BIBLIOMETRIC REVIEW PAPER DOI: 10.21844/16202118209

Vol. XVIII, No. 2; September 2025 - February 2026 Print ISSN: 0975-024X; Online ISSN: 2456-1371

Knowledge Dynamics in Cryptocurrency Volatility Forecasting: Methods, Trends and Collaborations (2018-2025)

Prashant Subhash Chougule[1], Syed Hasan Jafar[2]
[1]Assistant Professor, School of Business, Woxsen University, Hyderabad, Telangana
[2]Associate Professor & Vice-Dean, School of Business, Woxsen University, Hyderabad, Telangana

Abstract

The surge in cryptocurrency markets has amplified scholarly interest in volatility forecasting, a linchpin for risk mitigation and strategic financial planning. This state-of-the-art landscape review maps the intellectual landscape of cryptocurrency volatility forecasting between 2018-2025 by analyzing 132 SCOPUS-indexed publications. It integrates performance analysis, science mapping and network analysis to uncover dominant themes, evolving methodologies and collaborative structures. The field exhibits clear methodological progression from classical GARCH-type models to AI-driven and hybrid approaches, notably LSTM and hybrid neural architectures. Thematic evolution highlights growing sophistication, but critical voids persist in consideration of multiple assets (like Ethereum, Litecoin, etc.) and novel variables (like blockchain metrics, etc.), ESG integration, regional market representation and regulatory foresight. This review identifies underexplored areas that present strategic opportunities for inclusive, ethical and resilient research and offers a forward-looking agenda tailored to the evolving demands of researchers, institutions, practitioners and policymakers.

Keywords: Cryptocurrencies, Volatility Forecasting, Forecasting Models, Quantitative Literature Analysis, Performance Analysis, Science Mapping, Network Analysis, SCOPUS

Introduction

Background & Research Context

This inquiry aligns with the timeless Indian Philosophical pursuit of knowledge (*Jnana*) for informed discernment (*viveka*) and ethical stewardship (*dharma*) in rapidly evolving financial ecosystems rather than just for prediction and control.

Technology has always driven the evolution of banking and finance (Singh & Dahiya, 2023).The advent of cryptocurrencies has redefined the contemporary financial landscape. Led by Bitcoin (BTC) and Ethereum (ETH), these cryptocurrencies have evolved from their conceptualization (as decentralized, peer-to-peer digital assets) into complex financial instruments traded globally and characterized by high levels of speculation, statistically significant transmission of shocks, volatilities, and spillovers, even into other global financial markets (Liu & Serletis, 2019; Asif & Unar, 2024). As an emerging asset class, they have elicited interest across disciplines and fields, viz. Behavioral Finance, Econometrics, Economics and Computer Science (Corbet, Lucey, Urquhart, & Yarovaya, 2019).

Volatility forecasting assumes high importance in financial markets and has captured attention of academics and practitioners in investment, valuation, management of risks and making

Corresponding Author: Prashant Subhash Chougule, Assistant Professor, School of Business, Woxsen University, Hyderabad, Telangana, E-mail: chougule.prashant@woxsen.edu.in
How to Cite the article: Chougule; P.S., Jafar; S.H., (2025). Knowledge Dynamics in Cryptocurrency Volatility Forecasting: Methods, Trends and Collaborations (2018-2025), Purushartha, 18(2), 141-172
Source of Support: Nil
Conflict of interest: None

monetary policy since long (Poon & Granger, 2003). The same is true for cryptocurrencies due to observation of extreme fluctuations, absence of intrinsic value anchors, and high sensitivity to external news, social media trends and macroeconomic events (Thélissaint, 2025; Chu, Zhang, & Chan, 2019). This, along with its burgeoning adoption in recent years, translates into critical implications of volatility forecasting for investors, traders, regulators, developers and risk managers (Sharma, Verma, & Sam, 2021; Al-Amri, Zakaria, Habbal, & Hassan, 2019). These characteristics defy conventional modeling techniques and raise basic challenges in traditional financial theory applications (Boozary, Sheykhan, & GhorbanTanhaei, 2025).

Cryptocurrencies are different than other traditional assets (Li, Li, Yuan, & Zhu, 2021) have exhibited higher and more persistent volatility (Qureshi, Aftab, Bouri, & Saeed, 2020). Even if speculators are attracted to volatility (due to short-term arbitrage possibility), it is risky for institutional investors (aiming to hedge portfolios) and developers who build decentralized financial systems or products that rely on pricing stability. Also, regulators and central banks are increasingly concerned about the potential spillover effects of this instability on broader financial markets, as these crypto-assets gain systemic importance.

In this context, accurate and robust volatility forecasting models are more than just academic tools. They are also strategic instruments influencing portfolio optimization, derivative pricing, algorithmic trading strategies and macro-level policy formulation. The models employed for volatility forecasting encompass a wide array, including classic time-series approaches (viz. ARCH/ GARCH family tools) to more modern artificial intelligence & machine learning applications (viz. LSTM, Random Forests, Hybrid Deep Learning algorithms, etc.) (Fang, et al., 2022; Anas, Shahzad, & Yarovaya, 2024).

This has led to rise in new empirical evidence being produced at a fast rate, leading to a growing body of literature that analyses properties, estimation and forecasting of cryptocurrency volatility (Almeida & Gonçalves, 2022). Thus, consolidation and synthesis of existing knowledge, literature gap identification and contemplating future research direction assumes high importance (Corbet, Lucey, Urquhart, & Yarovaya, 2019; Angerer, Hoffmann, Neitzert, & Kraus, 2021). The intellectual structure, dominant themes, collaboration patterns, and methodological trends in this field remain largely unmapped, and thus there is a pressing need for a comprehensive quantitative literature review that can distill this body of knowledge and serve as a foundational reference for upcoming research.

Gaps in Existing Literature

Some papers have addressed cryptocurrencies as financial assets (Corbet, Lucey, Urquhart, & Yarovaya, 2019) and others have analyzed forecasting models with traditional asset perspective (Naimy, Haddad, Fernández-Avilés, & El Khoury, 2021). Still, there remains an absence of quantitative literature reviews focusing exclusively on volatility forecasting or prediction of cryptocurrencies. Despite the growing academic interest in cryptocurrency-related literature, prior reviews fall short in providing a focused, methodologically rigorous and updated synthesis of research dedicated specifically to cryptocurrency volatility forecasting. Existing reviews (Fang, et al., 2022; Anas, Shahzad, & Yarovaya, 2024; Almeida & Gonçalves, 2022; Bahoo, Cucculelli, Goga, & Mondolo, 2024; Boozary, Sheykhan, & GhorbanTanhaei, 2025) like Fang et al. (2022) provide a broad survey of cryptocurrency trading strategies, while Almeida & Gonçalves (2022) forego bibliometric depth and limit their investigation to volatility modeling and risk management. Recent state-of-the-art landscape reviews like Anas et al. (2024) and Boozary et al. (2025) either restrict their scope to a

narrow methodological or asset-specific viewpoint or forego critical intellectual structure mapping tools altogether. Then, reviews like Bahoo et al. (2024) adopt an all-encompassing panoramic view of AI in Finance and discuss volatility forecasting only marginally, thus resulting in thematic dilution. This is further elaborated in Table 1, as follows:

Table 1: Comparative positioning of present study

S.N.	Study	Scope & Focus	Methodology	Key Gaps	How our study addresses Key Gaps
1.	Fang et al. (2022)	Broad Review on Cryptocurrency Trading	Narrative	Volatility Forecasting treated as a sub-theme, absence of bibliometric analysis	exclusive focus on volatility forecasting, rigorous SCOPUS connected bibliometric mapping
2.	Almeida & Gonçalves (2022)	Risk Management and Volatility	Systematic Review & VOS Viewer	Not SCOPUS and lacks collaboration & trend analysis	Based on SCOPUS & integrates Performance Analysis, Science Mapping, and Network Analysis
3.	Anas et al. (2024)	High Frequency Data in Cryptocurrency Research	Bibliometric & meta review	Restricted to High Frequency Data & lacks full thematic scope	covers all data frequencies, maps all cryptocurrencies across all volatility related forecasting approaches.
4.	Bahoo et al. (2024)	AI in Finance (broadly)	Bibliometric & content analysis	Crypto-volatility minimally addressed, thematic dilution	Thematic precision, crypto-volatility forecasting is core, integrated mapping of trends and gaps
5.	Boozary et al. (2025)	Bitcoin Price Prediction using ML	Systematic Review	Bitcoin only, Price Forecasting Focus, lacks bibliometric tools, weak thematic integration	multi-crypto scope, Specific focus on Volatility Forecasting, connects not just Machine Learning, but also econometric & hybrid models with rigor.

Research Questions & Objectives

In response to the gaps identified above, this study is structured around the following Research Questions:

RQ1: In terms of influential authors, journals, institutions & countries, what are the performance indicators of the scholarly literature on cryptocurrency volatility and prediction.

RQ2: How have the various domain-related dominant conceptual themes and methodological trends evolved over time?

RQ3: Based on the author collaboration networks, co-citation patterns, keyword co-occurrences, etc. what is the intellectual and social structure of the domain of cryptocurrency volatility and prediction. To address these questions, the following research objectives were articulated:

RO1: to identify the leading contributors and publication venues of the field through performance analysis of scholarly literature.

RO2: to use keyword and trend analyses and thematic evolution indicators to trace the thematic and methodological evolution of the field.

RO3: To use co-authorship, co-citation and conceptual network analysis to map the intellectual and social linkages transforming the field

Methodology

Overview of approach & Rationale for this state-of-the-art landscape Review

Quantitative Literature analysis provides for a quantitative and objective examination of scholarly output, revealing the performance, structure and evolution of a given domain (Donthu, Kumar, Mukherjee, Pandey, & Lim, 2021). Researchers can examine author collaboration, co-citation networks, thematic development, keyword clustering, performance analysis, etc. (areas uncapturable by traditional reviews) using the Biblioshiny Application of the Bibliometrix R Package(Aria & Cuccurullo, 2017).

Recent studies in finance, innovation and risk modelling have successfully harnessed bibliometric methods to identify key intellectual pivot points and to forecast future research direction(Linnenluecke, Marrone, & Singh, 2020). This research constructs a visual, data-driven map of cryptocurrency volatility forecasting literature by offering the first comprehensive SCOPUS-based scholarly-ecosystem review (2018-25) by synthesizing insights from 132 peer-reviewed journal articles and addressing important gaps in prior literature by ensuring precision and thematic focus via a rigorous filtering process involving keyword-based selection, document-type restrictions and irrelevant record exclusion through employment of Biblioshiny tool (from Bibliometrix via RStudio). This study integrates Performance Analysis, Science Mapping, and Network Analysis to track the intellectual evolution of the field, highlight influential contributions and discover rising research paths. This review maps volatility forecasting-specific approaches across econometric, machine learning and hybrid methodologies unlike previous studies which were either too broad or narrowly focused. This robust and targeted approach provides actionable insights for researchers, practitioners, policymakers, crypto-financial product developers and marketers to navigate the increasingly complex landscape of cryptocurrency volatility & its forecasting.

The methodological rigor employed herein tries to emulate the Indo-spiritual principles of Rita (Cosmic Order, truth & harmonious regulation of the universe) and Viveka (Discernment of real from the illusory). In the same way Indian philosophical traditions emphasize discerning the truth from illusion, this review attempts to methodically discern relevant literature from thematic noise to uncover patterns of academic clarity and structural harmony.

Data sources & Search Strategy

The SCOPUS database was selected as the exclusive data source due to its broad multidisciplinary coverage, high peer-reviewed standards as well as strong integration with bibliometric tools (Biblioshiny from Bibliometrix in RStudio)(Aria & Cuccurullo, 2017). SCOPUS's comprehensive indexing ensures compatibility with institutional publication metrics and academic standards of reputable journals. This is in consonance with best practices for state-of-the-art-knowledge-domain mapping reviews in Finance & Technology (Donthu, Kumar, Mukherjee, Pandey, & Lim, 2021; Linnenluecke, Marrone, & Singh, 2020).

A step-wise filtering funnel was employed to

ensure high quality thematic relevance and methodological transparency. The following filters were systematically applied:

- Time Frame- 2015-2025 (Final results were from 2018 to 2025 due to availability)
- Document Type- Only peer-reviewed Journal Articles (Book Chapters, Reviews and Conference Papers were excluded to maintain high quality)
- Language- English only
- Publication Stage- only Final-stage publications
- Source Type- Journals only (SCOPUS-indexed)
- Exclusions- Records related to Price Prediction or speculative pricing (Keywords like "Price Prediction", "Price Forecasting", "Price Trends", "Price Trend Prediction", "Bitcoin Price Prediction", were excluded from the search to maintain focus on Volatility Forecasting/ Prediction and not dilute the results with Price Forecasting/ Prediction related literature)

The initial 485 results were filtered down to a final data set of 132 relevant documents and verified on 17th May 2025 as presented in Table 2:

Table 2: Search Strategy and Filtering Funnel

Stage	Query passed in SCOPUS	Output	Date conducted
1	(TITLE-ABS-KEY (cryptocurrenc**) AND TITLE-ABS-KEY (volatility) AND TITLE-ABS-KEY (forecasting) OR TITLE-ABS-KEY (prediction))	485 documents found	16th May 2025
2	(TITLE-ABS-KEY (cryptocurrenc**) AND TITLE-ABS-KEY (volatility) AND TITLE-ABS-KEY (forecasting) OR TITLE-ABS-KEY (prediction)) AND PUBYEAR > 2016 AND PUBYEAR < 2026	485 documents found	16th May 2025
3	(TITLE-ABS-KEY (cryptocurrenc**) AND TITLE-ABS-KEY (volatility) AND TITLE-ABS-KEY (forecasting) OR TITLE-ABS-KEY (prediction)) AND PUBYEAR > 2016 AND PUBYEAR < 2026 AND (LIMIT-TO (DOCTYPE , "ar")) AND (LIMIT-TO (PUBSTAGE , "final")) AND (LIMIT-TO (SRCTYPE , "j")) AND (LIMIT-TO (LANGUAGE , "English"))	255 documents found	16th May 2025
4	(TITLE-ABS-KEY (cryptocurrenc**) AND TITLE-ABS-KEY (volatility) AND TITLE-ABS-KEY (forecasting) OR TITLE-ABS-KEY (prediction)) AND PUBYEAR > 2016 AND PUBYEAR < 2026 AND (LIMIT-TO (DOCTYPE , "ar")) AND (LIMIT-TO (PUBSTAGE , "final")) AND (LIMIT-TO (SRCTYPE , "j")) AND (LIMIT-TO (LANGUAGE , "English")) AND (EXCLUDE (EXACTKEYWORD , "Price Prediction") OR EXCLUDE (EXACTKEYWORD , "Price Forecasting") OR EXCLUDE (EXACTKEYWORD , "Price Trends") OR EXCLUDE (EXACTKEYWORD , "Price Trend Prediction") OR EXCLUDE (EXACTKEYWORD , "Bitcoin Price Prediction"))	222 documents found	17th May 2025
5	Manual Screening: Further reduction based on suitability of title, abstract, keywords review for ensuring strict thematic alignment- Cryptocurrency Volatility Forecasting	132 documents found	17th May 2025

In line with rigorous knowledge-domain-mapping protocol, citation threshold was not imposed during document selection phase to allow inclusion of recent, yet relevant contributions, due to the fast-evolving nature of crypto-finance fields where citation accumulation lags innovation. The final collection represented a thematically coherent and methodologically sound sample of global research

on cryptocurrency volatility forecasting from 2018 to 2025.

