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Emerging Trends in Volatility Forecasting Using Machine Learning: A Bibliometric Analysis

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Abstract: Volatility forecasting remains a cornerstone of financial economics, offering critical insights into risk management, asset valuation, and investment strategy development. With the increasing complexity of financial markets, machine learning (ML) and deep learning (DL) techniques have significantly influenced the way volatility in financial time series is modeled and analyzed. This study presents a bibliometric analysis of academic publications from 2000 to 2025 that explore the use of ML and DL techniques within the context of volatility forecasting. The analysis is based on data extracted from the Web of Science database, a leading source of reliable and comprehensive scholarly literature in this field. The study analyzes the methodological development of models, such as Long Short-Term Memory (LSTM) networks, Support Vector Machines (SVM), and other ML-based models, which stand out for their capacity to model the complex and nonlinear dynamics of financial time series. In recent years, hybrid modeling strategies, based on the integration of traditional statistical methods with artificial intelligence algorithms, have emerged as prominent approaches in volatility forecasting. The study also highlights emerging trends, such as the use of transformer architectures and meta-learning strategies in high-frequency trading markets and cryptocurrency markets, where volatility is especially pronounced. Comparative analyses across different asset types and timeframes offer a comprehensive framework for understanding how these models perform under various financial conditions.The analysis conducted in this study critically examines the evolving paradigms of volatility forecasting, tracking methodological innovations and scientific developments. In doing so, it underscores the potential of ML and DL techniques to enhance forecasting accuracy, with an expectation that advancements in this field will guide future research directions. The insights derived from the findings not only contribute to the existing academic literature but also facilitate a more effective visualization of the structural dynamics of the literature, analyzed through the VOSviewer software.

Keywords: Volatility forecasting, Machine learning, LTSM, SVM, Financial time series

Introduction

Due to their inherent structure, financial markets are prone to high levels of volatility, which becomes particularly evident during periods of economic crises and market shocks. Volatility during such periods has the potential to significantly influence investor behavior and market dynamics (Schwert, 1989). As volatility forecasting plays an active role in financial decision-making processes, it relies on a robust framework composed of multiple components. The primary purposes of such forecasting include risk management, derivative pricing, investment strategy development, and portfolio optimization (Andersen et al., 2006; Poon & Granger, 2003). With the increasingly dynamic structure of financial markets, traditional econometric models—such as ARCH and GARCH—have become insufficient in capturing the nonlinear and complex patterns inherent in financial time series (Bollerslev, 1986; Engle, 1982).

In recent years, rapid advancements in technology have led to a transformative shift in forecasting financial time series through the integration of ML and DL techniques. These data-driven approaches play an effective role in

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identifying the intricate features of market volatility. In particular, algorithms such as LSTM and SVM have gained prominence due to their high performance in pattern recognition and time series learning (Fischer & Krauss, 2018; Zhang et al., 2017). As the application of these algorithms expands within the finance domain, a methodological transition from traditional statistical models to AI-supported frameworks has been increasingly observed.

This study provides a bibliometric analysis of academic publications (2000–2025) that apply ML and DL techniques to volatility forecasting models. The dataset used in this research was retrieved from the Web of Science database, one of the most comprehensive sources in the field. The analysis indicates a growing emphasis on the application of advanced AI techniques—such as meta-learning strategies—especially during periods of heightened volatility in high-frequency trading and cryptocurrency markets. Additionally, hybrid approaches combining ML methods with conventional econometric models have been investigated, highlighting their respective advantages (Kim et al., 2024). By visualizing the structural dynamics of the literature through the VOSviewer software, this research enhances comprehension of the academic landscape. Accordingly, by critically evaluating methodological trends, the study reveals that ML and DL approaches offer superior performance in volatility forecasting and shed light on the evolution of innovation in the field.

Literature

The concept of ML was first introduced in 1959 by computer scientist Arthur Samuel. According to Samuel's definition, ML is a scientific field that enables computers to perform specific tasks by systematically learning and improving their performance over time. This approach allows systems to learn from their own experiences and make decisions accordingly without being explicitly programmed, thus differing from the traditional understanding of software development (Samuel, 1959). ML is methodologically grounded within subfields of mathematics, particularly probability theory, statistics, and optimization. In this context, models developed using ML are capable of learning specific patterns from historical data and making future predictions based on these patterns. In contrast, classical software development processes require the programmer to identify data-based patterns through observation and code them manually. However, since these methods rely heavily on the individual judgment of the programmer, they tend to be unsystematic and often fail to accurately reflect real-world conditions (Grigorev, 2020). ML is now widely used in many fields where uncertainty is high and conventional methods prove inadequate. In this regard, notable application areas include the classification of diseases with overlapping symptoms, forecasting stock market movements under volatile conditions, filtering spam emails, and predicting future travel preferences based on customer experience (Keles et al., 2020).

The frequent fluctuations observed in financial markets and the growing economic uncertainty on a global scale have significantly increased the demand for accurate, timely, and reliable market forecasts by both financial institutions and individual or institutional investors. In the literature, it is observed that traditional methods used in volatility forecasting remain limited in handling complex and dynamic datasets. Specifically, the inability of linear models to adequately represent stock market data has led to the insufficiency of conventional analytical methods, which in turn has made the application of artificial intelligence, ML and DL techniques to such data increasingly widespread and effective (Egeli et al., 2003). In one study, based on economic and financial factors affecting the BIST-50 index, ML algorithms and artificial neural networks were employed, and stock performance was classified accordingly (Filiz et al., 2017). Sahin (2023) analyzed market volatility using both GARCH-type models and artificial neural networks (ANN), and determined that hybrid models produced more accurate results than classical ones. Aksehir and Kılıc (2019), in their study on stock index prediction, achieved successful results in forecasting bank stock prices using methods such as regression, random forest, and decision trees.

