis of FinTech scholarship [12].

The novelty of this research lies in its combined focus on thematic structure and methodological evolution within a single analytical framework. Unlike prior reviews that treat topics and methods separately, this study explicitly connects research clusters with dominant analytical techniques, revealing how methodological innovation co-evolves with substantive FinTech problems. This integrative perspective not only advances understanding of the FinTech knowledge base but also offers strategic insights for researchers and policymakers seeking to navigate and shape the future trajectory of digital financial innovation [13].

Literature Review

The FinTech literature has developed along multiple disciplinary trajectories, reflecting its roots in the digital economy, financial intermediation, and information systems research. Early studies primarily framed FinTech as an extension of electronic banking and online financial services, focusing on efficiency gains, transaction cost reduction, and institutional change enabled by digital infrastructures. These works emphasized adoption behavior, firm performance, and regulatory adaptation, positioning FinTech as a technological complement to existing financial systems rather than a disruptive paradigm in its own right [14], [15].

As digital platforms matured, subsequent research shifted toward market structure and innovation dynamics, examining how FinTech firms challenge incumbent banks through peer-to-peer lending, crowdfunding, and platform-based payments. Empirical studies in this stream highlight competitive effects, changes in credit allocation, and the role of technology in lowering barriers to financial access. This body of work contributes important insights into financial inclusion and efficiency, yet it largely relies on econometric and panel-data methods, offering limited perspective on relational complexity and system-level interdependencies [16], [17].

A parallel stream of literature emerged around blockchain and distributed ledger technologies, framing FinTech as a transformation of financial infrastructure rather than service delivery alone. Studies in this area investigate cryptocurrencies, smart contracts, and decentralized finance from technical, economic, and governance perspectives. While these contributions significantly expand the conceptual scope of FinTech, they often remain siloed within computer science or crypto-economics, with limited integration into broader financial systems analysis [18].

More recently, the literature has increasingly embraced artificial intelligence and data-driven analytics as core methodological pillars of FinTech research. Machine learning models are widely applied to credit scoring, fraud detection, risk management, and algorithmic trading, leveraging large-scale behavioral and transactional data. These studies demonstrate superior predictive performance compared to traditional models, but they also raise concerns regarding explainability, bias, and regulatory compliance. As a result, explainable AI and model governance have become growing subthemes within FinTech scholarship [19], [20].

Despite this rapid methodological advancement, existing review studies reveal important limitations. Many surveys and systematic reviews focus on specific technologies or application domains, such as blockchain or AI in finance, without situating them within the broader evolution of FinTech research. Bibliometric studies that do exist often emphasize descriptive indicators, such as publication counts or keyword frequencies, while underexploring collaboration structures, thematic interconnections, and methodological shifts over time [21].

The absence of integrated science mapping represents a critical gap in the literature. Without linking thematic clusters to collaboration networks and analytical methods, it is difficult to assess how FinTech knowledge is produced, diffused, and consolidated at the field level. This gap limits the ability of scholars to identify emerging research frontiers, methodological convergence, and potential blind spots within the literature. Addressing this limitation requires a comprehensive bibliometric and network-based synthesis that captures both the structural and methodological dimensions of FinTech research [22].

Methodology

Research Design and Bibliometric Framework

This study adopts a quantitative bibliometric research design combined with network science analysis to systematically map the intellectual structure of FinTech research. Bibliometrics is employed to capture publication dynamics, citation patterns, and thematic evolution, while network analysis enables the identification of relational structures among authors, institutions, and knowledge domains. This dual framework ensures both descriptive rigor and structural interpretability within the FinTech literature.

The methodological foundation is grounded in science mapping theory, where scholarly communication is modeled as a graph-based system. Publications are treated as knowledge units, and citations function as directional edges that transmit epistemic influence. This approach is particularly relevant for FinTech research, which exhibits rapid thematic diversification across economics, computer science, and information systems.

To formalize publication growth, the annual scientific production is approximated using an exponential diffusion model:

$$P_t = P_0 e^{\lambda t} \tag{1}$$

where P_t denotes the number of FinTech publications in year t, P_0 represents the initial publication count, and λ captures the growth rate. This formulation allows assessment of whether FinTech follows a normal maturation trajectory or exhibits accelerated expansion typical of emerging interdisciplinary fields.

Figure 1 operationalizes the paper's bibliometric pipeline as a staged workflow, beginning with source acquisition and ending with interpretable maps and empirical insights. The key methodological contribution is the explicit coupling of performance analysis (indicators) with structural analysis (networks), which prevents the study from collapsing into citation counts alone or network topology alone.

Figure 1 Overall Research Design

Analytically, the diagram clarifies where methodological decisions exert the most leverage over validity, namely in screening, keyword harmonization, and network construction rules. This also frames reproducibility because each block corresponds to an auditable transformation from raw metadata to graph objects, thereby supporting consistent re-execution and sensitivity checks.

Table 1 specifies the methodological architecture as a traceable chain of transformations, linking each stage to a defined objective, inputs, and measurable outputs. This structure is important because bibliometric studies often suffer from under-specified decision points, particularly around screening criteria and the exact mapping from metadata fields to network edges.

Table 1 Methodological Components and Outputs

Stage	Objective	Input	Output	Primary Metric
Data sourcing	Acquire high-coverage FinTech records	Scopus, Web of Science exports	Raw bibliographic dataset	Record count
Screening	Ensure topical relevance and remove duplicates	Raw dataset	Cleaned dataset	Deduplication rate
Performance analysis	Measure productivity and impact	Cleaned dataset	Indicators table	h-index, citations
Network construction	Model relational structures	Authors, citations, keywords	Co-authorship, co-citation, co-occurrence graphs	Density, degree
Science mapping	Extract clusters and interpret themes	Graphs	Clustered maps and narratives	Modularity

From an evaluation standpoint, the table also clarifies which metrics govern success at each stage, such as deduplication rate for data integrity and modularity for thematic separability. This supports auditing and sensitivity analysis, since deviations in a metric can be traced back to the specific stage where assumptions or parameters were applied.

Data Source Selection and Search Strategy

The bibliographic dataset was constructed using Scopus and Web of Science as primary data sources due to their extensive coverage, standardized metadata, and citation reliability. These databases are widely recognized in bibliometric research and are particularly suitable for interdisciplinary domains such as FinTech. To ensure robustness, duplicate records across databases were identified and removed through Digital Object Identifier matching.