The selected relevant records were exported in .CSV format directly from SCOPUS. The metadata included title, authors, abstract, keywords, sources, citations, affiliations, DOI and other publication details and was prepared for compatibility with Bibliometrix, a robust, user-friendly, R-based open-source bibliometric analysis tool (Aria & Cuccurullo, 2017), which facilitates systematic performance analysis, science mapping and network analysis, ensuring a comprehensive examination of the research domain.

This tool was accessed on 17th May 2025 and the workflow consisted of 3 complimentary analytical layers, as presented in Table 3 below:

Table 3: Overview of Analytical Layers used

Layer No.	Layer Name	Purpose	Key Techniques used
1	Performance Analysis	To identify the Who, What, When & Where of Scholarly Contributions. This forms the quantitative superstructure of the domain's productivity	Annual Scientific Production; Most Cited articles; h-index, g-index, m-index; Top Contributing Authors, Journals, Institutions, Countries, etc.
2	Science Mapping	To identify the Conceptual Structure of the domain and trace Intellectual Evolution over time	Keyword Co-occurrence (Author, abstract, title, etc.); Thematic Evolution Mapping (2017-20, 2021-23, 2024-25); Trend topics (eg. GARCH, APARCH, LSTM, LSTM ARIMA hybrids, etc.)
3	Network Analysis	To examine Collaborative Relationships and Intellectual Linkages across authors, institutions, countries, etc.	Co-authorship Networks (Author, Institution, Country); Co-citation & Bibliographic Coupling; 3-Field Plots (eg. Authors-Keywords-Sources).

This triangular methodological approach mirrors the vedic ideal of *Rita,* the search for underlying order amidst apparent complexity.

Results

After the methodological framework provided in the previous section, this segment presents the key findings of the quantitative literature analysis in a structured objective manner. To capture the intellectual contours of the domain (i.e. cryptocurrency volatility forecasting research), the results are organized across performance indicators, science mapping metrics and collaboration networks.

Overview of the Dataset

The dataset comprises 132 peer-reviewed, SCOPUS-indexed journal articles published between 2018 & 2025. These publications span 80 distinct sources, collectively citing 6017 references. The dataset reflects a modern and rapidly expanding research domain with an annual growth rate of 24.93% and an average document age of 2.49 years.

Each document receives 19.98 average citations per document, reflecting moderate academic engagement. Content-wise, the articles offer a diverse thematic landscape for keyword & thematic analysis through 408 Author Keywords (DE), reflecting author's thematic choices and 337 Keywords Plus (ID) generated from titles of articles' cited references.

With only 18 single-authored documents, a total of 355 authors contributed to these publications. The average number of co-authors per document is 2.86 and 34.09% of articles involve international collaboration, indicating substantial cross-border scholarly engagement. Peer-reviewed academic quality of all articles is ensured via choosing journal articles for analysis.

A summary of the dataset's core attributes is provided in Table 4:

Table 4: Summary of Main Dataset Characteristics

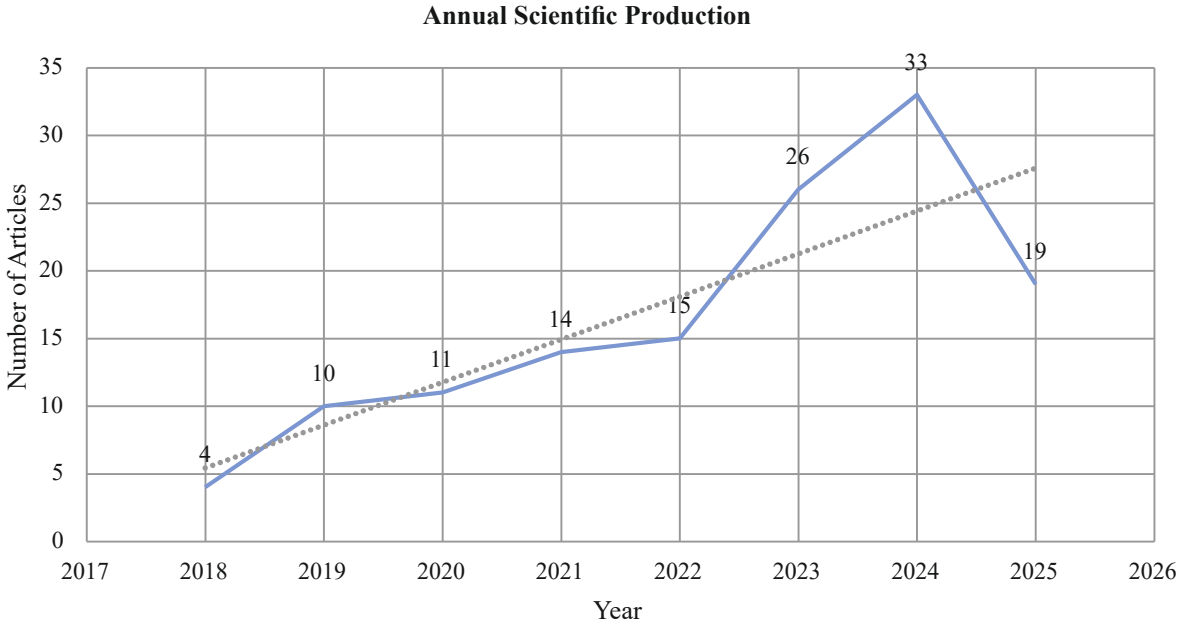
Description	
MAIN INFORMATION ABOUT DATA	
Timespan	2018:2025
Sources (Journals, Books, etc)	80
Documents	132
Annual Growth Rate %	24.93
Document Average Age	2.49
Average citations per doc	19.98
References	6017
DOCUMENT CONTENTS	
Keywords Plus (ID)	337
Author's Keywords (DE)	408
AUTHORS	
Authors	355
Authors of single-authored docs	18
AUTHORS COLLABORATION	
Single-authored docs	18
Co-Authors per Doc	2.86
International co-authorships %	34.09
DOCUMENT TYPES	
article	132

Performance Analysis

Annual Scientific Production

The dataset reveals growing academic interest in the domain via a marked upward trend in scholarly output between 2018-25. As illustrated in Figure 1, the annual number of publications has risen from a mere 4 articles in 2018 to a peak of 33 articles in 2024, representing a 725% growth over 7 years.
With fewer than 15 publications per year until 2021, early output can be considered modest. A noticeable inflection point arrives in 2023, when production almost doubles from previous year (15 in 2022 to 26 in 2023), and the trend continues in 2024 (33 articles). Due to partial year data at time of extraction (May 16th 2025), the number of articles shows a slight drop to 19 in 2025.

This consistent growth trajectory is reflective of the domain's rapid maturation and indicative that cryptocurrency volatility forecasting is moving from a niche research interest to mainstream scholarly topic.



(Source: Prepared by authors elaboration using the Bibliometrix R Package and MS Excel)

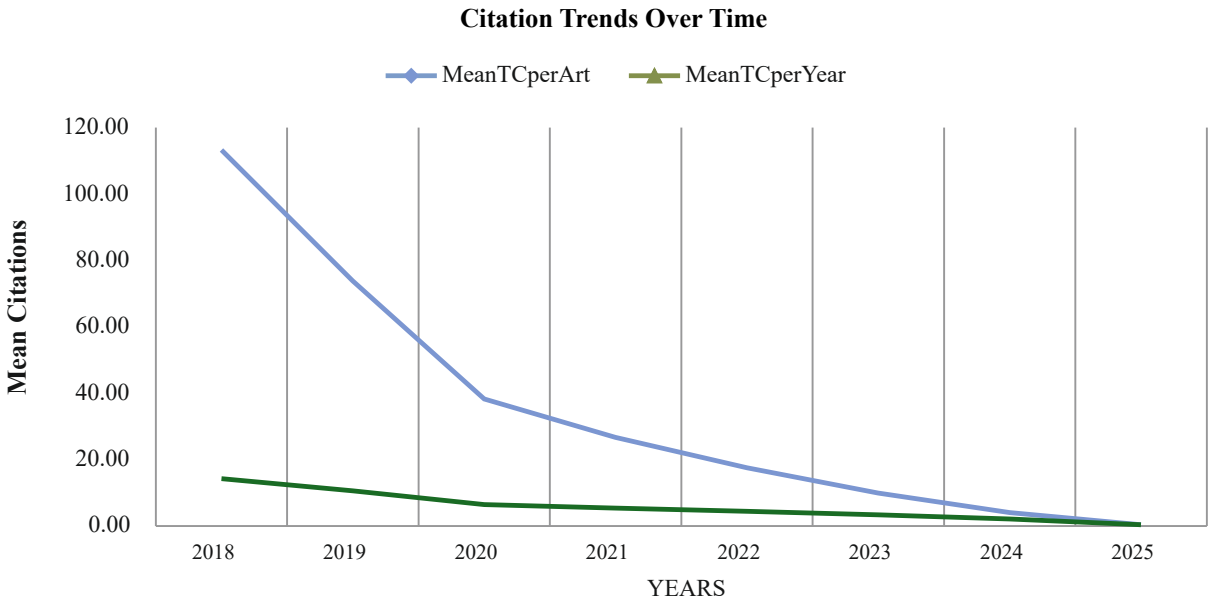
Figure 1: Annual Scientific Production

Citation Trends Over Time

The citation analysis reflects the temporal dynamics of scholarly impact within the domain. As evident in Figure 2, the mean total citations per article reveal a clear downward trend over time, which is expected due the citation lag inherent in new publications.

Articles published in 2018 possess the highest citation intensity (113.25 citations per article) followed by published in 2019 (73.80 citations per article) and 2020 (38.18 citations per article) and gradually declined to 0.32 citations per article for those published in 2025 due to limited citation time. Mean Citations per Year reveal a similar trend with drop in values from 14.16 in 2018 to 0.32 in 2025. This tracks closely with the decreasing number of citable years.

This observed pattern aligns with established intellectual-structure-mapping behaviour where earlier productions naturally accumulate more citations over time, while newer articles have not yet had enough exposure to garner citation traction, even though they may be equally impactful.



(Source: Prepared by authors elaboration using the Bibliometrix R Package and MS Excel)

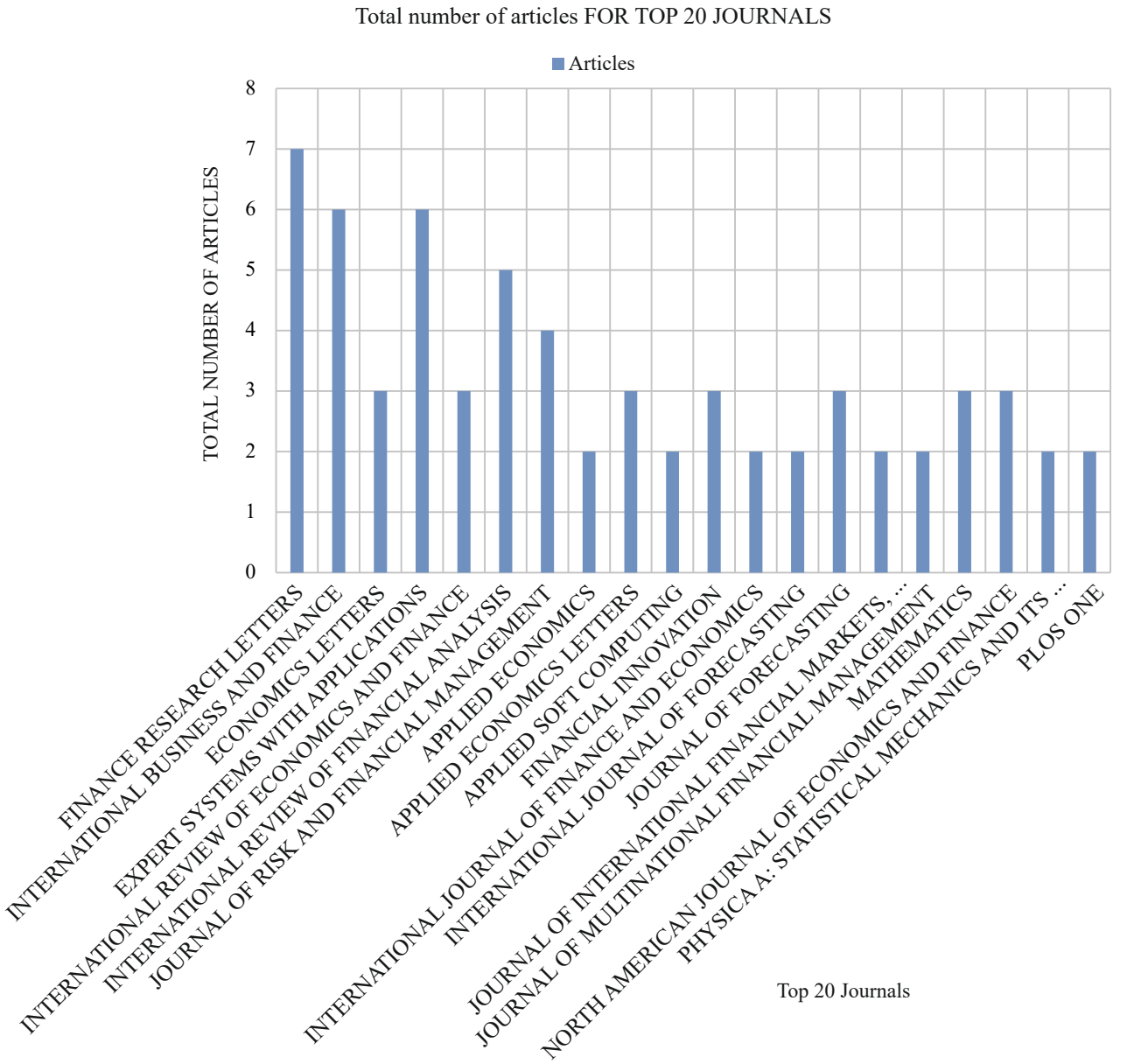
Figure 2: Citation Trends Over Time

Source Productivity & Impact

Source-level analysis (Figure 3a) points out that Finance Research Letters is the most prolific outlet in the field, producing 7 articles during 2019-25, followed by Research in International Business and Finance and Expert Systems with Applications (6 publications each) and International Review of Financial Analysis (5 publications). Rising publications across leading journals reflecting the field's growing consolidation, is revealed via studied temporal patterns (Figure 3d).