Akusta (2023) applied a machine learning–based method to monitor Bitcoin price movements and perform price forecasting. The findings indicated that this approach contributed to more rational investment decisions and risk reduction while enabling more effective monitoring of price movements in cryptocurrency markets. Moreover, this study provided an important framework regarding the potential impact of ML methods in financial markets, particularly in Bitcoin price forecasting. Sonmez and Arslan (2024), taking into account the complex and volatile structure of stock indices, used LSTM networks instead of traditional methods and achieved effective results in index forecasting by successfully modeling long-term relationships in time series. Ozcan (2023) asserted that ML methods were the most effective approach for predicting future movements in stock indices and securities markets using past data. His study compared nine different ML algorithms applied to the BIST100 index and evaluated their performance in predicting increases and decreases in the index. The findings revealed that linear methods yielded more accurate results compared to others. In their study on forecasting the

BIST100 index, Akbulut and Adem (2023) concluded that the LSTM model was an effective and successful method. Urgenc (2023) aimed to predict change points in Bitcoin prices using ML methods and comparatively evaluated their forecasting performance. Oncu (2022) assessed the applicability of ML methods in predicting the price trends of carbon futures based on carbon emissions. Based on the findings, given the increasing economic and environmental importance of carbon markets, data-driven models were applied to improve the accuracy of price forecasting. The results suggested that ML algorithms could model the complex structural characteristics of carbon contracts and contribute to risk management and strategic decision-making processes for market participants. In Ceyhan's (2023) study, it was determined that ML and DL methods were predominantly used in predicting future prices of financial assets, identifying financial risks, and optimizing portfolios. The analysis revealed that, in most cases, the performance of multiple algorithms was compared to determine the most efficient one.

In a study conducted by Colak (2025), a deep learning–based model was used to analyze stock price forecasts for Nike (NKE). The findings indicated that LSTM and GRU models produced reliable results in long-term analyses of financial time series. In another study, the predictability of the BIST100 index was measured using the LSTM model—one of the DL methods with high learning capacity—and the results showed that LSTM outperformed classical models, particularly in capturing nonlinear structures (Abizada, 2024). In their study, Gur and Esidir (2023) conducted a comparative analysis using DL, ML and ensemble learning methods to forecast the future values of scrap steel imports in Turkey. Their findings showed that LSTM achieved the highest success in learning long-term dependencies. Budak (2023), aiming to forecast the prices of financial instruments during global market crises, utilized ML algorithms—one of the emerging data science technologies—for price forecasting. A review of the related literature reveals that researchers such as Sarkar and Ali (2022), Wijayanti and Taufik (2022), Bhuriya et al. (2017), Lin et al. (2013), and Nuchitprasitchai et al. (2023) have utilized ML algorithms for forecasting a wide range of financial instruments. Their findings indicated that even in the presence of complex data structures, AI-based linear models demonstrated high forecasting performance. Eylasov and Cicek (2024), in their study on cryptocurrency price forecasting, compared ARIMA-GARCH and LSTM methods and evaluated the most effective forecasting approaches. In another study, SVM have been widely adopted for financial volatility modeling due to their robustness in handling nonlinear patterns (Gavrishchaka & Banerjee, 2006). Chen et al. (2010) demonstrated that SVM, as an advanced alternative to traditional artificial neural networks (ANN), have gained increasing attention in financial forecasting applications. In their study, SVM was applied within a volatility forecasting framework and evaluated using both simulated data and real-world datasets, including daily GBP exchange rates and the NYSE stock index. In their 2009 study, Tang et al. addressed the limitation of standard SVM kernels in capturing volatility clustering by developing a multidimensional wavelet kernel function. Their findings confirmed the effectiveness of the wavelet support vector machine (WSVM) in forecasting stock market volatility using both simulated and real-world data.

Method

The aim of this study is to conduct a comprehensive bibliometric analysis of the academic literature on volatility forecasting using ML and DL techniques, based on publications from the years 2000 to 2025. The research utilizes bibliographic data retrieved from the Web of Science database and aims to identify major publication trends, leading authors and institutions, frequently co-occurring keywords, and methodological developments within the field. The bibliometric analysis method employed in this study refers to the quantitative evaluation of scholarly publications related to a specific academic domain by analyzing various bibliographic indicators—such as authorship, countries of publication, keywords, institutional affiliations, citation counts, publication years, and source journals—using mathematical and statistical techniques (Pritchard, 1969).

Findings and Discussion

Publications related to volatility were examined by searching relevant keywords in the Web of Science database for the period between 2000 and 2025. The search was conducted using the Keywords Plus feature, with the Boolean combination of terms as follows: "Volatility Forecasting" OR "Volatility Modeling" AND "Machine Learning" OR "Deep Learning" OR "LSTM" OR "SVM" AND "Financial Time Series".

This approach was adopted to capture a broad yet focused set of studies at the intersection of volatility analysis and emerging computational techniques. Accordingly, a total of 2,278 publications were identified during the specified years. The annual distribution of these publications is presented in Table 1.