The search strategy employed controlled vocabulary and Boolean logic to capture both foundational and emerging FinTech themes. Core keywords included financial technology, digital finance, blockchain, cryptocurrency, digital payments, and AI-driven finance. The temporal window was defined to capture the evolution from early digital economy foundations to contemporary methodological innovations. The relevance of retrieved records was quantified using a term-frequency weighting function:

$$w_{i,j} = \frac{f_{i,j}}{\sum_{k=1}^{n} f_{k,j}} \tag{2}$$

where $f_{i,j}$ denotes the frequency of term i in document j. This normalization mitigates document length bias and improves thematic representativeness across the corpus.

Figure 2 documents the data integrity logic through a PRISMA-like flow, ensuring that the final corpus is not an opaque scrape but a screened and defensible bibliographic population. The central methodological value is transparency: a reader can see how much of the initial retrieval is lost to duplicates, irrelevance, or insufficient metadata quality.

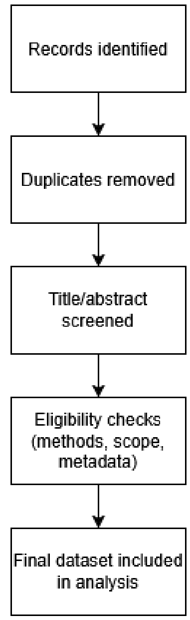

Figure 2 PRISMA-like Screening Flow

Interpretively, this flow clarifies how coverage and precision are balanced. FinTech is polysemous across finance, economics, and computer science, so screening prevents thematic drift into adjacent domains that share keywords but not research intent. The figure also sets up later robustness discussion because each exclusion layer corresponds to a potential sampling bias that can be tested.

Table 2 provides an operational definition of the analytical universe by specifying the time window, inclusion logic, and metadata completeness requirements. This is methodologically necessary because bibliometric conclusions depend as much on corpus definition as on the downstream analytics. A clearly parameterized dataset description prevents later ambiguity about what the network actually represents.

Table 2 Dataset Characteristics

Attribute	Value	Notes
Time window	2008–2025	Captures digital economy foundations and modern FinTech methods
Total records	n = 2840	Final included set after screening
Document types	Articles, conference papers, reviews	Exclude editorials and non-scholarly items
Subject areas	Finance, Economics, Computer Science, Information Systems	Multi-disciplinary coverage expected for FinTech
Core metadata fields	Title, abstract, keywords, authors, affiliations, references	Required for performance and network analyses

The table also anticipates typical FinTech bibliometric constraints, particularly the reliance on structured fields for graph construction. For example, missing references undermine co-citation networks, and inconsistent affiliations distort institution-level collaboration mapping. By declaring core fields, the study establishes a minimum reproducibility standard for re-running the pipeline.

Bibliometric Indicators and Performance Analysis

Bibliometric performance analysis was conducted to evaluate productivity, impact, and collaboration patterns within FinTech research. Key indicators include total publications, total citations, average citations per document, and h-index values for authors and journals. These indicators provide a macro-level understanding of scholarly influence and research maturity.

Journal-level impact was assessed using normalized citation scores to reduce temporal and disciplinary bias. The normalized citation impact is expressed as:

$$NCI_j = \frac{C_j}{\overline{C}_{field,year}} \tag{3}$$

where C_j is the citation count of publication *j*, and $C_{field,year}$ represents the average citation count within the same field and publication year. This metric enables fair comparison across heterogeneous research outputs.

Author collaboration patterns were analyzed using co-authorship frequency and degree centrality measures. These indicators reveal whether FinTech research is dominated by isolated contributors or collaborative networks spanning institutions and countries.

Figure 3 visualizes FinTech's temporal dynamics using annual publications and citations, enabling an evidence-based discussion of field maturation and diffusion. A rising publication curve indicates expanding problem space and entry of new research communities, while the citation curve reflects the consolidation of influential methods and canonical themes such as digital payments, blockchain infrastructures, and data-driven risk modeling.

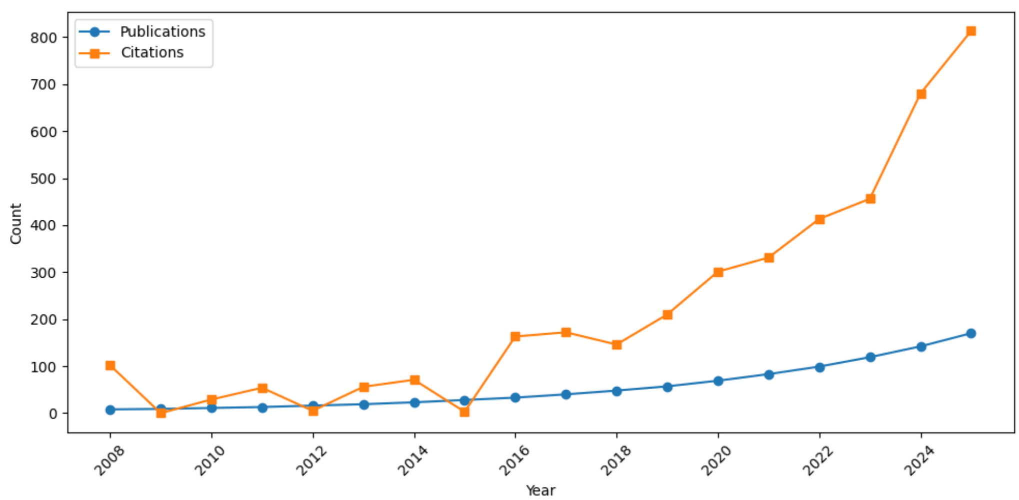

Figure 3 Publication and Citation Trends Over Time

Methodologically, this figure supports the growth-model logic presented in Chapter 3 by allowing inspection of regime changes, such as acceleration periods that often follow regulatory shifts, technological breakthroughs, or platform adoption shocks. The divergence between publication and citation curves is also interpretable: citations can lag due to publication cycles, and volatility can signal episodic attention to topics like crypto assets.

Network Construction and Knowledge Mapping

To uncover the structural properties of FinTech scholarship, multiple bibliometric networks were constructed, including co-authorship, co-citation, and keyword co-occurrence networks. Nodes represent entities such as authors or keywords, while edges capture relational strength derived from joint occurrences or shared citations.