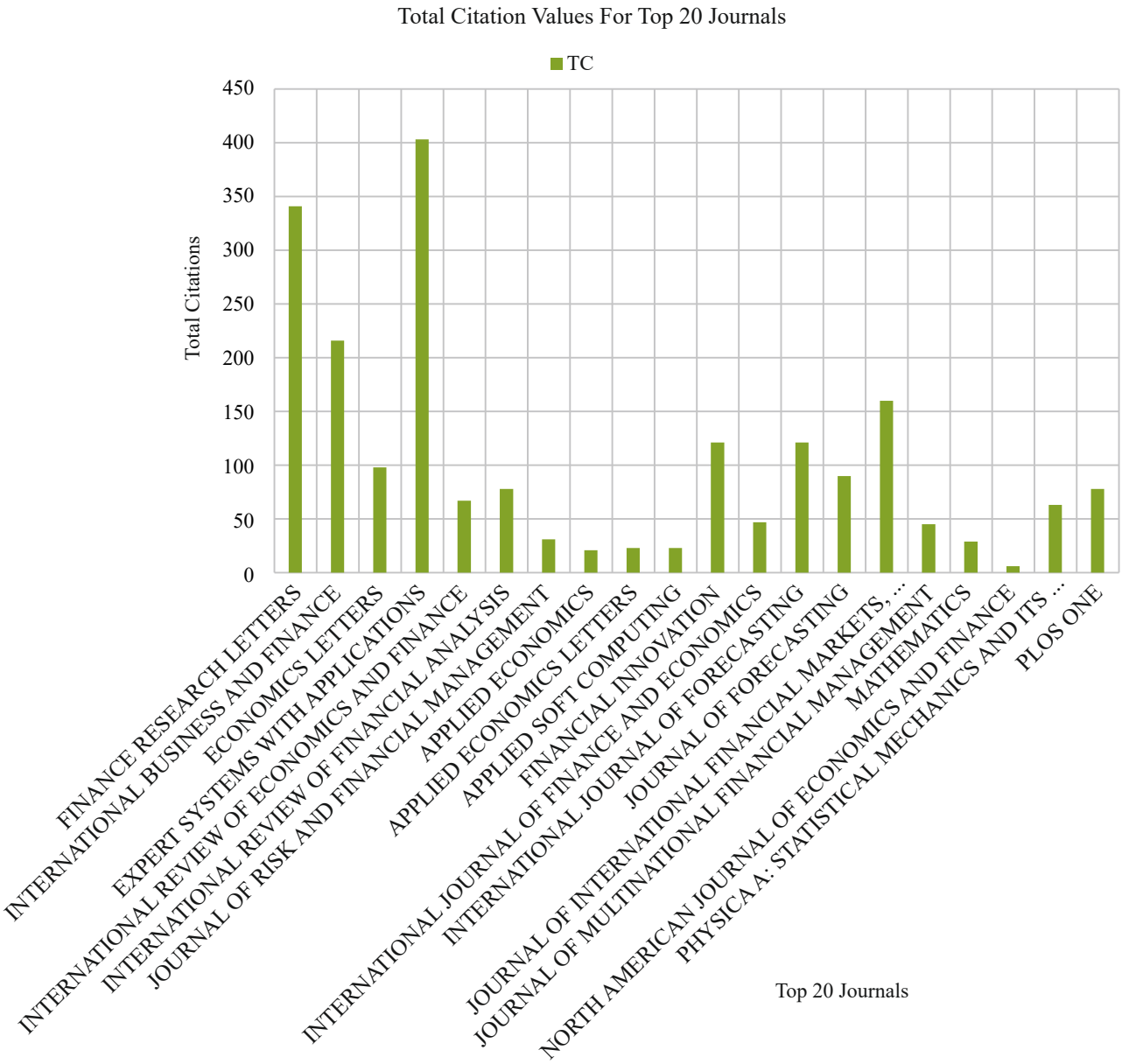
In citation terms (Figure 3b), Expert Systems with Applications emerges as the most influential outlet with 403 total citation, even exceeding Finance Research Letters (341 citations) despite comparable output, suggesting that production and influence do not necessarily coincide. Composite influence indicators (Figure 3c) reinforce this finding, where Finance Research letters leads in cumulative and consistent citation performance (h=6, g=7, m=0.857), while Applied Soft Computing records the highest m-index (1.0), notwithstanding its smaller article base. Other notable contributors include International Review of Financial Analysis, Journal of Risk and Financial Management and Economics Letters.

Bradford's law (Figure 3e) further confirms partial source consolidation, where 11 core journals constitute the nucleus of the field while a wider scattering over more than 60 sources highlights its distinctly interdisciplinary character across finance, economics, forecasting and computational analytics.



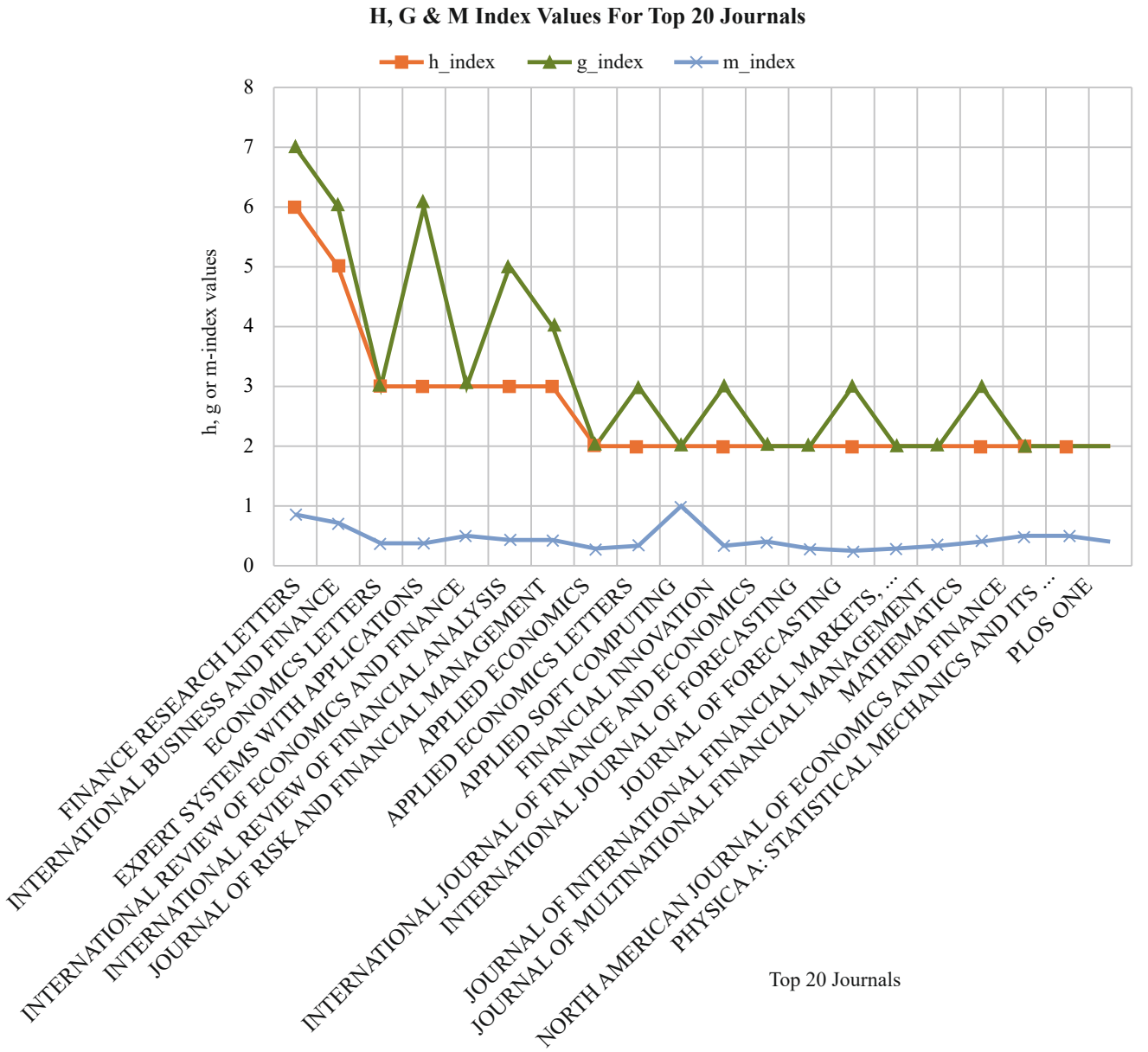
(Source: Prepared by authors elaboration using the Bibliometrix R Package and MS Excel)

Figure 3a: Total number of Articles from Top 20 most impactful Journals



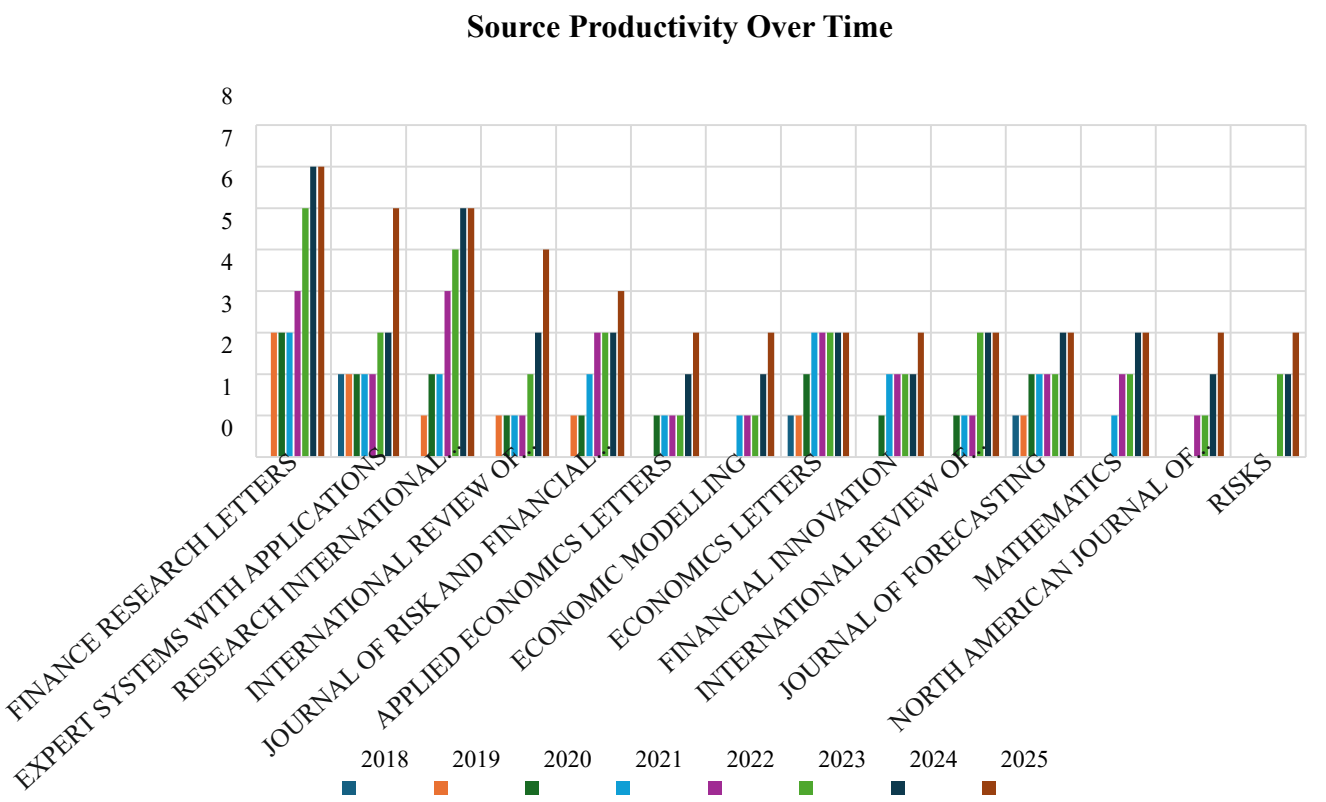
(Source: Prepared by authors elaboration using the Bibliometrix R Package and MS Excel)