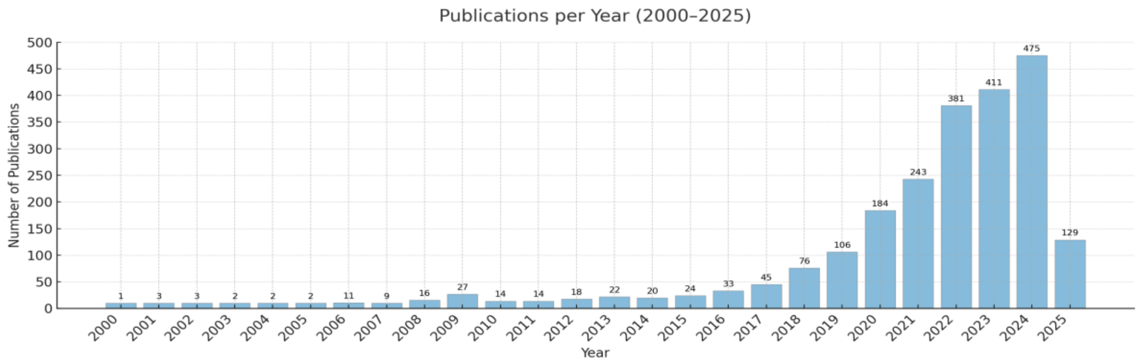

Figure 1. Publications per year (2000-2025)

As shown in Figure 1, the number of publications started to increase from 2006 onward, with the highest number recorded in 2024. Since only a certain period of 2025 was included in the analysis, it is anticipated that related studies in the field will continue to increase in the coming years based on the trend observed in previous years. In recent years, ML and DL techniques have emerged as prominent topics in financial forecasting. Among these techniques, models such as LSTM networks and SVM have attracted attention due to their ability to model nonlinear and complex patterns in financial time series data. As a result, these methods are increasingly applied to volatility forecasting, reflecting their growing importance as trending topics in academic literature and practical financial applications.

Table 1.Publications per year (2000-2025)

Years	Count	Years	Count	Years	Count
2000	1	**2010**	14	**2020**	184
2001	3	**2011**	14	**2021**	243
2002	3	**2012**	18	**2022**	381
2003	2	**2013**	22	**2023**	411
2004	2	**2014**	20	**2024**	475
2005	2	**2015**	24	**2025**	129
2006	11	**2016**	33		
2007	9	**2017**	45		
2008	16	**2018**	76		
2009	27	**2019**	106		

Based on the data obtained from the analyzed publications, the authors with the highest number of publications and their respective counts are presented in Figure 2. According to the results, Zhang, Yaojie stands out as the most prolific author with 25 publications, indicating the author's active involvement in the research field. Other prominent researchers include Ma, Feng (22 publications), Ting, Daniel S. W. (16 publications), Wang, Yiyi (15 publications), Karniadakis, George Em (14 publications), Liang, Chao (13 publications), and Gupta, Rangan (11 publications). Additionally, Wong, Tien Yin (8 publications), Feng, Xin-Long (7 publications), and Wei, Yu (7 publications) have also made notable contributions to the literature.

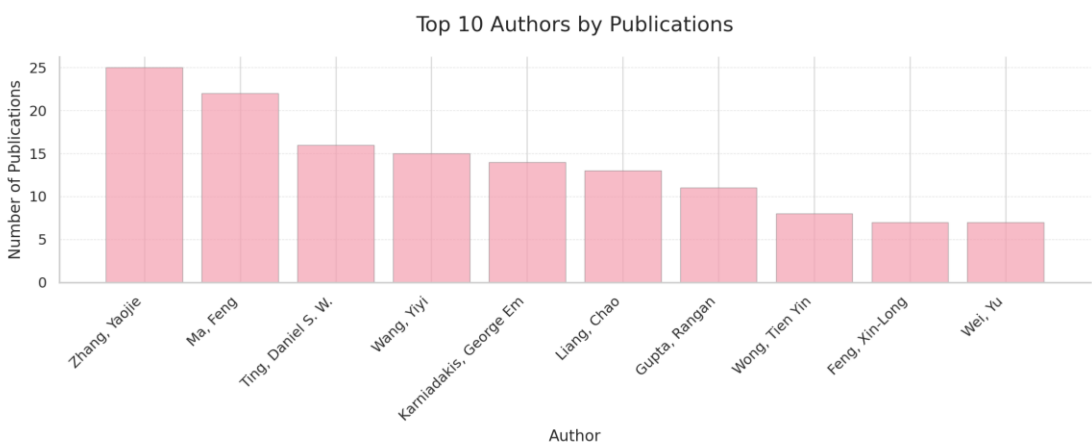

Figure 2.Top 10 authors by publications

The distribution of the total 2,278 publications examined from the Web of Science database by document type is presented in Figure 3. According to this distribution, original research articles constitute the dominant publication type, accounting for 78.3% of the total. These are followed by review articles (13.8%) and conference papers (4.6%). Additionally, early access publications make up 1.5%, book chapters 0.8%, and editorial materials 0.7%. The dataset also includes a small proportion of retracted publications (0.1%) and books (0.1%). This distribution indicates that the relevant research field is largely shaped by original research articles, while review studies occupy a secondary position.