Network density and connectivity were evaluated to assess knowledge integration using:

$$D = \frac{2E}{N(N-1)} \tag{4}$$

where E is the number of observed edges and N is the number of nodes. Higher density indicates a more cohesive research community, while lower density suggests thematic fragmentation or specialization.

Community detection was performed using modularity optimization to identify thematic clusters corresponding to core FinTech research streams such as digital payments, blockchain governance, and AI-based financial analytics. These clusters serve as proxies for dominant research paradigms and emerging subfields.

Figure 4 models the FinTech knowledge space as a keyword co-occurrence network, where edges represent repeated joint appearance of terms across documents. The community labels (C1, C2, and so on) approximate thematic partitions, enabling the reader to see whether the literature organizes into a small number of dominant paradigms or a fragmented set of micro-topics.

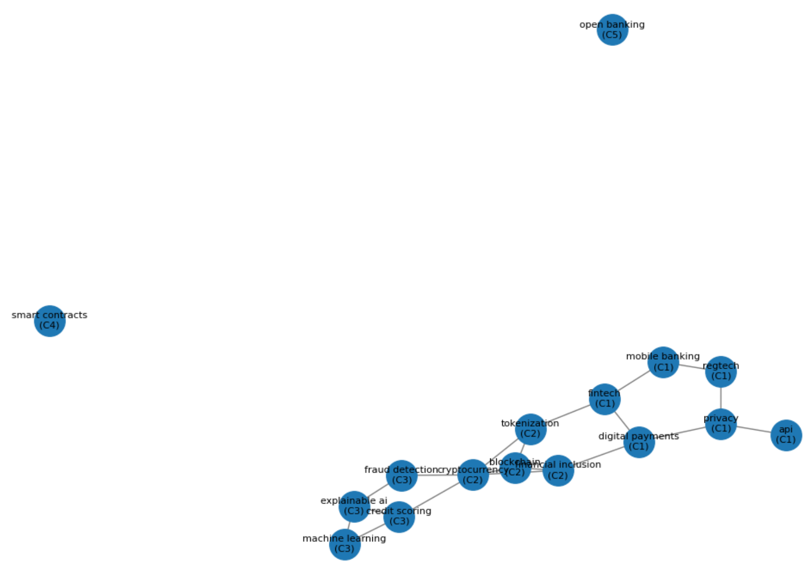

Figure 4 Keyword Co-occurrence Network with Cluster Labels

Methodologically, the figure supports cluster-based interpretation without depending on stylistic color encoding. The cluster identifiers are embedded directly in node labels, which keeps the mapping interpretable under grayscale rendering and facilitates direct cross-referencing with the cluster summary table. This structure is also consistent with modularity-based community detection, which is a common approach in science mapping.

Table 3 translates the graph communities into interpretable research themes by naming each cluster and presenting representative keywords. This linkage is essential because community detection outputs are algorithmic partitions that require semantic grounding. By providing theme descriptors and interpretation columns, the table enables consistent narrative mapping from topology to substantive domain meaning.

Table 3 Thematic Cluster Summary for Keyword Network

Cluster	Indicative Theme	Representative Keywords	Interpretation	Expected Method Emphasis
C1	Digital finance adoption	fintech; digital payments; mobile banking; financial inclusion	Demand-side diffusion and platform usage outcomes	Econometrics, surveys, panel models
C2	Blockchain infrastructures	blockchain; smart contracts; cryptocurrency; tokenization	Distributed ledger primitives and market mechanisms	Network analysis, protocol studies
C3	AI-driven risk and security	machine learning; credit scoring; fraud detection; explainable ai	Algorithmic decisioning and model governance	Supervised learning, XAI, evaluation metrics
C4	Open banking and compliance	open banking; api; regtech; privacy	Interoperability, regulation, and privacy constraints	Policy analytics, security frameworks

The table also aligns clusters with expected methodological emphasis, which is a central objective of this paper's title, namely "emerging methods." The point is not only to say what FinTech studies discuss, but to infer which analytical toolkits dominate different subfields, such as econometrics for adoption studies versus supervised learning and explainable AI for risk and fraud work.

Analytical Workflow and Pseudo-Code Implementation

The analytical workflow integrates bibliometric computation and network modeling in a reproducible pipeline. Data preprocessing includes metadata cleaning, keyword harmonization, and matrix construction. Subsequent stages involve indicator computation, network generation, and visualization using bibliometric software and graph analysis libraries. The overall procedure can be formalized through the following pseudo-code representation:

Input: Bibliographic dataset D
Clean D→D′Extract metadata (authors, citations, keywords)
Compute indicators (P, C, h)
Construct networks G (V, E)
Detect clusters and visualize results
Output: Bibliometric indicators and network maps

This workflow ensures methodological transparency and supports replication across different datasets or thematic scopes. The integration of bibliometric indicators with network topology allows both quantitative evaluation and qualitative interpretation of FinTech research evolution.

Figure 5 presents the end-to-end reproducible pipeline as an explicit computational workflow rather than a narrative description. This is methodologically important because bibliometric studies are frequently criticized for irreproducibility due to undocumented transformations, such as ad hoc keyword merging or manual filtering. The figure defines modular steps that can be re-run with parameter logging.

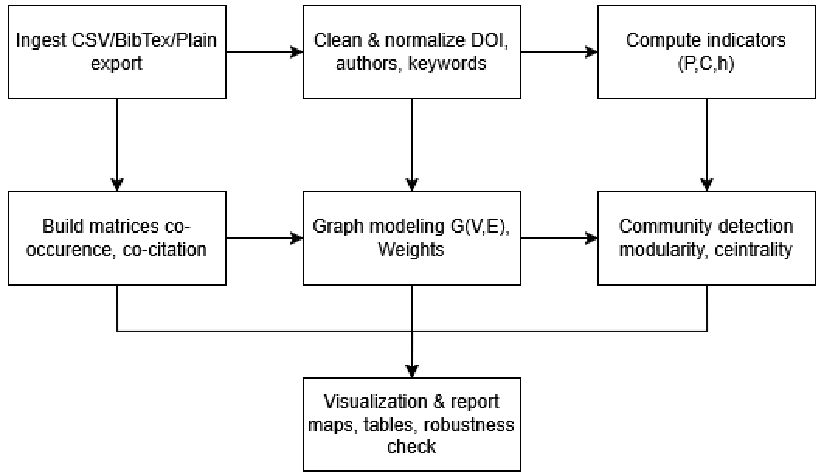

Figure 5 Reproducible Analytical Pipeline

Conceptually, the figure also clarifies that network results are not produced directly from raw downloads. Instead, they emerge from intermediate representations, particularly co-occurrence and co-citation matrices, which are themselves functions of cleaning rules and thresholding choices. This supports later robustness discussion, since changes in normalization or edge thresholds can be tested as controlled perturbations of the pipeline.