Figure 3b: Total Citation values of Top 20 most impactful Journals



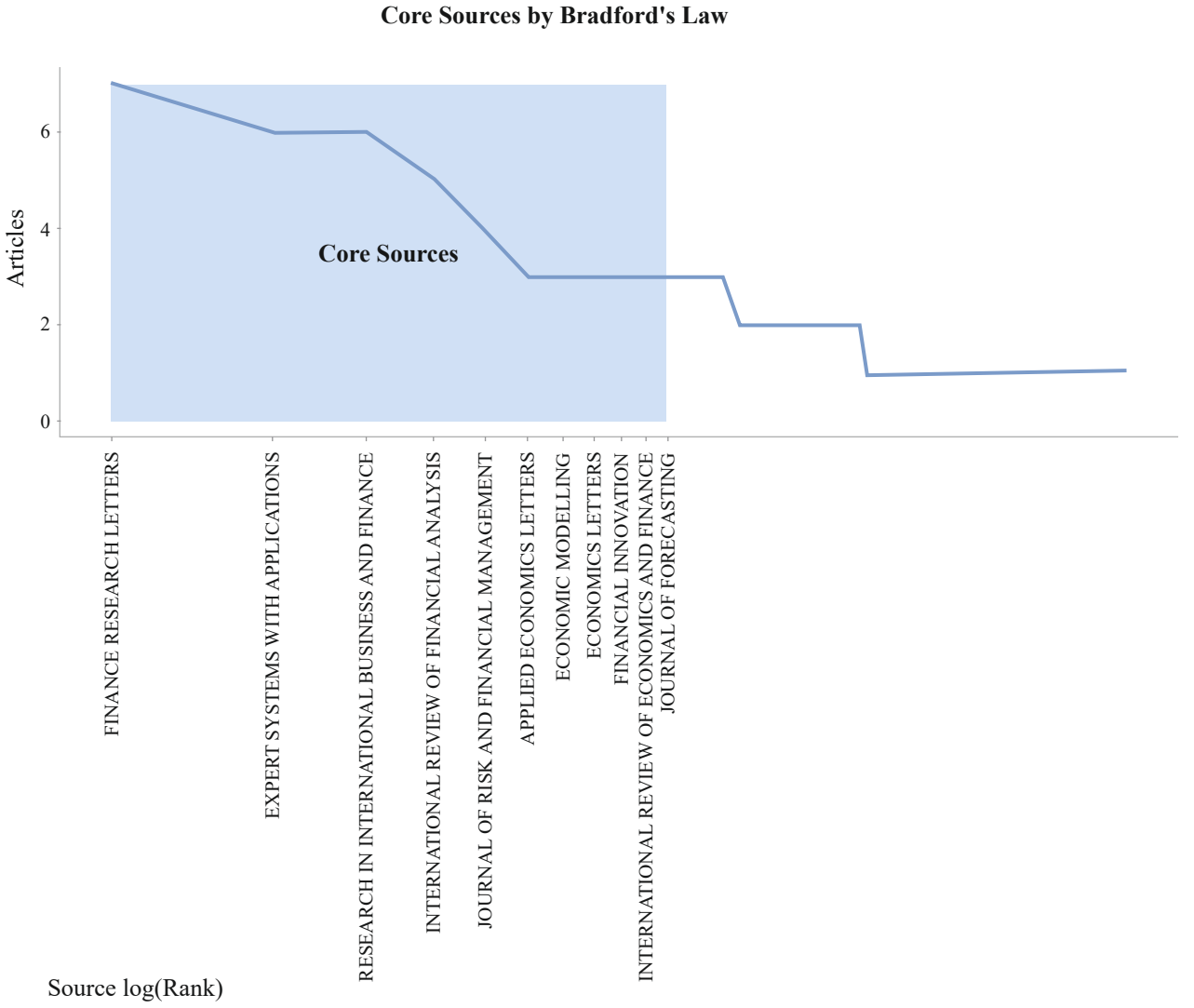
(Source: Prepared by authors elaboration using the Bibliometrix R Package and MS Excel)

Figure 3c: h-index, g-index and m-index values of Top 20 most impactful Journals



(Source: Prepared by authors elaboration using the Bibliometrix R Package and MS Excel)

Figure 3d: Source Productivity Over Time



(Source: Prepared by authors elaboration using the Bibliometrix R Package)

Figure 3e: Bradford's Law

Author Productivity and Influence

The authorship landscape in the domain is marked by wide participation but low consolidation. As per Figure 4a, Wang Y. (TC=87, h-index=4, g-index=5, m-index=0.8) emerges as the most prolific contributor with 5 publications since 2021 displaying both consistency as well as scholarly influence. Other productive authors include 10. Fiszeder P. & Zhang Y., each with 3 articles.

Temporal Analysis (Figure 4b.) reveals that Wang Y.'s research peaked in 2023, when 2 of his papers garnered 64 citations (TCpY=21.333) in a single year, matching the high citation velocity of Kristjanpoller W., whose 2018 article achieved 171 citations (TCpY=21.375) by itself. Such patterns suggest that some authors have contributed consistently over time and some others have produced highly influential single works. Furthermore, based on Table 5, while Wang Y. leads in cumulative output, Kristjanpoller W. and Zhang Y. display high citation per publication influence. Interestingly, most highly cited authors are

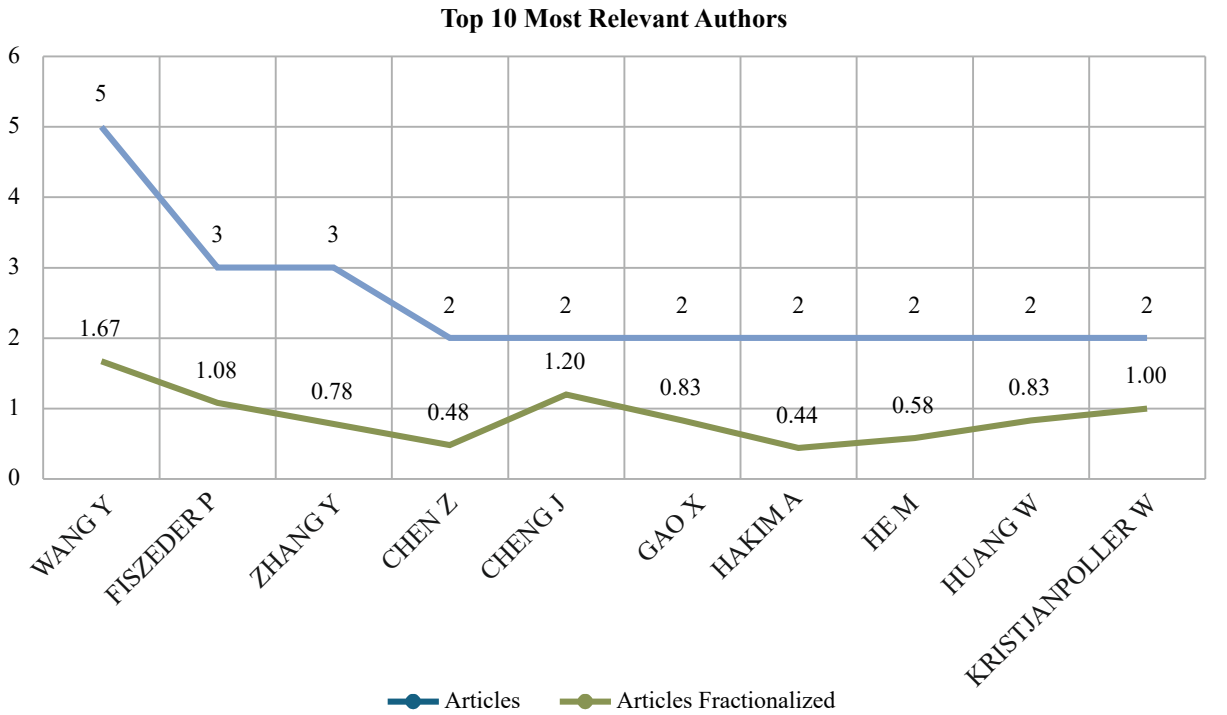
affiliated with Finance and Econometrics Department, but their contributions cover interdisciplinary domains including applied mathematics and computational forecasting.

The field's authorship structure is further clarified through Lotka's Law analysis (Figure 4c). Out of 355 unique contributors, 94.9% authored only 1 article, which far exceeded the theoretical prediction of 71.4% and merely 18 authors (5.1%) published more than 1 article. This steep skewness indicates a predominantly transient authorship base, typical of emerging or niche domains, where research is often exploratory or conducted collaboratively across disciplines.

These findings reveal a domain still in its infancy or formative stages, where scholarly leadership is just beginning to crystallize, and knowledge diffusion is broadly distributed, rather than concentrated.

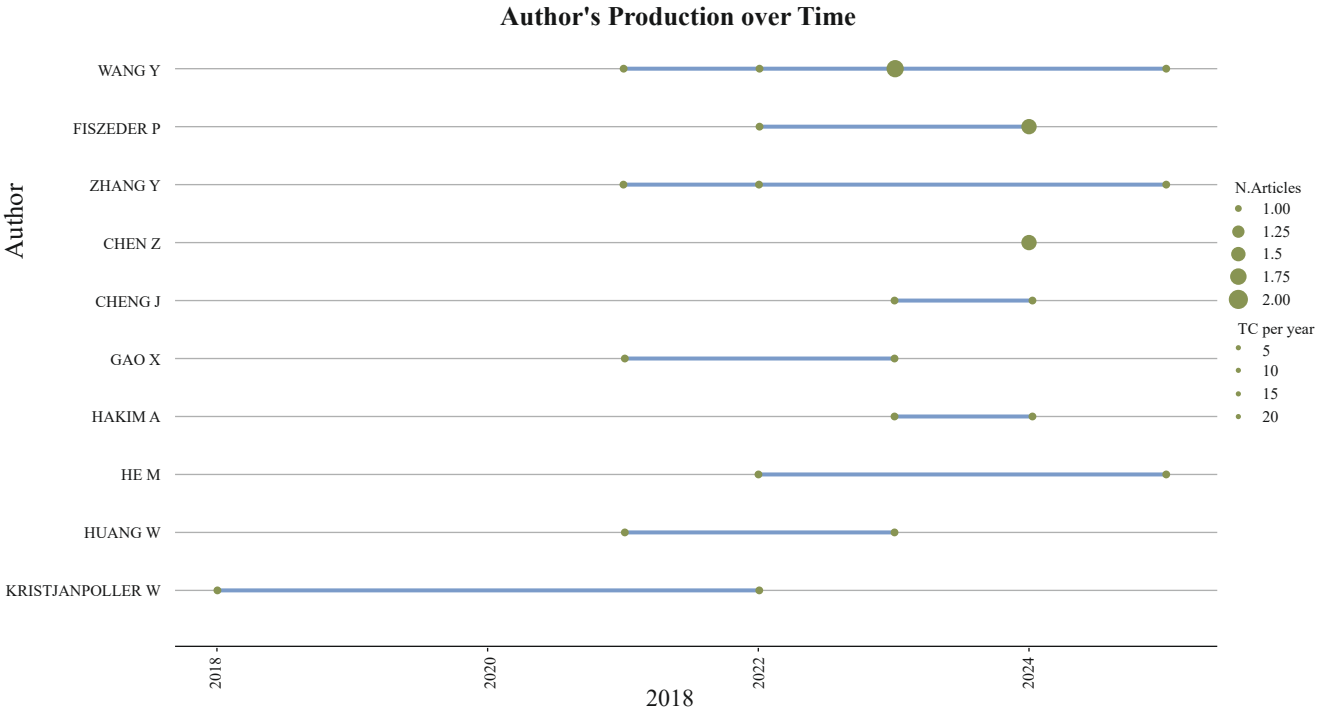
Table 5: Impact Metrics for top 20 Authors

Author	h_index	g_index	m_index	TC	NP	PY_start
WANG Y	4	5	0.8	87	5	2021
CHENG J	2	2	0.667	43	2	2023
FISZEDER P	2	3	0.5	46	3	2022
GAO X	2	2	0.4	29	2	2021
HAKIM A	2	2	0.667	8	2	2023
HUANG W	2	2	0.4	29	2	2021
KRISTJANPOLLER W	2	2	0.25	185	2	2018
LI L	2	2	0.667	24	2	2023
SYUHADA K	2	2	0.667	8	2	2023
WANG H	2	2	0.4	29	2	2021
YANG X	2	2	1	8	2	2024
ZHANG Y	2	3	0.4	50	3	2021
ABAKAH EJA	1	1	0.167	56	1	2020
ABDULLAH HS	1	1	0.5	2	1	2024
ABUHOMMOUS AA	1	1	0.167	10	1	2020
ADEWUYI AO	1	1	0.25	7	1	2022
AGUAYO-MORENO E	1	1	0.5	26	1	2024
AHARON DY	1	1	0.143	74	1	2019
AKCORA CG	1	1	0.125	43	1	2018
AKGUN OB	1	1	1	1	1	2025



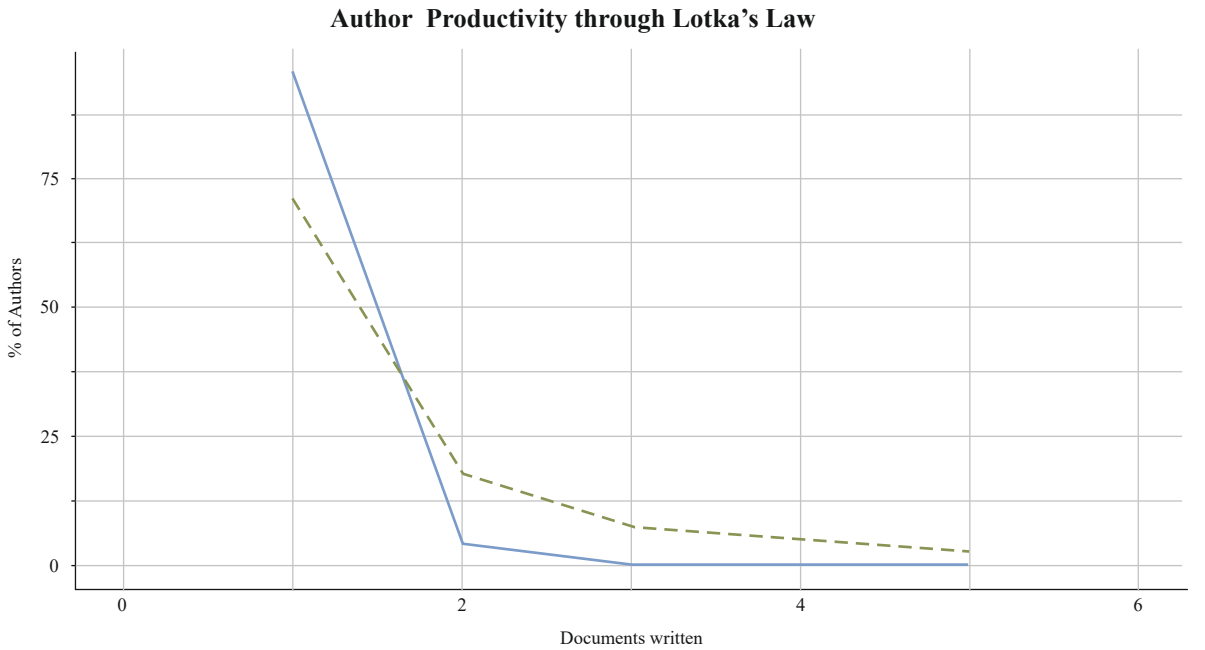
(Source: Prepared by authors elaboration using the Bibliometrix R Package & MS Excel)

Figure 4a: Top 10 Most Relevant Authors



(Source: Prepared by authors elaboration using the Bibliometrix R Package)