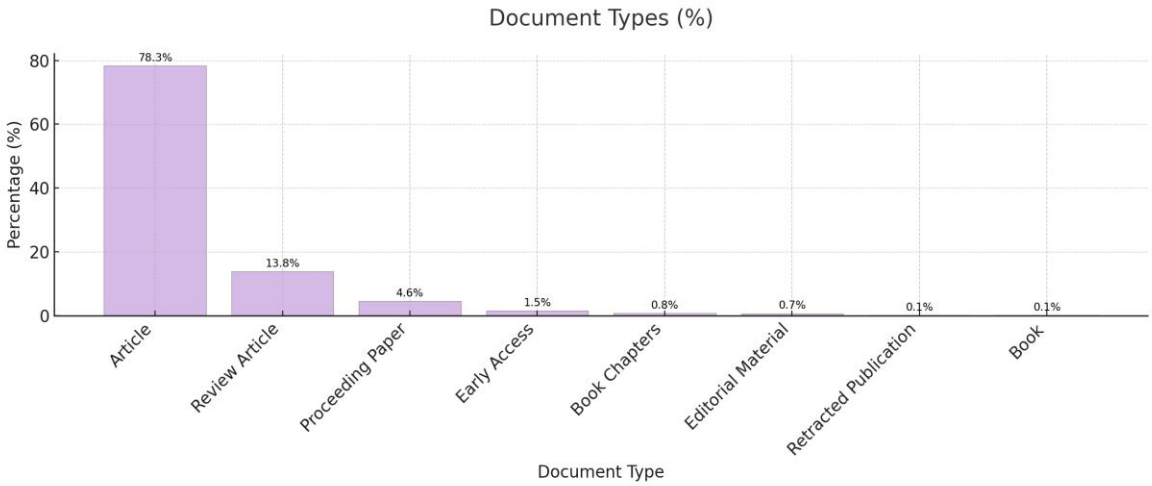

Figure 3. Types of data analyzed

As a result of the analysis conducted in this study, the distribution of the relevant literature by subject categories is presented in Figure 4. Accordingly, the majority of the studies were conducted in the field of Electrical and Electronic Engineering. This is followed by categories such as Economics, Computer Science—Information Systems, and Artificial Intelligence. In addition, a considerable number of publications were observed in areas like Business and Finance, Telecommunications, Computer Science—Interdisciplinary Applications, and Computer Science—Theory and Methods. Based on the figure, it was found that studies combining ML and financial applications are relatively prominent. The results of the distribution suggest that the research has evolved toward an interdisciplinary direction focused on technology, economics, and computer science. In particular, the concentration of studies in the fields of artificial intelligence and information systems indicates that research trends are increasingly shaped around themes of digitalization and automation.

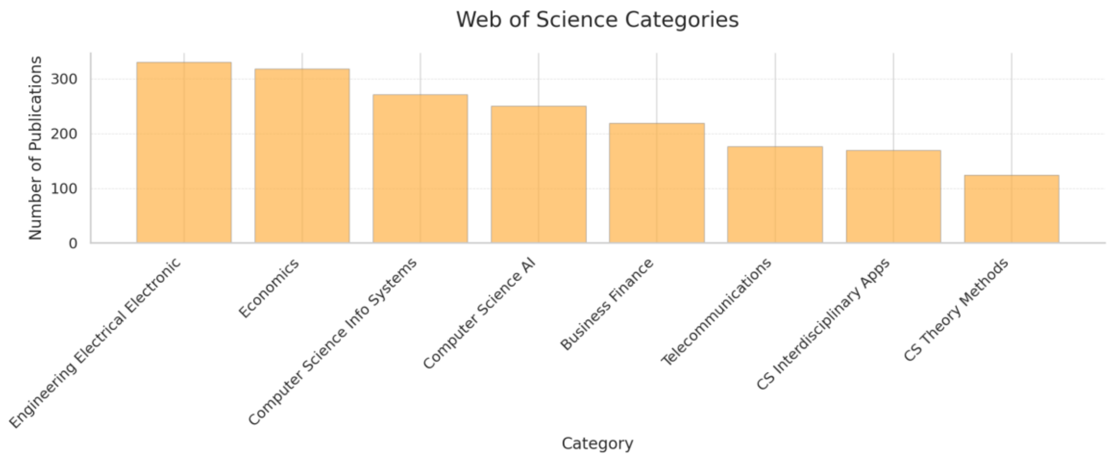

Figure 4. Categories of analyzed publications

Considering the research outputs, the country-wise distribution of the analyzed publications is presented in Figure 5. The analysis reveals that China ranks first with 864 publications, followed by the United States with 478 publications, and India in third place with 188 publications. The significantly higher number of publications from China and the U.S. indicates a strong academic interest in this research field within these countries. Other major contributors include the United Kingdom (144 publications), Australia (113 publications), and Germany

(104 publications), suggesting a broad geographical distribution of research activity. Additionally, South Korea (102 publications) and Canada (87 publications) have also demonstrated notable contributions, reflecting substantial interest in the field. This distribution highlights that countries from Asia, North America, and Europe have played a prominent role in the scientific output, suggesting that the research area has garnered global attention and is the focus of active academic work across diverse regions.