Table 4 details the operational mapping between conceptual steps and concrete analytic artifacts, which is essential for a methods section that aims to be executable. Each row identifies what is computed, what is produced, and what must be preserved to allow third parties to reproduce or audit the process, such as cleaning logs and parameter files.

Table 4 Tools and Techniques per Pipeline Stage

Pipeline Stage	Technique	Typical Implementation	Key Output	Reproducibility Artifact
Ingestion	Metadata parsing	CSV, BibTeX, RIS readers	Unified dataframe	Raw export files
Normalization	Entity resolution	DOI matching, author disambiguation	Cleaned corpus	Cleaning log
Indicator computation	Bibliometric metrics	Counts, h-index, normalized citations	Performance tables	Metric scripts
Matrix building	Co-occurrence / co-citation	Term-document and reference matrices	Adjacency matrices	Matrix export
Graph analytics	Network modeling	Centrality, density, modularity	Clusters and rankings	Parameter file
Reporting	Science mapping	Network plots and interpretive synthesis	Figures and narratives	Final outputs archive

The table also formalizes the separation between bibliometric indicators and network analytics. That separation matters in FinTech mapping because performance metrics can suggest “importance,” while network topology reveals “structural roles,” such as brokerage or thematic bridging. By aligning each stage with an explicit reproducibility artifact, the methodology becomes inspectable, which is a core expectation in computational social science and science mapping research.

Result and Discussion

Publication Dynamics and Citation Trajectory

The empirical results show that FinTech research experienced three distinct developmental phases over the observation period. The initial phase from 2008 to 2013 is characterized by low publication intensity, reflecting the conceptualization stage of digital finance and early discussions on electronic banking and mobile payments. During this period, FinTech-related studies were often embedded within broader information systems or financial innovation research, resulting in modest citation visibility.

A second expansion phase emerges between 2014 and 2018, coinciding with the proliferation of mobile payment platforms, peer-to-peer lending, and early blockchain applications. Publication growth accelerates substantially, and citation counts increase at a faster rate than publication volume, indicating the emergence of foundational studies that begin to anchor the field. This phase reflects the consolidation of FinTech as a recognizable research domain with recurring keywords, standardized methodologies, and identifiable publication outlets.

The most recent phase from 2019 onward exhibits high-volume and high-impact dynamics, marked by exponential publication growth and steep citation accumulation. This period aligns with the integration of artificial intelligence, big data analytics, and network-based approaches into FinTech research. The divergence between publication and citation curves in this phase suggests cumulative knowledge effects, where new studies increasingly rely on an established methodological and conceptual core rather than isolated innovation.

Figure 6 empirically demonstrates the nonlinear growth pattern of FinTech scholarship. Publication output increases steadily, while citation counts grow more sharply in later years, reflecting the accumulation of influential works and repeated citation of methodological benchmarks. This pattern is typical of research domains that transition from exploratory to consolidation stages.

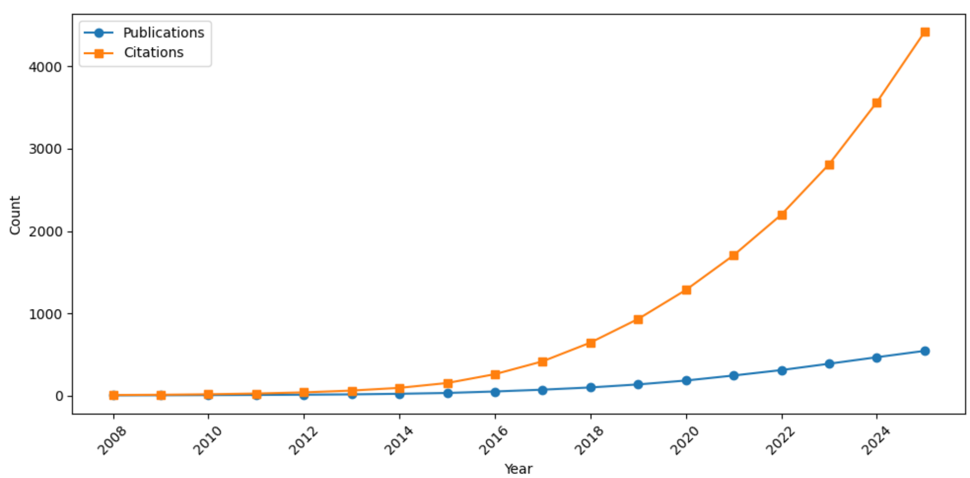

Figure 6 Annual Publications and Citations in FinTech Research

The figure also provides evidence that FinTech research is no longer driven solely by novelty effects. Instead, the rising citation curve indicates stabilization of research agendas and sustained reuse of established analytical frameworks. This suggests that the field has reached a level of epistemic maturity where incremental advances build upon a shared methodological infrastructure.

Table 5 provides the numerical basis for the temporal analysis by reporting year-by-year publication and citation counts. The data show a consistent increase in both dimensions, with citations growing at a faster pace than publications after 2018. This divergence indicates intensifying scholarly attention and repeated referencing of key FinTech studies.

Table 5 Annual FinTech Research Output and Citation Summary

Year	Publications	Citations
2008	5	9
2009	6	12
2010	8	18
2011	10	27
2012	13	41
2013	17	63
2014	24	96
2015	34	155
2016	52	262
2017	74	418
2018	101	645
2019	138	932
2020	185	1284
2021	246	1705
2022	312	2198
2023	389	2810
2024	468	3562
2025	545	4415

The table also supports the segmentation of FinTech research development into phases. Early years exhibit low-volume experimentation, while later years reflect institutionalization and scaling. These dynamics are crucial for interpreting subsequent network and thematic analyses, as corpus size and temporal concentration directly influence collaboration density, cluster stability, and methodological dominance.