Figure 4b: Authors Production over Time



(*Source: Prepared by authors elaboration using the Bibliometrix R Package*)

Figure 4c: Authors Distribution Based on Lotka's Law

Institutional and Country-level Output

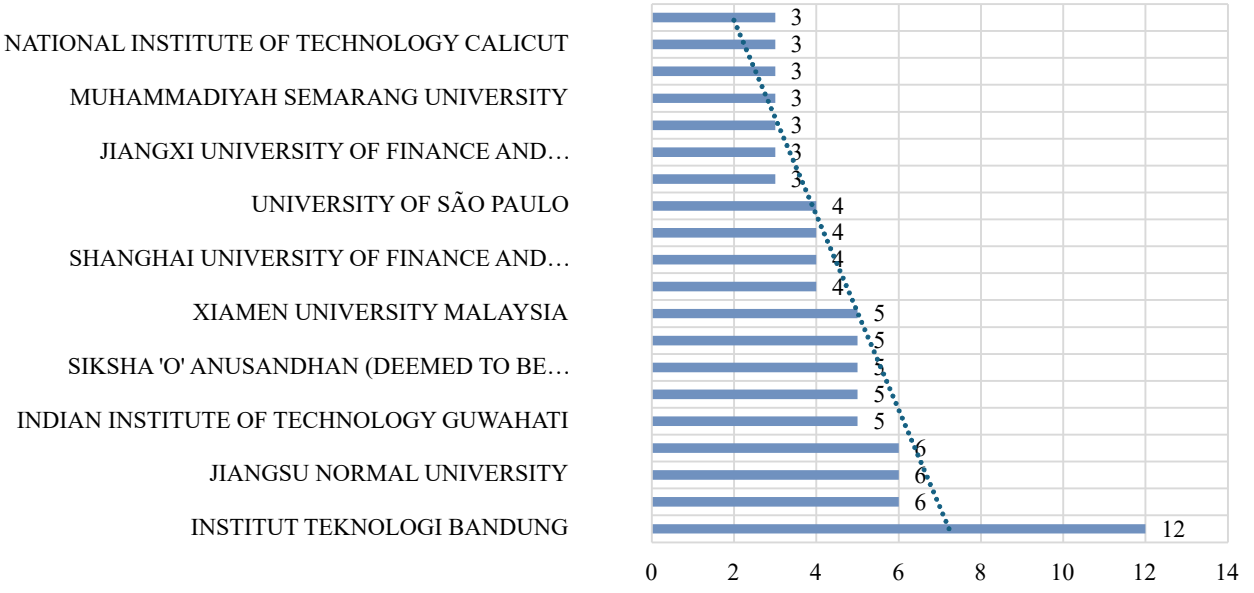
This reveals a geographically diverse but unevenly influential knowledge ecosystem. At the institutional level (Figures 5a & 5b), Institut Teknologi Bandung emerges as the most copious provider, driven by sharp surge in 2024-2025, while the University of Brasilia shows remarkably stable production across the entire period. Other steadily detectable contributors include Xiamen University Malaysia, University of Sao Paulo, Shanghai University of Finance and Economics and Nanjing University of Science and Technology, with newer entrants like Bucharest University of Economic Studies, United Arab Emirates University and the Indian Institute of Technology, Guwahati acquiring impetus after 2022. Lotka's law distribution also supports this pattern, corroborating the high author dispersion and low concentration of research leadership at institutional level.

At the national level (Figures 5c & 5d), China dominates output (86 publications, i.e. 18.2% contribution) followed by India, UK and the USA. Australia, Brazil, Germany, Italy and Spain also contribute significantly. Temporal Patterns (Figure 5d) indicate especially strong post-2022 growth in China, the USA, and the UK, while Indonesia and UAE later but accelerated entrants. As seen before, citation influence (Figure 5e) is decoupled from volume, where Oman, Chile and the Netherlands report the highest average citations despite lower output, while Brazil and Spain stand out in citation quality. This disparity revisits the complicated relationship between research scale and influence, indicating that citation density, rather than sheer volume, is a more reliable indicator of intellectual leadership. Collaboration patterns (Table 6) show UK as the most internationalized, whereas India, Brazil, Germany and Indonesia remain comparatively domestically oriented.

Table 6: Top 20 Most Relevant Countries Article Production & Collaboration Patterns

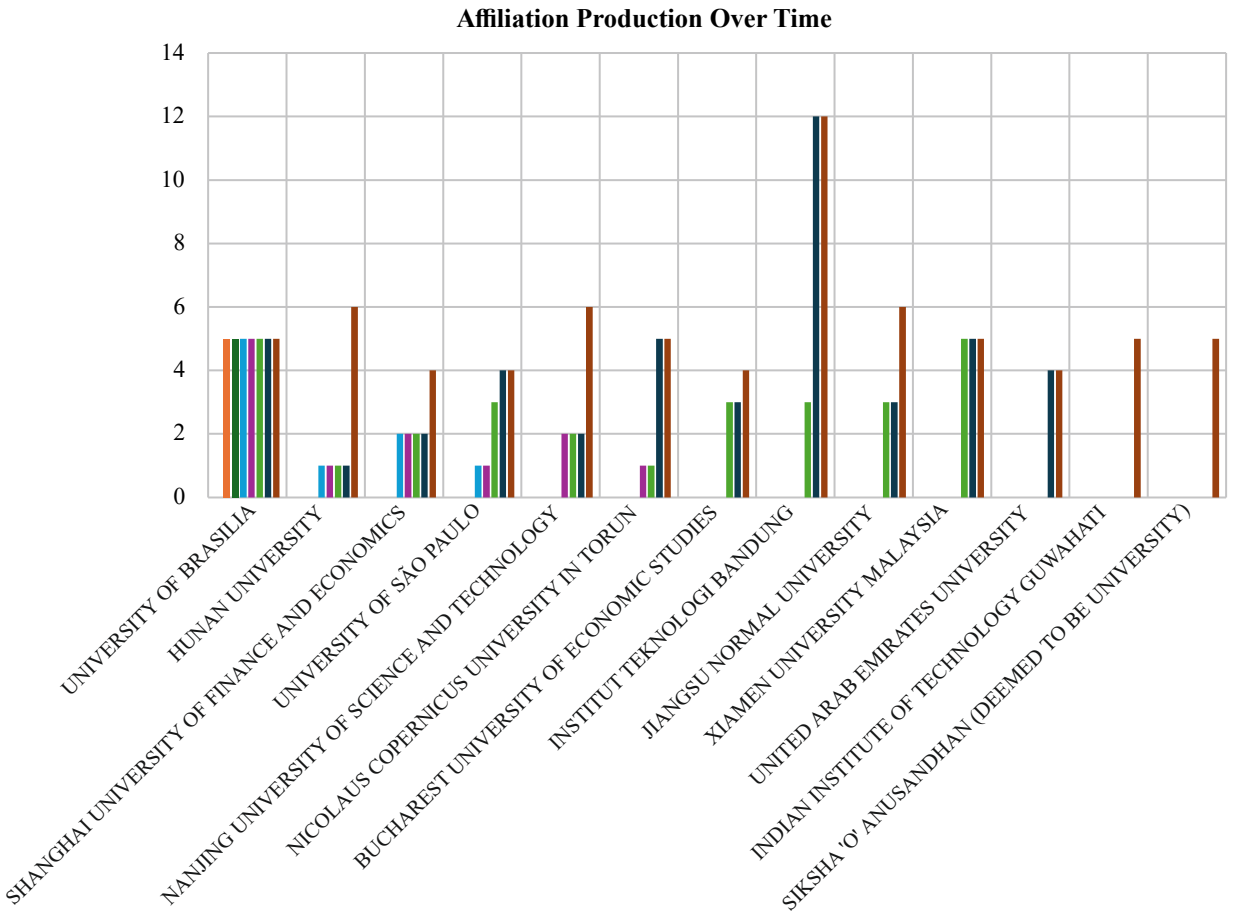
Country	Articles	Articles %	SCP	MCP	MCP %
CHINA	24	18.2	19	5	20.8
UNITED KINGDOM	9	6.8	4	5	55.6
INDIA	5	3.8	5	0	0
ITALY	5	3.8	1	4	80
SPAIN	5	3.8	1	4	80
BRAZIL	4	3	4	0	0
CANADA	4	3	1	3	75
GERMANY	4	3	4	0	0
INDONESIA	4	3	4	0	0
SAUDI ARABIA	4	3	3	1	25
USA	4	3	2	2	50
AUSTRALIA	3	2.3	3	0	0
PAKISTAN	3	2.3	3	0	0
POLAND	3	2.3	0	3	100
CHILE	2	1.5	1	1	50
DENMARK	2	1.5	0	2	100
FRANCE	2	1.5	2	0	0
MALAYSIA	2	1.5	1	1	50
NETHERLANDS	2	1.5	1	1	50
NEW ZEALAND	2	1.5	1	1	50

Top 20 Most Relevant Affiliations



(Source: Prepared by authors' elaboration using the Bibliometrix R Package & MS Excel)

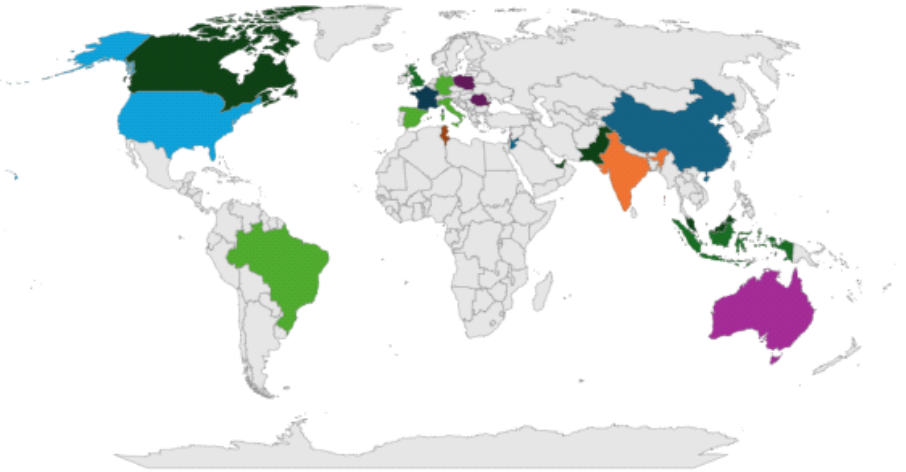
Figure 5a: Top 20 Most Relevant Affiliations



(Source: Prepared by authors' elaboration using the Bibliometrix R Package & MS Excel)

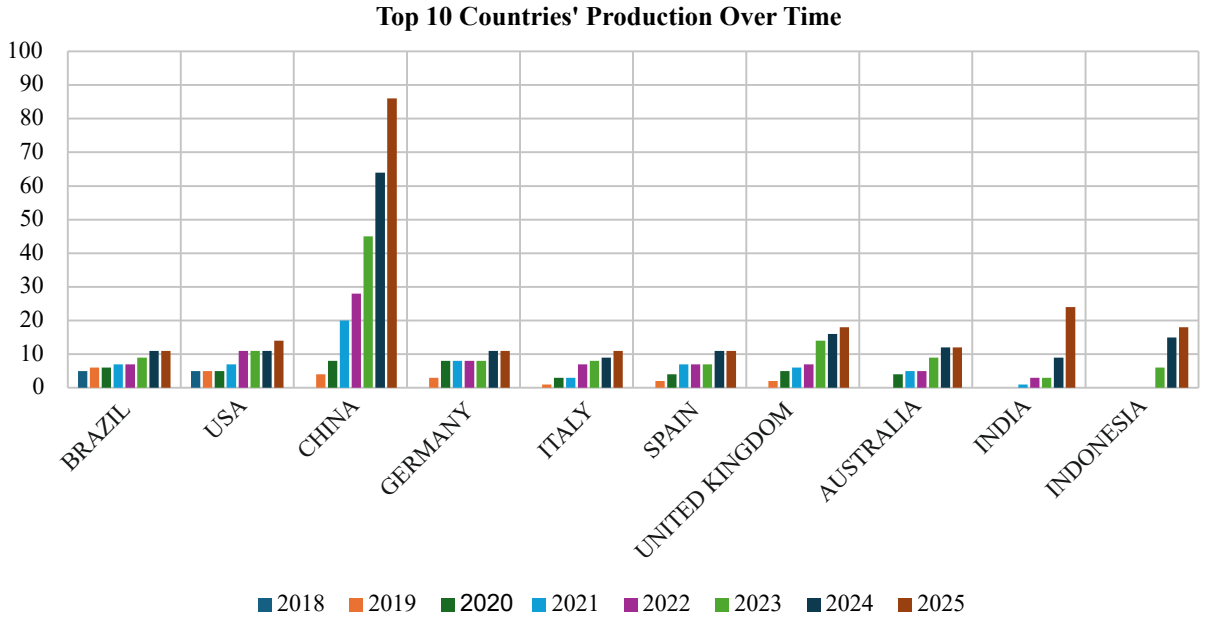
Figure 5b: Affiliations' Production over Time

Top Countries' Production



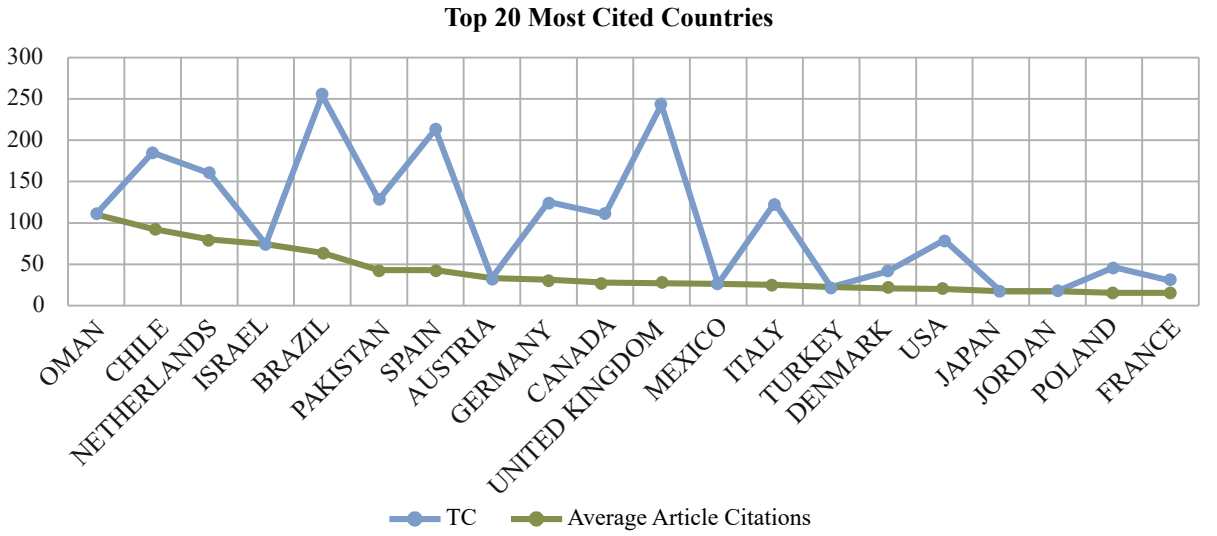
(Source: Prepared by authors' elaboration using the Bibliometrix R Package & MS Excel)