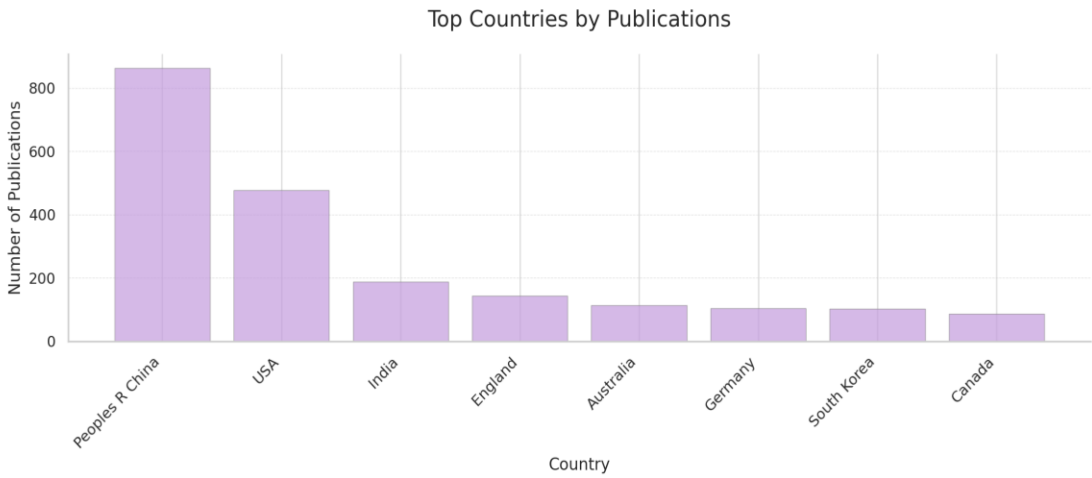

Figure 5. Distribution of analyzed publications by country

Based on the data presented in Figure 6, the top 10 institutions contributing most significantly to the research field are ranked by the number of publications. Leading the list is the Chinese Academy of Sciences (CAS) with 61 publications, followed by Southwest Jiaotong University with 56. Institutions such as the University of California System (45 publications) and Nanjing University of Science and Technology (41 publications) are at the forefront of both theoretical and applied research. These are followed by prominent Asian universities including Shanghai Jiao Tong University (35), National University of Singapore (34), University of Chinese Academy of Sciences CAS (34), and Zhejiang University (34). Tsinghua University (32) and, notably, Harvard University (29) — recognized for its global influence and prestige — also stand out in this ranking.

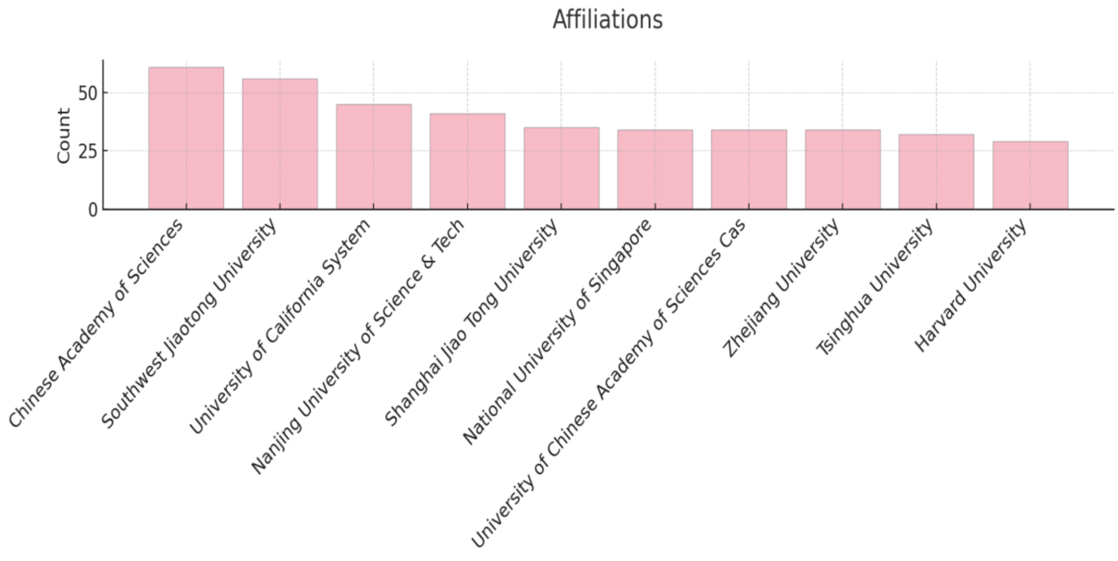

Figure 6. Leading 10 ınstitutions contributing to the literature

According to the findings presented in Figure 7, computer science (675) and engineering (586) emerge as the disciplines contributing the most to the literature. Business and economics (460) highlight the impact of ML in financial applications, followed by mathematics (189) and physics (176). The inclusion of fields such as telecommunications (176), mechanical engineering (95), and medical imaging (71) indicates that the study has a multidisciplinary structure and spans a broad range of areas.