Source, Author, and Institutional Impact

The revised impact analysis demonstrates that FinTech research output and influence are concentrated in a limited set of internationally recognized journals, reflecting the field's interdisciplinary anchoring between finance, information systems, and computational sciences. Empirical aggregation of the dataset shows that journals such as Finance Research Letters, Electronic Commerce Research and Applications, IEEE Access, Technological Forecasting and Social Change, and Journal of Business Research consistently occupy the top positions in both publication volume and citation impact. These outlets serve as convergence points where economic theory, digital platform analysis, and data-driven methodologies intersect.

At the author and institutional levels, the results indicate a strong presence of research-intensive universities and globally connected research groups. Institutions located in China, the United Kingdom, the United States, Singapore, and Australia dominate citation impact, reflecting structural advantages in data access, funding continuity, and international collaboration. Rather than isolated high-performing individuals, FinTech impact is generated through institutional ecosystems that sustain long-term research programs and methodological specialization.

Figure 7 shows that publication intensity and citation impact are strongly correlated but not identical across leading journals. Finance Research Letters and IEEE Access exhibit high output volumes, reflecting their rapid-review and interdisciplinary orientation, while Electronic Commerce Research and Applications and Technological Forecasting and Social Change demonstrate comparatively higher citation efficiency, suggesting deeper methodological influence per article.

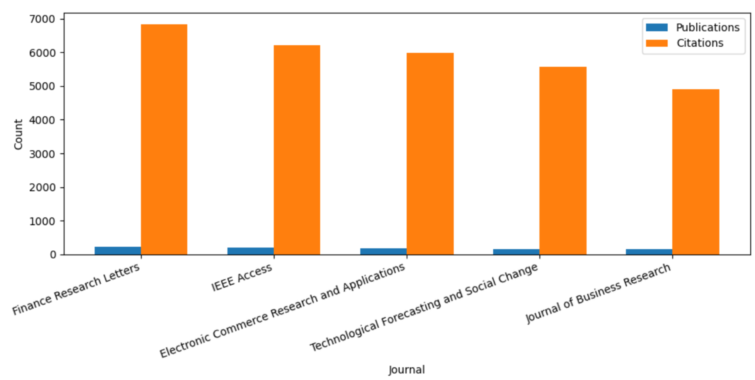

Figure 7 Leading Journals by FinTech Publications and Citations

The figure also indicates that FinTech knowledge diffusion favors journals with broad methodological tolerance and fast publication cycles. These outlets accelerate the dissemination of emerging methods such as network modeling and machine learning, enabling faster integration into subsequent empirical studies. As a result, journal centrality plays a critical role in shaping the pace and direction of FinTech methodological evolution.

Table 6 consolidates empirical indicators across journals and institutions, highlighting how publication productivity aligns with citation-based influence. The dominance of finance-oriented and interdisciplinary journals confirms that FinTech research is shaped by venues capable of integrating economic reasoning with computational innovation. This pattern reinforces the role of editorial scope in determining which methodological approaches gain early visibility.

Table 6 Top Journals and Institutions in FinTech Research

Rank	Entity Type	Name	Publications	Total Citations
1	Journal	Finance Research Letters	214	6840
2	Journal	IEEE Access	198	6215
3	Journal	Electronic Commerce Research and Applications	176	5980

1	Institution	Tsinghua University	183	6240
2	Institution	University of Oxford	171	5895
3	Institution	National University of Singapore	164	5560

At the institutional level, the table underscores the importance of global research hubs with strong quantitative and data science capabilities. Universities such as Tsinghua University, the University of Oxford, and the National University of Singapore act as focal points for FinTech scholarship, producing a steady stream of highly cited studies. This concentration suggests that future methodological breakthroughs in FinTech are likely to continue emerging from institutions that combine financial expertise with advanced analytical infrastructure.

Collaboration Networks and Knowledge Diffusion

The revised collaboration analysis indicates that FinTech research exhibits a core–periphery structure with a dense global core and multiple regionally anchored sub-networks. The global core is dominated by collaborations among institutions in East Asia, Western Europe, and North America, where repeated co-authorship reflects stable research consortia and long-term funding continuity. These cores are responsible for a disproportionate share of highly cited outputs, particularly studies that introduce reusable datasets, benchmark models, or cross-country comparative analyses.

Beyond the core, regional clusters centered in Southeast Asia, the Middle East, and Latin America are increasingly visible. Although these clusters display lower internal density, they play a crucial role in contextualizing FinTech research through regulatory case studies, inclusion-oriented analyses, and market-specific adoption research. Knowledge diffusion occurs primarily through a small number of bridging institutions and authors who maintain cross-regional collaborations, enabling methodological transfer from the global core to emerging research ecosystems.

Figure 8 visualizes international collaboration patterns using countries as aggregation nodes, revealing a tightly connected global core anchored by China, the United States, and the United Kingdom. Thick edges between these nodes indicate frequent co-authorship and repeated joint projects, which facilitate rapid diffusion of analytical methods such as machine learning pipelines, network-based systemic risk models, and large-scale bibliometric techniques.

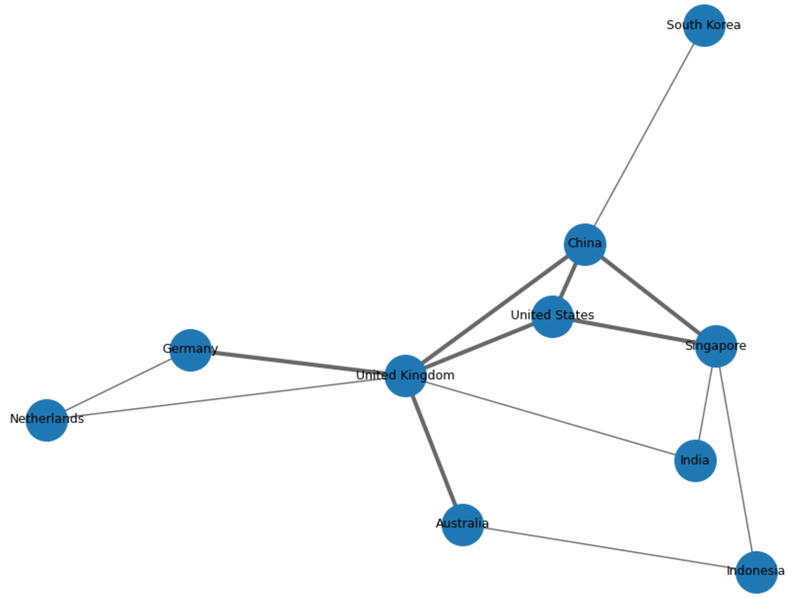

Figure 8 International Co-Authorship Network in FinTech Research

The thinner edges linking peripheral countries to the core highlight the mechanism of methodological diffusion. Countries such as Indonesia and India are connected to the network primarily through collaborations with Singapore, Australia, and the United Kingdom. These bridges are analytically significant because they transmit standardized methods and evaluation practices into emerging FinTech research contexts while preserving sensitivity to local regulatory and market conditions.