Figure 5c: Top Countries' Production



(Source: Prepared by authors' elaboration using the Bibliometrix R Package & MS Excel)

Figure 5d: Top 10 Countries' Production Over Time



(Source: Prepared by authors' elaboration using the Bibliometrix R Package & MS Excel)

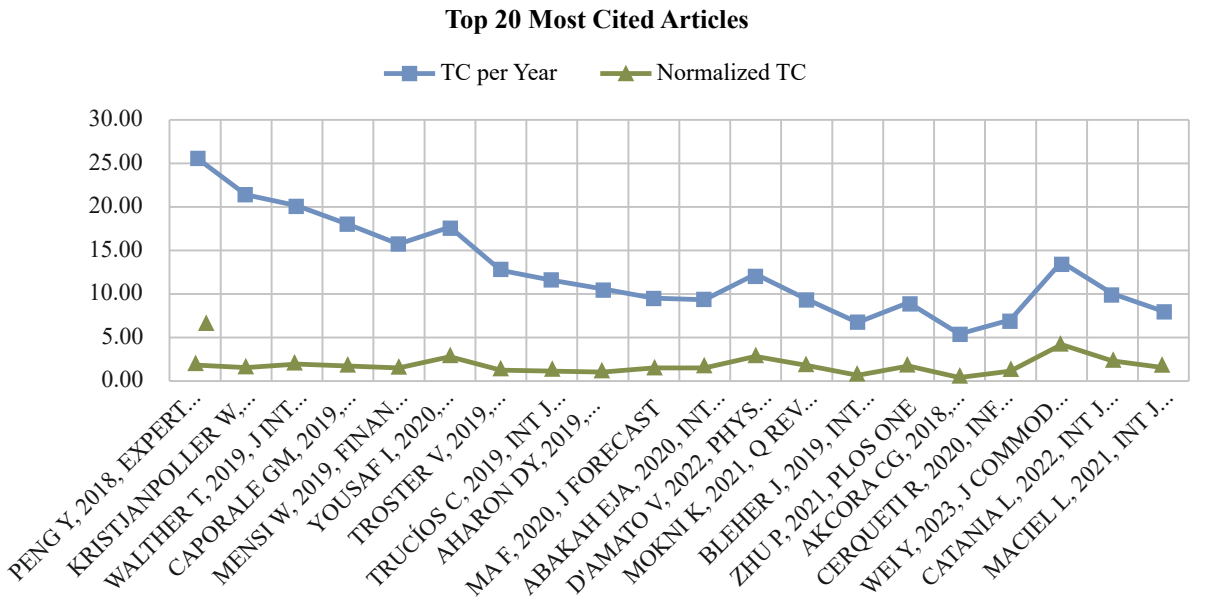
Figure 5e: Top 20 Most Cited Countries

Most Cited Papers

Figure 6 displays the top 20 most cited papers, highlighting the foundational intellectual pillars and evolving methodological sophistication of the field. Seminal works by Peng et al. (2018) and Kristjanpoller & Minutolo (2018), both published in Expert Systems and Applications, lead in total citations, reflecting early efforts to apply machine learning and hybrid GARCH models to Crypto-markets (Peng, Albuquerque, de Sá, Padula, & Montenegro, 2018; Kristjanpoller & Minutolo, 2018). Alongside them, Walther et al (2019) and Caporale et al. (2019) set benchmarks in both theory and empirical rigor by formalizing the understanding of volatility spillovers and contagion effects. These high-impact studies introduced innovations like regime-switching models, GARCH-MIDAS applications and related volatility estimations (Caporale & Zekokh, 2019;

Walther, Klein, & Bouri, 2019).

From 2020 onwards, the field demonstrated a clear shift towards interdisciplinarity and algorithmic experimentation. Contributions by Yousaf et al. (2020), D'Amato et al. (2022) and García-Monleón et al. (2021) introduced tools from statistical physics, AI and ESG Finance, with rising normalized Citation Counts underscoring their rapid academic influence. Notably, recent works by Cheng et al. (2024) and Dudek et al. (2024) exhibit exceptional normalized citations per year, signaling a change in direction towards real-time forecasting, explainable AI and policy-aware modeling strategies, marking a transition from descriptive analysis to globally applicable predictive intelligence '(Yousaf & Ali, 2020; D'Amato, Levantesi, & Piscopo, 2022; García-Monleón, Danvila-del-Valle, & Lara, 2021; Cheng, Tiwari, Khaled, Mahendru, & Shahzad, 2024; Dudek, Fiszeder, Kobus, & Orzeszko, 2024). Papers published in interdisciplinary journals enjoy wider reach as compared to others.



(Source: Prepared by authors' elaboration using the Bibliometrix R Package & MS Excel)

Figure 6: Top 20 Most Cited Articles

3.Science Mapping

Keyword Co-occurrence and conceptual themes

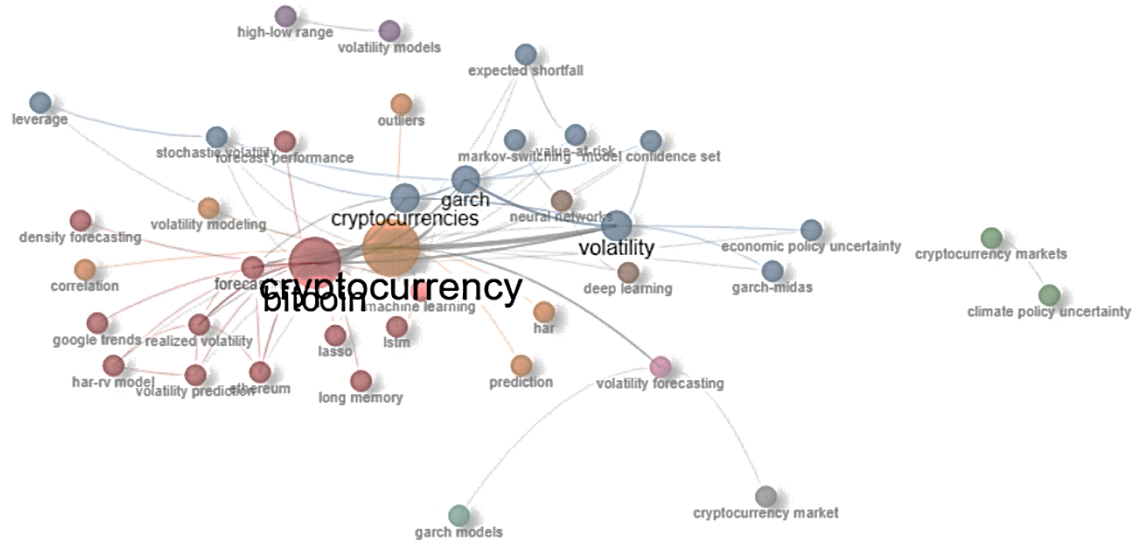
A dense, yet discernible landscape is revealed by the conceptual & co-occurrence mapping (Figures 7a & 7b). The keyword co-occurrence structure is organized around three core thematic axes: volatility modeling, cryptocurrency instruments and forecasting methodologies. Primarily, the conceptual nucleus of the field is formed by 'volatility', co-occuring strongly with forecasting, GARCH, models, value-at-risk and returns, confirming that quantification of uncertainty and prediction of volatility stay the prominent scholarly preoccupation. A mature econometric foundation rooted in risk management is reflected via its repeated association with realized volatility, stochastic volatility, conditional heteroskedasticity and related time-series terms.

Secondarily, the asset-focused axis is anchored by cryptocurrency, bitcoin, ethereum, cryptocurrency market and cryptocurrency volatility. Here, Bitcoin remains the principal empirical reference point, but the appearance of terms such as cryptocurrency returns, portfolio risk, and Ethereum-related keywords suggest

gradual diversification away from a single-asset lens. Tertiarily, the methodological axis reveals an important convergence between classical econometrics and emerging AI/ML paradigms. Terms such as LSTM, machine learning, neural networks, support vector regression, and model confidence set increasingly co-occur with GARCH, HAR and related forecasting frameworks, pointing towards augmentation, rather than replacement. Peripheral, yet notable themes, like economic policy uncertainty, climate policy uncertainty, investor attention and pandemic-related shocks highlight an emerging move toward exogenous and policy-sensitive volatility modeling.

(Source: Prepared by authors' elaboration using the Bibliometrix R Package)

Figure 7a: Co-occurrence network- Keywords Plus



(Source: Prepared by authors' elaboration using the Bibliometrix R Package)

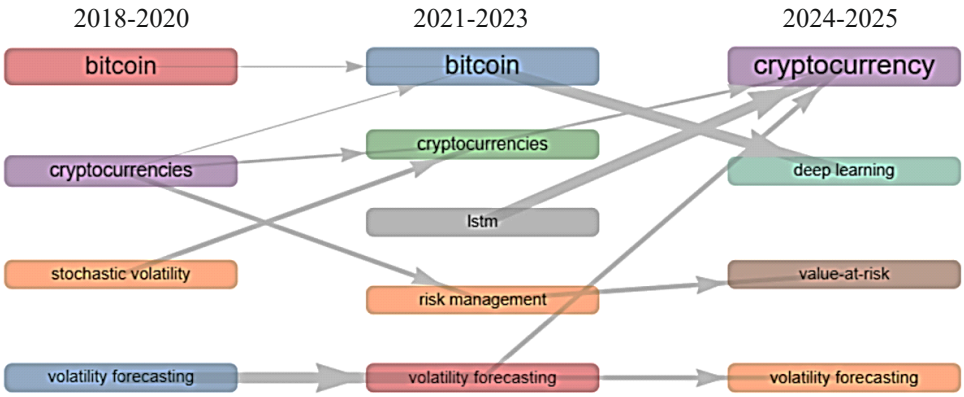
Figure 7b: Co-occurrence network- Authors Keywords

Thematic Evolution over time

A clear progression from asset-specific enquiry to risk-aware modelling and onwards to AI-integrated predictive analytics is revealed from the thematic evolution of cryptocurrency volatility forecasting from 2018 to 2025. During 2018-2020, the field was anchored by terms such as bitcoin, cryptocurrencies, stochastic volatility and volatility forecasting, exposing early efforts to understand price instability via largely long-established econometric perspectives. Themes like long memory or numerical model remained marginal, indicating limited conceptual consolidation.

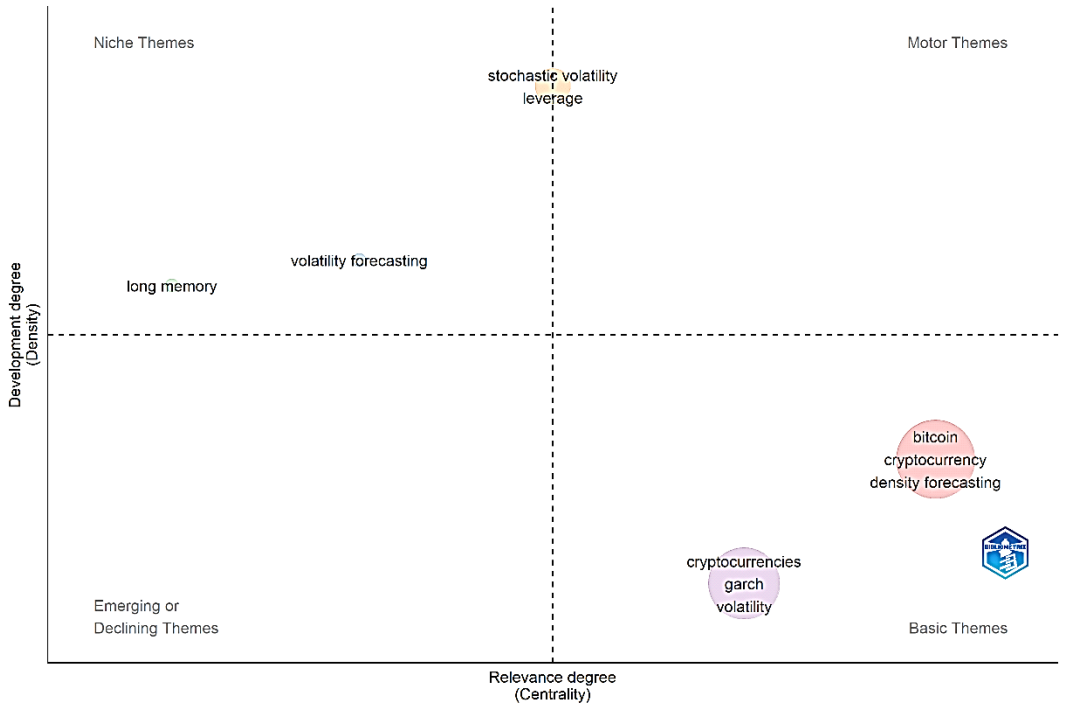
During the 2021-2023 phase, the literature stepped into a methodological expansion phase, where keywords like LSTM, risk management and cryptocurrencies achieved dominance and terms like machine learning, autoregressive conditional heteroskedasticity and volatility models moved towards greater centrality, while sentiment, portfolio risk, regime switching and broader market indicators, etc. showed growing incorporation.

By 2024-2025, a more consolidated and interdisciplinary structure had emerged. Cryptocurrency increasingly replaced bitcoin as the macro-theme, while volatility forecasting became more tightly linked with deep learning, value-at-risk and expected shortfall. The appearance of themes such as climate policy uncertainty further suggests transition towards system-level, policy-relevant and more sustainable forecasting frameworks.