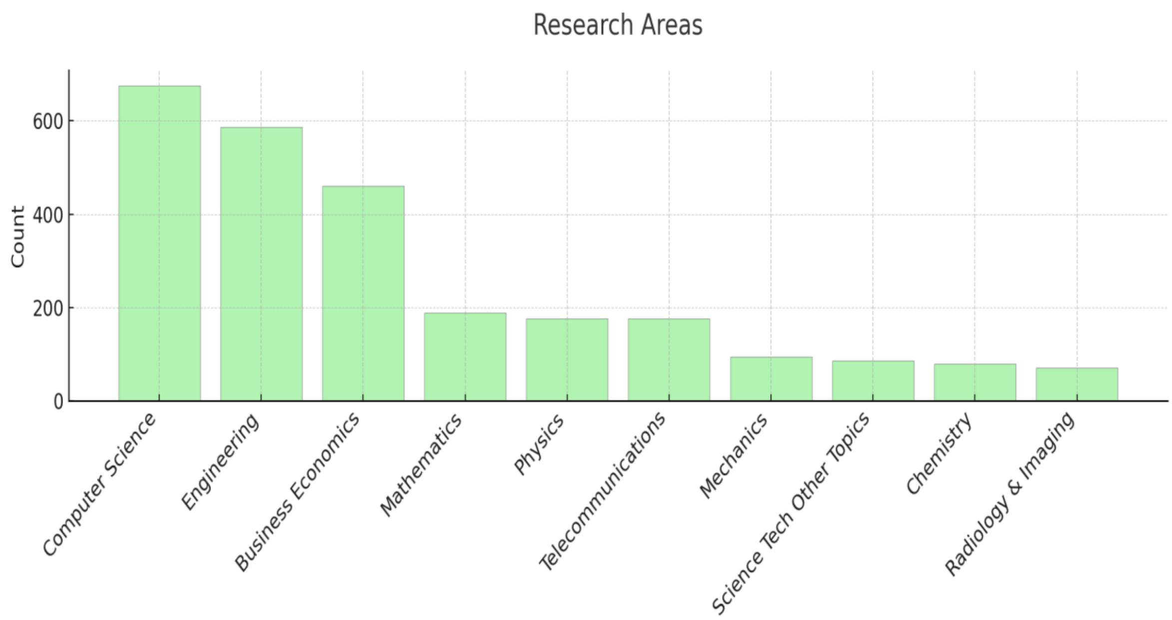

Figure 7. Distribution of research areas in the relevant literature

Based on the observations from the literature review, the mid-level (meso) distribution of citation topics shows that the literature predominantly focuses on areas such as economics (579), artificial intelligence and ML (255), and modeling and simulation (255), as shown in Figure 8. Additionally, the inclusion of topics like image processing, telecommunications, engineering, and health-related subjects indicates that the research has a multidisciplinary nature.

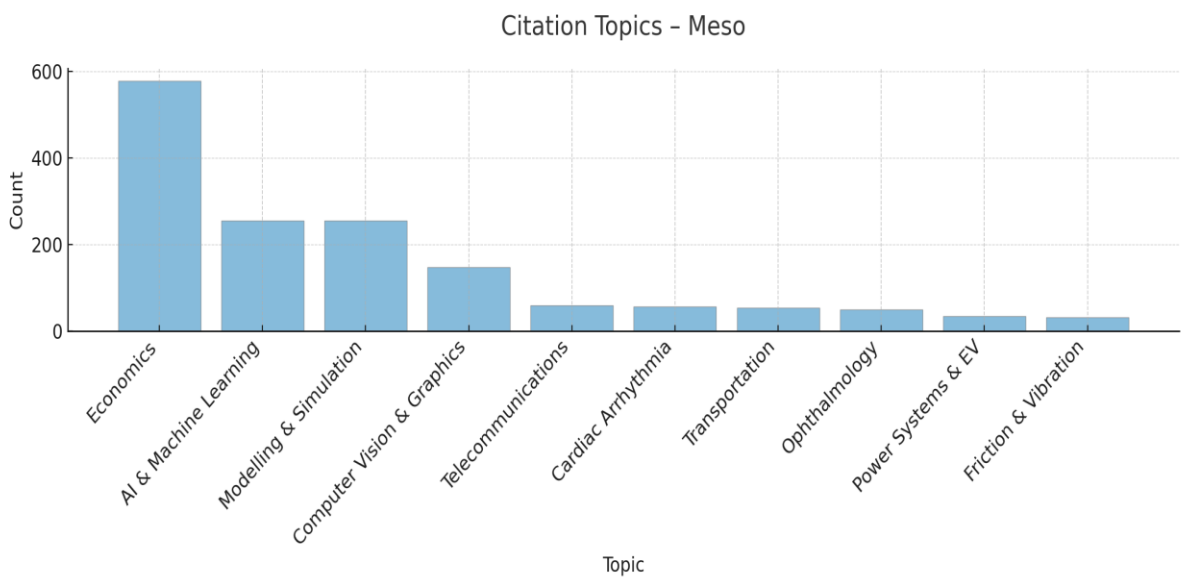

Figure 8. Citation topics at the meso level

In the second part of the methodology, bibliometric maps—such as keyword co-occurrence, author collaboration, and country-based publication networks—were created using VOSviewer software as part of the bibliometric analysis method. In this context, visualizations based on the frequency of keywords and cluster analysis were conducted. In addition to these network analyses, raw publication data (e.g., number of publications by year, document types, institutional distribution, etc.) presented in the first part of the methodology were processed and visualized using the Python programming language (version 3.10). In this section, a comprehensive analysis is planned by evaluating content maps based on VOSviewer in conjunction with Python-based statistical distribution graphs. Based on the data presented in Table 2, the most frequently used keywords in the literature are identified according to the results of the relevant research.

Table 2. The most frequently used keywords in the literature

Keyword	Occurrences	Total link strength
Deep Learning	437	1254
Machine Learning	226	785
Artificial Intelligence	202	634
Feature Extraction	64	453
Training	35	274
Data Models	26	261
Intrusion Detection	53	230
Neural Networks	51	196
Anomaly Detection	32	176
Internet of Things	34	172
Convolutional Neural Networks	30	169
Network Security	26	167
Classification	42	159
Computational Modeling	17	155
Intrusion Detection	31	140
Convolutional Neural Network	56	135
Security	17	125
Predictive Models	13	120
Accuracy	11	112
Feature Selection	25	105

In this study, the keyword analysis conducted using VOSviewer software presents the development and connection intensity of keywords over time in Figure 9. This visualization illustrates how the connection intensity and frequency of each keyword have changed over time, showing the evolution of the most frequently used keywords. On the other hand, the intensity of keywords is further detailed in Figure 10. In this visualization, the connection intensity and frequency of keywords are highlighted through color tones, with keywords that exhibit stronger relationships and higher levels of focus being emphasized more intensely and distinctly. The goal of this visualization is to identify thematic clusters within the research field and determine the most interactive topics in the literature.