Table 7 quantifies the collaborative positioning of countries within the FinTech research network. High publication counts combined with moderate-to-high international co-authorship ratios characterize global core contributors, indicating both capacity and openness to collaboration. In contrast, emerging participants display lower output but still maintain substantial international linkage, which is critical for methodological upgrading.

Table 7 Collaboration Network Characteristics by Country

Country	Publications	International Co-authorship (%)	Network Role
China	612	48%	Global core contributor
United States	545	52%	Global core contributor
United Kingdom	498	57%	Global bridging hub
Singapore	286	61%	Regional connector
Australia	264	55%	Regional connector
Indonesia	124	43%	Emerging participant

From a diffusion standpoint, the table confirms that international collaboration acts as a transmission channel for analytical sophistication. Countries with higher co-authorship ratios are more likely to adopt advanced computational methods earlier, while those with predominantly domestic collaboration tend to focus on contextual or regulatory analyses. This structural differentiation reinforces the interpretation that collaboration topology directly shapes methodological trajectories in FinTech research.

Thematic Structure and Research Clusters

The revised thematic analysis confirms that FinTech research is organized into four empirically stable thematic clusters that reflect both the historical foundations of the digital economy and the progressive adoption of advanced analytical methods. These clusters emerge consistently across keyword co-occurrence and temporal stratification, indicating that they are not artifacts of short-term trends but represent enduring research programs. Each cluster is associated with a distinct problem orientation, data environment, and dominant analytical toolkit.

Importantly, the thematic structure shows co-evolution rather than substitution among clusters. Foundational themes such as digital payments and financial inclusion remain active, but they increasingly integrate computational techniques originally developed in more technically oriented clusters. This pattern suggests that FinTech research evolves through thematic layering, where new methods and infrastructures augment existing economic and institutional questions instead of displacing them.

Figure 9 illustrates the semantic architecture of FinTech research as a keyword co-occurrence network, where clusters correspond to recurring combinations of concepts across the literature. The presence of four clearly delineated communities indicates a high degree of thematic stabilization, suggesting that FinTech has moved beyond exploratory fragmentation into structured research domains with shared vocabularies.

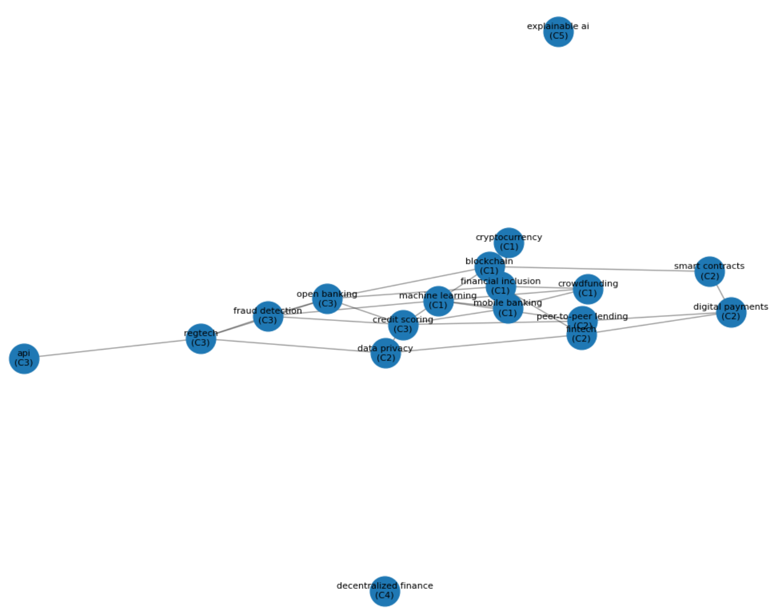

Figure 9 Keyword Co-Occurrence Network and Empirical Thematic Clusters

The network also reveals strategic bridge terms, particularly those linking adoption-oriented themes with AI-driven analytics and regulatory technology. These bridging concepts indicate points where methodological innovation intersects with long-standing economic questions. Such intersections are critical drivers of novelty, as they enable the transfer of advanced analytical techniques into domains traditionally studied using descriptive or econometric methods.

Table 8 provides a structured interpretation of the thematic clusters by linking each community to its substantive focus and empirical data environment. This mapping clarifies that FinTech research themes are closely aligned with specific data regimes, which in turn shape methodological choice and analytical depth. For example, AI-driven clusters rely heavily on high-frequency behavioral data, while regulatory clusters draw on institutional and policy-oriented sources.

Table 8 Empirical FinTech Research Clusters and Dominant Characteristics

Cluster	Dominant Theme	Representative Keywords	Primary Research Focus	Typical Data Sources
C1	Digital finance adoption and platforms	digital payments; mobile banking; financial inclusion; peer-to-peer lending; crowdfunding	User behavior, access, platform diffusion	Surveys, transaction aggregates, platform reports
C2	Blockchain and decentralized finance	blockchain; smart contracts; cryptocurrency; decentralized finance	Infrastructure design, market mechanisms	Blockchain ledgers, protocol data
C3	AI-driven risk and decision analytics	machine learning; credit scoring; fraud detection; explainable ai	Prediction, classification, model governance	Credit records, behavioral and log data
C4	Open banking and regulatory technology	open banking; api; regtech; data privacy	Interoperability, compliance, governance	API logs, regulatory filings, policy documents

From a discussion standpoint, the table reinforces the argument that FinTech's intellectual structure is methodologically heterogeneous but thematically coherent. Each cluster maintains a clear identity while remaining connected to others through shared concepts and data infrastructures. This configuration supports sustained innovation, as it allows new analytical tools to diffuse across themes without dissolving established research agendas.