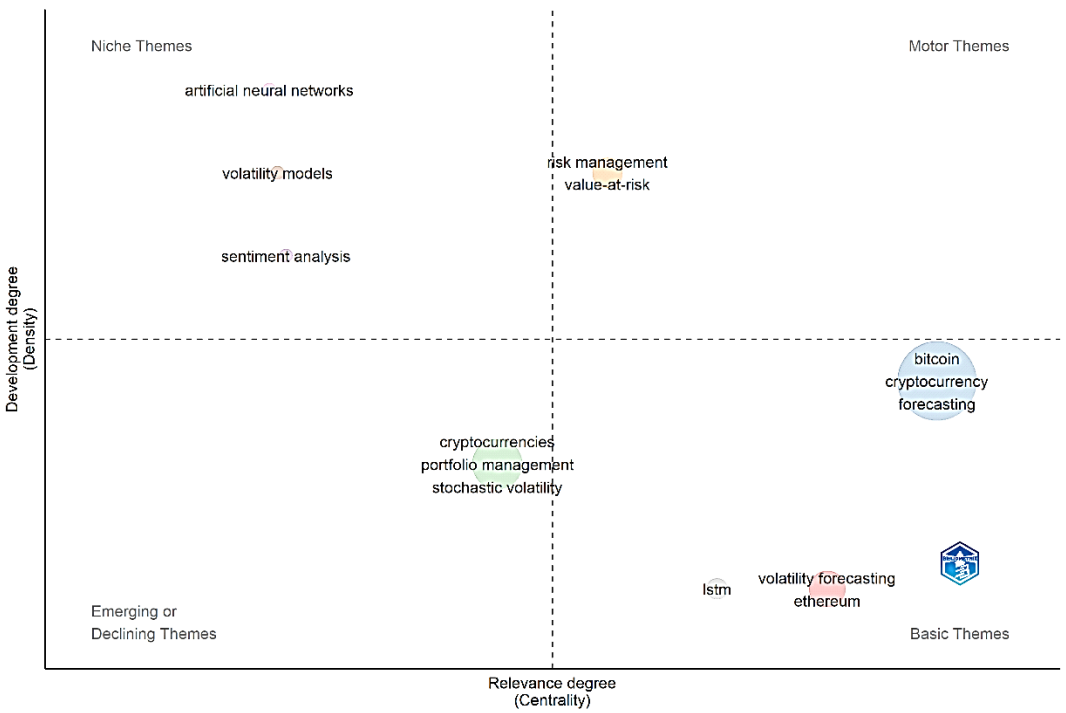
(Source: Prepared by authors' elaboration using the Bibliometrix R Package)

Figure 8a: Thematic Evolution



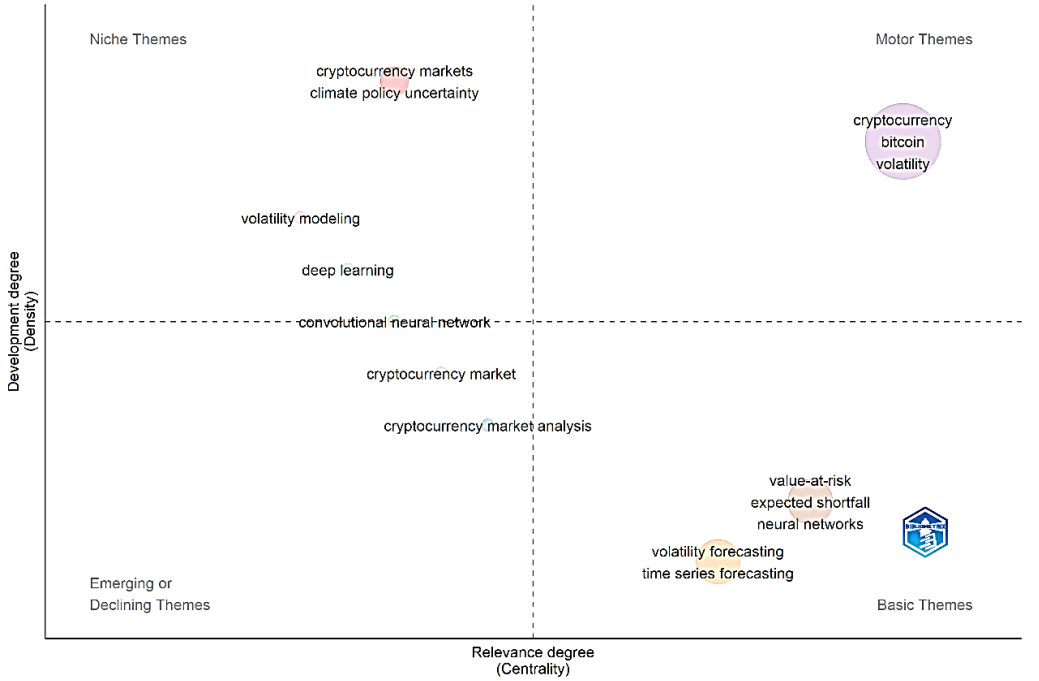
(Source: Prepared by authors' elaboration using the Bibliometrix R Package)

Figure 8b: Thematic Evolution Map- 2018 to 2020



(Source: Prepared by authors' elaboration using the Bibliometrix R Package)

Figure 8c: Thematic Evolution Map- 2021 to 2023



(Source: Prepared by authors' elaboration using the Bibliometrix R Package)

Figure 8d: Thematic Evolution Map- 2024 to 2025

Table 7: Trend Topics- Keywords Plus

Term	Frequency	Year (Q1)	Year (Median)	Year (Q3)
economic analysis	2	2018	2018	2019
stochastic systems	2	2018	2019	2020
volatility forecasting	7	2019	2020	2024
cryptocurrency	6	2021	2021	2024
currency	5	2021	2022	2023
forecasting	23	2021	2023	2024
forecasting method	8	2021	2024	2024
volatilization	2	2025	2025	2025

Table 8: Trend Topics- Authors' Keywords

Term	Frequency	Year (Q1)	Year (Median)	Year (Q3)
density forecasting	2	2018	2018	2019
arji	1	2019	2019	2019
stochastic volatility	6	2020	2020	2021
long memory	4	2020	2021	2022
bitcoin	44	2020	2022	2024
cryptocurrency	52	2021	2023	2024
volatility forecasting	17	2022	2024	2025
anfis	1	2025	2025	2025

4.Network Analysis

Co-authorship Networks, Co-citation Analysis & Collaboration Networks

A field shaped by moderate intellectual concentration but fragmented collaboration is revealed by the network structure. Coupling patterns identify Wang Y., Kristjanpoller W. Fiszeder P. and Hakim A. at the author level as visible intellectual anchors suggesting recurring thematic influence. Sparse interlinkages point out that knowledge development remains clustered rather than fully integrated. Co-citation patterns further reveal a 2-pillar intellectual base, one stream rooted in classical volatility econometrics (centered on foundational scholars like Bollerslev, Diebold, Andersen and Hansen) and another oriented toward applied crypto-financial enquiry (centered on Corbet, Bouri, Urquhart and Katsiampa), indicating that the field continues to draw simultaneously on methodological depth and market-specific application.

This semi-fragmented structure is reinforced by collaboration networks, where author collaborations are largely organized in small dyads and triads, indicating productive, localized or limited scholarly enclaves, while at the country level, China emerges as the principal collaborative hub, linking Asian, European, and selected global south partners and the USA, UK and Canada form a comparatively separate western collaboration bloc. Institution-wise, Jiangsu Normal University, University of Sao Paulo, Nicolaus Copernicus University in Torun and the Shanghai Business School appear as dominant nodes, highlighting that institutional productivity and collaboration remain shaped by geography, national ecosystems and concentrated research capacity.

Discussion, Interpretations & Implications

Interpretation of Major Trends & Patterns

The knowledge-domain landscape has evolved with distinct thematic, conceptual and methodological trajectories from 2018 to 2025. An examination of author keywords and keywords plus reveals a significant shift from asset-centric enquiries (eg. “bitcoin”, “cryptocurrencies”) to volatility-oriented discourse (as evidenced by rising prominence of terms like “volatility forecasting”, “value-at-risk”, “GARCH” and “stochastic volatility” from 2020 onwards). This aligns with the maturing of the domain from technical curiosity and speculative exploration to risk-sensitive modeling frameworks, consistent with broader financial econometrics transitions.

This trajectory is further confirmed by thematic maps. In the early period (2018-2020), Bitcoin dominated as a conceptual nucleus, with “stochastic volatility” and “volatility forecasting” emerging as niche yet foundational concerns. Then, in 2021-23, this enlarged to include “risk management”, “forecasting method” and “LSTM”, indicating growing methodological sophistication. Finally, in 2024-25, themes such as “cryptocurrency”, “deep learning”, “value-at-risk”, and “volatilization” had become mainstream. This points towards integration of machine learning into volatility modeling and inclusion of crypto-assets beyond Bitcoin.

A geographically diversified, but thematically convergent scholarly ecosystem was uncovered by the co-authorship and collaboration networks. Chinese authors and institutions (like Shanghai Business School, Jiangsu Normal University) lead the centrality and density of the research area, while collaborating often with researchers in India, Pakistan and the Gulf. Simultaneously, citation coupling reveals 2 large epistemic clusters, one anchored in volatility econometrics (eg. Bollerslev, Diebold, Andersen) and the other in crypto-financial modeling (Corbet, Bouri, Urquhart), underscoring the ongoing synthesis of traditional

financial econometrics with novel blockchain-driven market dynamics.

Forecasting remains the fields intellectual spine, with consistent dominance across both keywords and methodologies, as suggested by trend topic evolution. “LSTM”, “deep learning” and “anfis are the new additions to the lexicon in 2023-25, suggesting a paradigm shift toward non-linear, AI-powered novel modeling frameworks and a departure from classical volatility models, not by replacing them, but by augmenting them. This dual trajectory (non-negotiable econometric rigor & adoption of computer innovation) symbolizes the domain's intellectual trajectory.

Dominant Methodologies and Emerging Paradigms

A dynamic convergence of traditional econometrics and modern machine learning techniques is revealed by the methodological evolution within the domain from its conventional econometric frameworks to maturity as more advanced hybrid and AI-driven paradigms. Early literature is predominantly structured around classical econometric models such as GARCH, ARJI, EGARCH, TGARCH etc. which remain foundational, especially for capturing volatility clustering and leverage effects in high-frequency return series. These models laid the groundwork for initial volatility explorations, especially in the early years when data availability was limited (Yahaya, Oyinloye, & Adams, 2022). However, their limitations in capturing the non-linearity and structural breaks (inherent in the crypto-asset class) have led to increased adoption of machine learning (ML) and deep learning (DL) techniques.

Among the most prominent are LSTM (Long-Short-Term-Memory) & BE-LSTM (Backward Elimination Long-Short-Term-Memory) networks, which have demonstrated superior performance in modeling sequential dependencies in time-series data (Jafar, Akhtar, El-Chaarani, Khan, & Binsaddig, 2023). These are frequently hybridized with ARIMA or GARCH models to harness their statistical rigor and enhance their learning adaptability (García-Medina & Aguayo-Moreno, 2024). Ensemble methods like Random Forest and boosting techniques have also become popular due to their robustness in non-parametric setting '(DAmato, Levantesi, & Piscopo, 2022). Additionally, ANFIS (Adaptive Neuro-Fuzzy Inference System) and SVR (Support Vector Regression) have been proposed as effective tools for volatility approximation and noisy datasets. (Nadarajah, Mba, Rakotomarolahy, & Ratolojanahary, 2025; Khan, Khan, & Shaikh, 2023).

Emerging paradigms also reflect a move towards explainable AI (XAI) to enhance explainability and interpretability in model design and to mitigate the black-box limitations of deep neural networks (Fior, Cagliero, & Garza, 2022). Integrated models combining financial data with blockchain data and market sentiments are gaining prominence and will mark the path for future research as methodological forerunners (Zhou, Song, Xiao, & Ren, 2023). These are already being utilized for price prediction and can be applied to volatility forecasting in the coming future.

The current trajectory indicates a methodological convergence wherein traditional econometric precision meets the adaptive power of artificial intelligence, machine learning and deep learning, thus, enhancing predictive accuracy and introducing a novel ethos of strategic forecasting, representing a move from mere short-term forecasting for accuracy to forecasting for utility.

Gaps, Silences & Underrepresented Areas

The domain exhibits structural gaps and thematic omissions that constrain its epistemic breadth and practical utility, despite a clear surge in scholarly

output during 2018-2025.

Literature remains heavily skewed towards Bitcoin (BTC), whereas Ethereum (ETH), Ripple (XRP), Litecoin (LTC) and Dogecoin (DOGE) despite having sizeable market capitalization, are relegated to secondary status. This single-asset focus limits the ecological validity of volatility insights and obscures inter-asset dynamics essential for a comprehensive understanding of Crypto-market behaviour, especially when large-cap assets with different protocol-level characteristics are considered (i.e. Asset Concentration & Ecosystem Imbalance).

There is a conspicuous lack of integrative approaches that unify financial indicators (like closing price, market volume, etc.), blockchain metrics (like transaction volume, miner activity, NVT ratio, etc.) and real-time sentiment signals, despite advancements in forecasting techniques. The siloed treatment of these dimensions weakens predictive robustness and limits the development of generalizable models for policy & institutional use (i.e. Fragmented Modeling of Volatility Drivers).

Despite being acknowledged, volatility clustering and asymmetric responses to market shocks are not explicitly modeled. Despite their relevance in forecasting extreme volatility events and systemic risks, techniques capturing regime switches, leverage effects and contagion pathways remain underutilized (i.e. Lack of Attention to Regime Shifts & Temporal Dynamics).
Current models have not yet begun appropriately considering the market impact of global regulatory pronouncements, macroeconomic upheavals or geopolitical events, leading to creation of a strategic blind spot, especially when external factors are main culprits behind volatility spikes (i.e. Lack of Exogenous Event Sensitivity).

Network analyses have revealed that North American and Western European institutions dominate knowledge production, which underrepresents regions like South Asia, Africa, Latin America, etc., despite their high crypto-adoption for remittances, hedging and financial inclusion, leading to marginalizing of context-specific volatility insights.

Thematic maps and co-citation clusters show limited engagement with ESG frameworks, SDG alignment, or ethical AI integration in forecasting models. Such omissions signal an urgent need for re-orientation in a world increasingly guided by forces of sustainable finance and responsible innovation.

Finally, there is the aspect of underexplored human-centric volatility dimensions. Cultural investor behaviour, sentiment asymmetry, and behavioural-finance grounded frameworks remain on the periphery. Their integration should improve explanation of non-linear regime transitions and help in superior modeling of volatility spikes caused by collective market psychology.