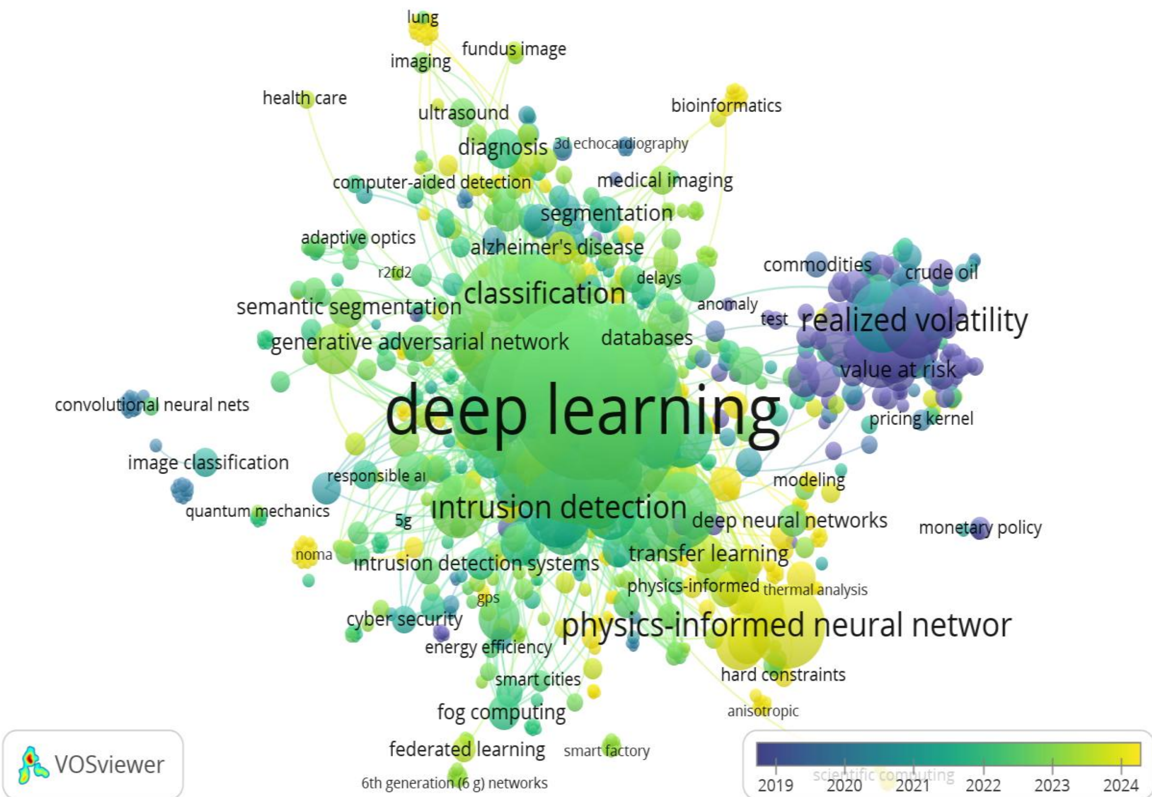

Figure 9. Keyword co-occurrence visualization (VOSviewer output)