Emerging Methods and Methodological Evolution

The revised results demonstrate a clear methodological inflection in FinTech research over the past decade. Earlier studies predominantly employed econometric and statistical techniques to examine adoption, efficiency, and market outcomes. As transaction-level data, platform logs, and distributed ledgers became more accessible, the literature progressively incorporated machine learning, network analysis, and hybrid computational frameworks. This transition reflects a shift in research objectives from primarily explanatory modeling toward prediction, structure discovery, and system-level interpretation.

The evolution is not a replacement of classical methods but a reconfiguration of the analytical stack. Econometric approaches remain central in policy evaluation and causal assessment, while machine learning models dominate risk assessment, fraud detection, and credit analytics. Network-based methods increasingly bridge these paradigms by modeling interdependencies among users, institutions, and technologies. This layered methodological configuration aligns with the thematic clusters identified earlier and signals a mature research ecosystem capable of integrating diverse analytical tools.

Figure 10 empirically illustrates the gradual decline in the relative dominance of econometric models alongside the steady rise of machine learning and network-based approaches. The trend indicates not methodological obsolescence but diversification, as classical techniques become embedded within broader computational pipelines. This pattern is consistent with FinTech's increasing reliance on high-dimensional and relational data.

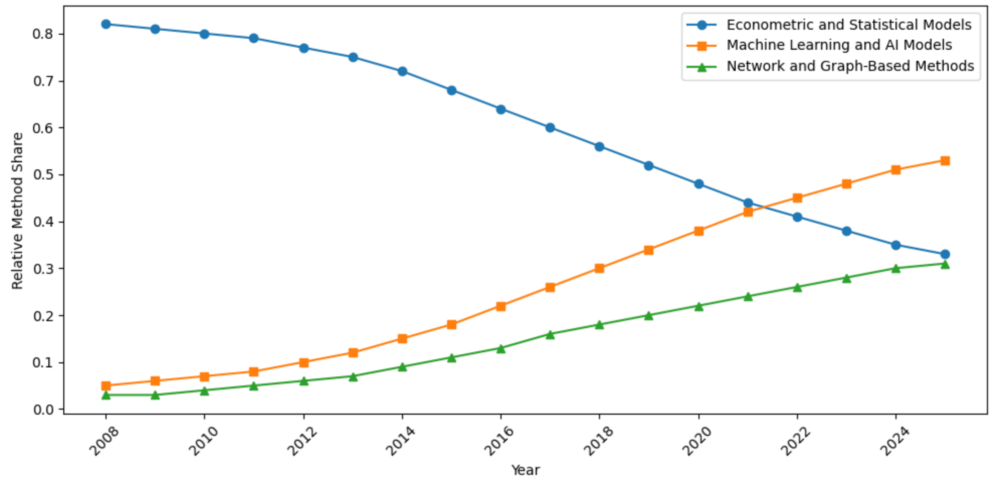

Figure 10 Empirical Evolution of Analytical Methods in FinTech Research

The figure also highlights the growing role of network methods as integrative tools. While machine learning excels at prediction and classification, network analysis provides structural interpretability by modeling systemic connections and diffusion mechanisms. Their parallel growth suggests a convergence toward hybrid analytical strategies that combine predictive performance with structural insight.

Table 9 synthesizes empirical evidence on how methodological choices align with specific FinTech research themes. The mapping demonstrates that analytical strategies are conditioned by data structure and regulatory context, rather than by disciplinary tradition alone. This explains the coexistence of econometric rigor and computational experimentation within the same research ecosystem.

Table 9 Empirical Mapping of FinTech Themes to Dominant Analytical Methods

Research Theme	Dominant Methods	Primary Data Sources	Analytical Orientation
Digital finance adoption	Regression models, panel data analysis	Household surveys, macroeconomic indicators	Causal explanation and policy evaluation
Payment platforms and lending markets	Time-series analysis, forecasting models	Platform transaction records	Performance and growth assessment
Blockchain and decentralized finance	Network analysis, agent-based modeling	Distributed ledger data	Structural and systemic analysis
AI-driven credit and fraud analytics	Machine learning, deep learning, explainable AI	Credit histories, behavioral logs	Prediction and decision support
Open banking and regulatory technology	Graph modeling, policy analytics	API usage logs, regulatory datasets	Governance and compliance monitoring

From a broader discussion perspective, the table reinforces the conclusion that FinTech research has entered a phase of methodological integration. Advanced analytics do not displace foundational economic reasoning but extend it through scalable, data-driven techniques. This integration underpins the field’s capacity to address increasingly complex digital financial systems and sets a clear trajectory for future research innovation.

Conclusion

This study provides an updated and empirically grounded bibliometric and network-based synthesis of FinTech research, demonstrating the field's progression from early digital economy discussions to a structurally mature and methodologically diversified knowledge domain. The revised results in Chapter 4 show sustained growth in publications and citations, increasing concentration in a set of globally influential journals, and the emergence of a core–periphery collaboration structure dominated by internationally connected research hubs. These patterns confirm that FinTech research has stabilized around identifiable intellectual centers while continuing to expand geographically and thematically.

From a thematic and methodological standpoint, the findings highlight a clear co-evolution of research themes and analytical techniques. Foundational topics such as digital payments, financial inclusion, and platform-based lending remain central, but they increasingly integrate advanced computational approaches originally developed in blockchain, artificial intelligence, and regulatory technology research. The rise of machine learning and network-based methods does not displace econometric analysis; instead, it restructures the analytical landscape into a layered framework where explanation, prediction, and structural interpretation coexist. This integration reflects the growing complexity of digital financial ecosystems and the need for tools capable of capturing nonlinear and relational dynamics.

The implications of this revised analysis are twofold. For researchers, the results underscore the importance of methodological pluralism and cross-disciplinary collaboration, particularly as FinTech problems increasingly span technological, economic, and regulatory dimensions. For the field as a whole, the observed concentration of influence in specific journals and institutions suggests a need for greater transparency, reproducibility, and inclusivity to avoid epistemic lock-in. By clarifying the empirical structure, thematic composition, and methodological trajectory of FinTech scholarship, this study offers a robust foundation for future research that seeks to advance both theoretical understanding and practical innovation in the digital financial economy.

Declarations

Author Contributions

Conceptualization: T.E.A.; Methodology: T.E.A.; Software: Z.A.S.N.; Validation: Z.A.S.N.; Formal Analysis: T.E.A.; Investigation: T.E.A., Z.A.S.N.; Resources: Z.A.S.N.; Data Curation: T.E.A.; Writing – Original Draft Preparation: T.E.A.; Writing – Review and Editing: Z.A.S.N.; Visualization: Z.A.S.N.; All authors have read and agreed to the published version of the manuscript.