Future Research Directions

More than mere absences are signaled by these foregoing gaps. These represent strategic voids whose resolution can significantly advance the scientific and policy relevance of the domain. The field, as of now, rests at a critical juncture, where isolated technical innovations must give way to holistic, context-aware and purpose-aligned paradigms. Addressing these gaps requires methodological innovation as well as an expansion of conceptual boundaries toward integrated systems thinking, cross-asset modeling and socially responsible uses of the forecasting.

Future studies must transcend Bitcoin's dominance and develop multi-asset volatility frameworks, especially considering Ethereum, Ripple, Litecoin and Memecoins (eg. Dogecoin), as these also acquire large market capitalizations (i.e. beyond 1

Billion US Dollars). These ecosystems display different volatility triggers (like gas fee congestion or governance proposals or even forks) that demand differentiated but interconnected treatment. Inter-asset volatility transmission mechanisms remain poorly understood and offer fertile ground for advanced econometric and network-based modeling (i.e. Multi-Asset, Ecosystem-Level Volatility Modeling).

To enhance explanatory power, and also to enhance effectiveness, volatility forecasting models must incorporate blockchain-native indicators such as on-chain volumes, hash rate fulctuations, miner incentives and smart contract activity. Structural stress points, often ignored in closing-price-based models, are captured by these variables and can improve predictive precision when used with deep learning architectures or time-series (i.e. Integration of Blockchain-Specific Metrics).

That ESG and SDG criteria be incorporated in volatility forecasting model, is today a global mandate surrounding the discourse of sustainable finance. Research could offer actionable intelligence to policymakers and impact investors significantly by exploring frameworks that consider environmental externalities of crypto-protocols or incorporate regulatory sustainability ratings into volatility predictions (i.e. ESG & SDG-Aligned Forecasting Models).

Future models must quantify sentiment asymmetries, social contagion, and media-induced volatility by building on contemporary NLP (Natural Language Processing) advancements. These variables will surely serve as leading indicators of volatility regime changes considering the growing influence of influencer commentary and crowd psychology on crypto-return volatility (i.e. Sentiment-Driven Forecasting).

There is a notable under-theorizing of the Global South's crypto-adoption for remittances, hedging and microfinance purposes. Future research must develop models to capture localized volatility that consider socio-economic, institutional and behavioural heterogeneity across markets like BRICS nations or Africa or Southeast Asia (i.e. Localised/ Culturally Sensitive Volatility Forecasting).

Hybridizing econometric models (eg. ARMA-GARCH, DCC, HAR, etc.) with ML/DL/AI architectures (like LSTM, GRU, Transformers, Bagging & Boosting techniques, etc.) present a compelling research trajectory into the future. Such Ensemble models promise a synthesis of interpretability and adaptability, especially under highly volatile or non-linear market conditions (like those found with crypto-assets).

Volatility clustering and regime switches are often assumed, rather than modeled explicitly, despite empirical evidence. Future works should strive to integrate structural break detection, Markov Switching Models, and leverage-sensitive architectures to model regime-dependent behaviours in crypto markets.

Researchers must model systemic volatility transmission using CoVar, SRISK, and network-based simulations to enhance macroprudential utility. Central banks and regulatory bodies can monitor contagion pathways and implement pre-emptive controls by embedding volatility forecasts into stress-test environments (i.e. Systemic Risk and Contagion Forecasting).

The demand for explainable and ethically aligned models rise as AI-based forecasting becomes the norm. Model transparency, fairness in feature representation and auditability must be prioritized by future research to enable informed decision-making by stakeholders (i.e. Explainable Forecasting).

Efforts must be made by future research to align

evolving regulatory frameworks (connected with cryptocurrencies, like taxation regimes, anti-money laundering directives or CBDC rollouts) with effective forecasting models. Greater real-world relevance will be ensured by responsive architectures that incorporate external shock variables into forecasting volatility (i.e. Policy-Integrated Modeling Frameworks).

Strategic Implications

For researchers, this study compiles the current literature about the domain, identifies and provides a roadmap to address empirical blind spots and fragmented methodologies by advancing multi-asset, sentiment-sensitive, and policy-integrated volatility models. It encourages deeper theoretical anchoring and ethical AI adoption in future work.

For institutions, the findings spotlight collaborative disparities and underrepresentation of emerging economies. Strategic alliances across, localities, geographies and disciplines can elevate global relevance in crypto-financial research.

For policymakers, insights on volatility clustering, regime shifts and forecasting limitations offer a foundation to design risk-informed, anticipatory regulatory frameworks-especially crucial in volatile, borderless crypto-markets.

For practitioners, including asset managers, risk strategists, product developers, etc. the thematic and methodological evolution mapped herein supports improved market timing, stress testing, and strategic hedging, thus, paving the way for more resilient, informed decision-making in crypto-finance.

Conclusion

This state-of-the-art landscape review provides a comprehensive cartography of the scholarly terrain in cryptocurrency volatility forecasting from 2018-2025, leveraging 132 robustly chosen SCOPUS-indexed studies and applying a rigorous suite of performance, conceptual and network analyses. A vibrant yet unevenly distributed terrain is traced by the findings, which is methodologically rich, yet thematically concentrated, technologically ambitious yet still ethically under-examined.

The migration from traditional econometric GARCH-type models to sophisticated AI-driven and hybrid architectures signals the field's maturation trajectory, but this advancement is not without accompanying growing pains. Persistent gaps in interdisciplinary integration, asset concentration & ecosystem imbalance, fragmented modeling of volatility drivers, regime shifts & temporal dynamics, exogenous event sensitivity, geographic equity, ESG alignment, and policy adaptability are revealed by key insights. These silences are not limitations, but invitations to transcend conventional forecasting boundaries, and to innovate at the confluence of finance, data science, behavioural insights and sustainability.

As volatility in crypto-markets becomes increasingly systemic and globally consequential, the stakes of precise, ethical and adaptable (also pre-emptive) forecasting have risen higher than ever. As volatility forecasting evolves, the intellectual compass guiding its future must balance accuracy with discernment (*viveka*), innovation with ethics (*dharma*) and market foresight with social good, stability & collective well-being (*lokasangraha*) to fulfil its role within the broader *purushartha* (the ethical-spiritual framework through which life is balanced and fulfilled) of scholarly & societal contribution. This state-of-the-art landscape review acts as a reflective mirror, or a directional compass and advocates for a paradigm shift from siloed technicism to integrative scholarship that engages with real-world complexity and actual stakeholder needs, thus positioning for the next wave of research.

References

Al-Amri, R., Zakaria, N. H., Habbal, A., & Hassan, S. (2019). Cryptocurrency adoption: current stage, opportunities, and open challenges. . *International journal of advanced computer research, 9(44),* , 293-307.

Almeida, J., & Gonçalves, T. C. (2022). A systematic literature review of volatility and risk management on cryptocurrency investment: A methodological point of view. . *Risks, 10(5),* , 107.

Anas, M., Shahzad, S. J., & Yarovaya, L. (2024). The use of high-frequency data in cryptocurrency research: a meta-review of literature with bibliometric analysis. . *Financial Innovation, 10(1),* , 90.

Angerer, M., Hoffmann, C. H., Neitzert, F., & Kraus, S. (2021). Objective and subjective risks of investing into cryptocurrencies. . *Finance Research Letters, 40, 101737.*

Aria, M., & Cuccurullo, C. (2017). bibliometrix: An R-tool for comprehensive science mapping analysis. . *Journal of informetrics, 11(4),* , 959-975.

Asif, Z., & Unar, S. (2024). Cryptocurrency market dynamics: Trends, volatility, and regulatory challenges. . *Bulletin of Business and Economics (BBE), 13(1).*

Bahoo, S., Cucculelli, M., Goga, X., & Mondolo, J. (2024). Artificial intelligence in Finance: a comprehensive review through bibliometric and content analysis. . *SN Business & Economics, 4(2), 23.*

Boozary, P., Sheykhan, S., & GhorbanTanhaei, H. (2025). Forecasting the Bitcoin price using the various Machine Learning: A systematic review in data-driven marketing. . *Systems and Soft Computing, 200209.*

Caporale, G. M., & Zekokh, T. (2019). Modelling volatility of cryptocurrencies using Markov-Switching GARCH models. . *Research in International Business and Finance, 48,* , 143-155.

Chatterjee, S., & Datta, D. (2016). *An introduction to Indian philosophy.* . Motilal Banarsidass.

Cheng, J., Tiwari, S., Khaled, D., Mahendru, M., & Shahzad, U. (2024). Forecasting Bitcoin prices using artificial intelligence: Combination of ML, SARIMA, and Facebook Prophet models. . *Technological Forecasting and Social Change, 198, 122938.*

Chu, J., Zhang, Y., & Chan, S. (2019). The adaptive market hypothesis in the high frequency cryptocurrency market. . *International Review of Financial Analysis, 64,* , 221-231.

Corbet, S., Lucey, B., Urquhart, A., & Yarovaya, L. (2019). Cryptocurrencies as a financial asset: A systematic analysis. . *International Review of Financial Analysis, 62,*, 182-199.

D'Amato, V., Levantesi, S., & Piscopo, G. (2022). Deep learning in predicting cryptocurrency volatility. . *Physica A: Statistical Mechanics and its Applications, 596, 127158.*

Donthu, N., Kumar, S., Mukherjee, D., Pandey, N., & Lim, W. M. (2021). How to conduct a bibliometric analysis: An overview and guidelines. . *Journal of business research, 133,* , 285-296.

Dudek, G., Fiszeder, P., Kobus, P., & Orzeszko, W. (2024). Forecasting cryptocurrencies volatility using statistical and machine learning methods: A comparative study. . *Applied Soft Computing, 151, 111132.*

Fang, F., Ventre, C., Basios, M., Kanthan, L., Martinez-Rego, D., Wu, F., & Li, L. (2022). Cryptocurrency trading: a comprehensive survey. . *Financial Innovation, 8(1), 13.*

Fior, J., Cagliero, L., & Garza, P. (2022). Leveraging explainable AI to support cryptocurrency investors. . *Future Internet, 14(9), 251.*

García-Medina, A., & Aguayo-Moreno, E. (2024). LSTM–GARCH hybrid model for the prediction of volatility in cryptocurrency portfolios. . *Computational Economics, 63(4),* , 1511-1542.

García-Monleón, F., Danvila-del-Valle, I., & Lara, F. J. (2021). Intrinsic value in crypto currencies. *Technological Forecasting and Social Change 162: 120393.*

Jafar, S. H., Akhtar, S., El-Chaarani, H., Khan, P. A., & Binsaddig, R. (2023). Forecasting of NIFTY 50 index price by using backward elimination with an LSTM model. . *Journal of Risk and Financial Management, 16(10), 423.*

Khan, F. U., Khan, F., & Shaikh, P. A. (2023). Forecasting returns volatility of cryptocurrency by applying various deep learning algorithms. . *Future Business Journal, 9(1), 25.*

Kristjanpoller, W., & Minutolo, M. C. (2018). A hybrid volatility forecasting framework integrating GARCH, artificial neural network, technical analysis and principal components analysis. . *Expert Systems with Applications, 109,* , 1-11.

Li, R., Li, S., Yuan, D., & Zhu, H. (2021). Investor attention and cryptocurrency: Evidence from wavelet-based quantile Granger causality analysis. *Research in International Business and Finance 56: 101389.*

Linnenluecke, M. K., Marrone, M., & Singh, A. K. (2020). Conducting systematic literature reviews and bibliometric analyses. *Australian journal of management, 45(2),* , 175-194.

Liu, J., & Serletis, A. (2019). Volatility in the cryptocurrency market. *Open Economies Review, 30(4),* , 779-811.

Nadarajah, S., Mba, J. C., Rakotomarolahy, P., & Ratolojanahary, H. T. (2025). Ensemble Learning and an Adaptive Neuro-Fuzzy Inference System for Cryptocurrency Volatility Forecasting. . *Journal of Risk and Financial Management, 18(2), 52.*

Naimy, V., Haddad, O., Fernández-Avilés, G., & El Khoury, R.

(2021). The predictive capacity of GARCH-type models in measuring the volatility of crypto and world currencies. . *PloS one, 16(1), e0245904.*

Peng, Y., Albuquerque, P. H., de Sá, J. M., Padula, A. J., & Montenegro, M. R. (2018). The best of two worlds: Forecasting high frequency volatility for cryptocurrencies and traditional currencies with Support Vector Regression. . *Expert Systems with Applications, 97*, 177-192.

Poon, S. H., & Granger, C. W. (2003). Forecasting volatility in financial markets: A review. . *Journal of economic literature, 41(2),* , 478-539.

Qureshi, S., Aftab, M., Bouri, E., & Saeed, T. (2020). Dynamic interdependence of cryptocurrency markets: An analysis across time and frequency. . *Physica A: Statistical Mechanics and Its Applications, 559, 125077.*

Radhakrishanan, S., & Moore, C. A. (1957). *A source book in Indian philosophy.*

Sharma, D., Verma, R., & Sam, S. (2021). Adoption of cryptocurrency: an international perspective. . *International Journal of Technology Transfer and Commercialisation, 18(3),* , 247-260.

Singh, M., & Dahiya, R. (2023). Understanding the Adoption of Mobile Wallets Amongst Rural Indian Women. . *Purushartha, 16(2),* , 48-64.

Thélissaint, J. (2025). Assessing Cryptomarket Risks: Macroeconomic Forces, Market Shocks and Behavioural Dynamics. Market Shocks and Behavioural Dynamics. *Available at SSRN: https://ssrn.com/abstract=5213592*. doi:http://dx.doi.org/10.2139/ssrn.5213592

Walther, T., Klein, T., & Bouri, E. (2019). Exogenous drivers of Bitcoin and Cryptocurrency volatility–A mixed data sampling approach to forecasting. . *Journal of International Financial Markets, Institutions and Money, 63, 101133.*

Yahaya, H. U., Oyinloye, J. S., & Adams, S. O. (2022). Modeling and Forecasting Cryptocurrency Returns and Volatility: An Application of GARCH Models. . *Universal Journal of Finance and Economics, 2, 497.*

Yousaf, I., & Ali, S. (2020). Discovering interlinkages between major cryptocurrencies using high-frequency data: new evidence from COVID-19 pandemic. . *Financial Innovation, 6(1), 45.*

Zhou, Z., Song, Z., Xiao, H., & Ren, T. (2023). Multi-source data driven cryptocurrency price movement prediction and portfolio optimization. *Expert Systems with Applications, 219, 119600.*