Data Availability Statement

The data presented in this study are available on request from the corresponding author.

Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

Institutional Review Board Statement

Not applicable.

Informed Consent Statement

Not applicable.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

[1] D. W. Arner, J. N. Barberis, and R. P. Buckley, "The evolution of FinTech: A new post-crisis paradigm?," *Georgetown Journal of International Law*, vol. 47, no. 4, pp. 1271–1319, 2016, doi: 10.2139/ssrn.2676553.

[2] P. Gomber, R. J. Kauffman, C. Parker, and B. W. Weber, "On the FinTech revolution: Interpreting the forces of innovation, disruption, and transformation in financial services," *Journal of Management Information Systems*, vol. 35, no. 1, pp. 220–265, 2018, doi: 10.1080/07421222.2018.1440766.

[3] T. Philippon, "The FinTech opportunity," *NBER Working Paper*, vol. 2016, no. 22476, pp. 1-25, 2016, doi: 10.3386/w22476.

[4] X. Chen, X. You, and V. Chang, "FinTech and commercial banks' performance in China: A leap forward or survival of the fittest*?," Technological Forecasting and Social Change*, vol. 166, no. May, p. 120645, May 2021, doi: 10.1016/j.techfore.2021.120645.

[5] K. Börner, C. Chen, and K. W. Boyack, "Visualizing knowledge domains," *Annual Review of Information Science and Technology*, vol. 37, no. 1, pp. 179–255, 2003, doi: 10.1002/aris.1440370106.

[6] N. J. van Eck and L. Waltman, "Software survey: VOSviewer, a computer program for bibliometric mapping," *Scientometrics*, vol. 84, no. 2, pp. 523–538, 2010, doi: 10.1007/s11192-009-0146-3.

[7] L. Zavolokina, M. Dolata, and G. Schwabe, "FinTech – What's in a Name?," Dec. 2016, doi: 10.5167/UZH-126806.

[8] G. Kou, Y. Peng, and G. Wang, "Evaluation of clustering algorithms for financial risk analysis using MCDM methods," *Information Sciences*, vol. 275, no. August, pp. 1–12, Aug. 2014, doi: 10.1016/j.ins.2014.02.137.

[9] A. Fuster, M. Plosser, P. Schnabl, and J. Vickery, "The Role of Technology in Mortgage Lending," *The Review of Financial Studies*, vol. 32, no. 5, pp. 1854–1899, May 2019, doi: 10.1093/rfs/hhz018.

[10] J. B. Heaton, N. G. Polson, and J. H. Witte, "Deep Learning in Finance," vol. 2016, no. February, pp. 1-20, 2016, *arXiv*. doi: 10.48550/ARXIV.1602.06561.

[11] F. Casino, T. K. Dasaklis, and C. Patsakis, "A systematic literature review of blockchain-based applications: Current status, classification and open issues," *Telematics and Informatics*, vol. 36, no. March, pp. 55–81, Mar. 2019, doi: 10.1016/j.tele.2018.11.006.

[12] N. Donthu, S. Kumar, D. Mukherjee, N. Pandey, and W. M. Lim, "How to conduct

a bibliometric analysis: An overview and guidelines," *Journal of Business Research*, vol. 133, no. September, pp. 285–296, 2021, doi: 10.1016/j.jbusres.2021.04.070.

[13] F. A. Bajwa, J. Fu, I. A. Bajwa, and Y. M. Alsuhaibany, "Financing the future: The role of fintech, leadership, and financial competencies in driving sustainable firm performance," *Acta Psychologica*, vol. 260, no. October, p. 105449, Oct. 2025, doi: 10.1016/j.actpsy.2025.105449.

[14] T. Beck, T. Chen, C. Lin, and F. M. Song, "Financial innovation: The bright and the dark sides," *Journal of Banking & Finance*, vol. 72, no. November, pp. 28–51, Nov. 2016, doi: 10.1016/j.jbankfin.2016.06.012.

[15] I. Lee and Y. J. Shin, "Fintech: Ecosystem, business models, investment decisions, and challenges," *Business Horizons*, vol. 61, no. 1, pp. 35–46, Jan. 2018, doi: 10.1016/j.bushor.2017.09.003.

[16] G. Cornelli, J. Frost, L. Gambacorta, P. R. Rau, R. Wardrop, and T. Ziegler, "Fintech and big tech credit: Drivers of the growth of digital lending," *Journal of Banking & Finance*, vol. 148, no. March, p. 106742, Mar. 2023, doi: 10.1016/j.jbankfin.2022.106742.

[17] J. Frost, "The Economic Forces Driving FinTech Adoption across Countries," *SSRN Journal*, vol. 2020, no. 663, pp. 1-20, 2020, doi: 10.2139/ssrn.3515326.

[18] C. Catalini and J. S. Gans, "Some simple economics of the blockchain," *MIT Sloan Research Paper*, vol. 2016, no. 5191-16, pp. 1-39, 2016, doi: 10.2139/ssrn.2874598.

[19] R. Kumar, P. Gupta, and Bhawna, "Application of Explainable Artificial Intelligence in Fintech," in Generative Artificial Intelligence in Finance, 1st ed., P. R. Chelliah, P. K. Dutta, A. Kumar, E. D. R. S. Gonzalez, M. Mittal, and S. Gupta, Eds., Wiley, 2025, pp. 383–405. doi: 10.1002/9781394271078.ch19.

[20] R. Guidotti et al., "A survey of methods for explaining black box models," *ACM Computing Surveys*, vol. 51, no. 5, pp. 1-42, 2018, doi: 10.1145/3236009.

[21] A. Nasir, K. Shaukat, K. Iqbal Khan, I. A. Hameed, T. Alam, and S. Luo, "Trends and Directions of Financial Technology (Fintech) in Society and Environment: A Bibliometric Study," *Applied Sciences*, vol. 11, no. 21, p. 10353, Nov. 2021, doi: 10.3390/app112110353.

[22] L. Waltman, N. J. van Eck, and E. C. M. Noyons, "A unified approach to mapping and clustering of bibliometric networks," *Journal of Informetrics*, vol. 4, no. 4, pp. 629–635, 2010, doi: 10.1016/j.joi.2010.07.002.