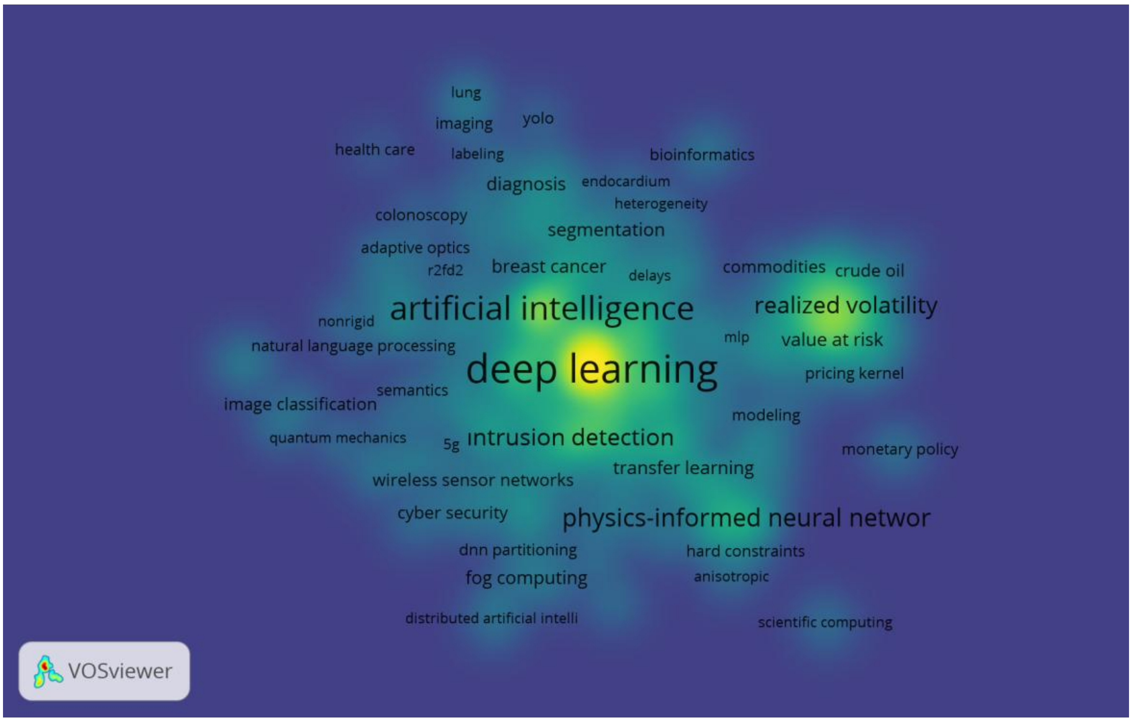

Figure 10. VOSviewer density visualization of most frequent keywords

Based on the data presented in Table 3, the co-authorship network between authors, derived from the author collaboration analysis conducted using the VOSviewer database, is provided. As a result of this analysis, the number of publications authored by each researcher, the citation count received, and the total link strength values with other relevant authors were calculated.

Table 3. Co-authorship and impact indicators of leading authors

Author	Documents	Citations	Total link strength
Zhang, Yaojie	25	1092	49
Li, Huating	3	93	47
Wong, Tien Yin	6	78	42
Park, Yongkeun	2	71	38
Sheng, Bin	4	138	37
Tan, Gavin Siew Wei	3	22	36
Guan, Zhouyu	2	92	34
Jia, Weiping	2	92	34
Bee, Yong Mong	2	24	31
Li, Fei	3	21	31
Lim, Lee-ling	2	24	31
Sabanayagam, Charumathi	2	24	31
Chikama, Tai-ichiro	2	1	30
Kato, Naoko	2	1	30
Kitaguchi, Yoshiyuki	2	1	30
Lim, Gilbert	4	186	30
Maehara, Hiroki	2	1	30
Miyazaki, Dai	2	1	30
Nejima, Ryohei	2	1	30
Oda, Masahiro	2	1	30

In Figure 11, the network structure obtained visually represents both the individual scientific productivity and the interaction strength of authors within the network. Through this network structure, pioneering authors in the literature are assessed alongside bibliometric indicators such as the number of publications, citation counts, and total link strength. The density visualization in Figure 12 highlights the identification of the most influential authors and the dense collaboration clusters in the literature. In this context, the brightness levels on the map are defined according to the authors' publication counts, citations received, and total link strength, thereby clearly illustrating the academic focal points with the highest interaction in the literature.

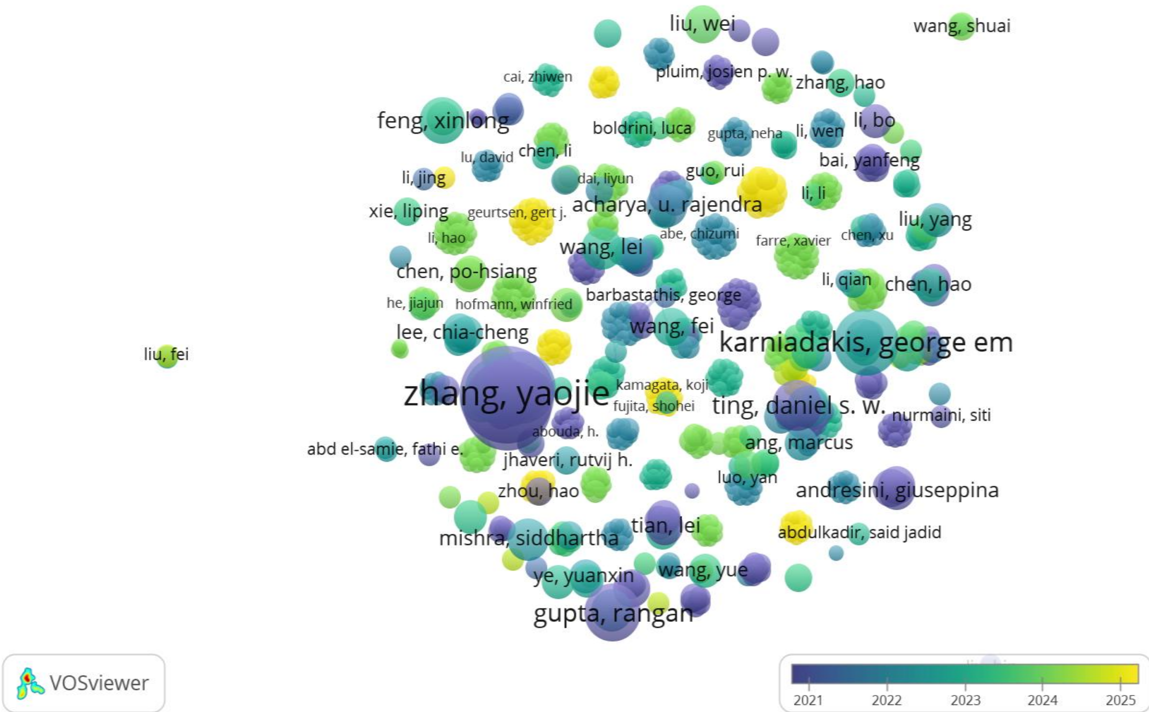

Figure 11. Overlay visualization of author collaboration network (VOSviewer output)

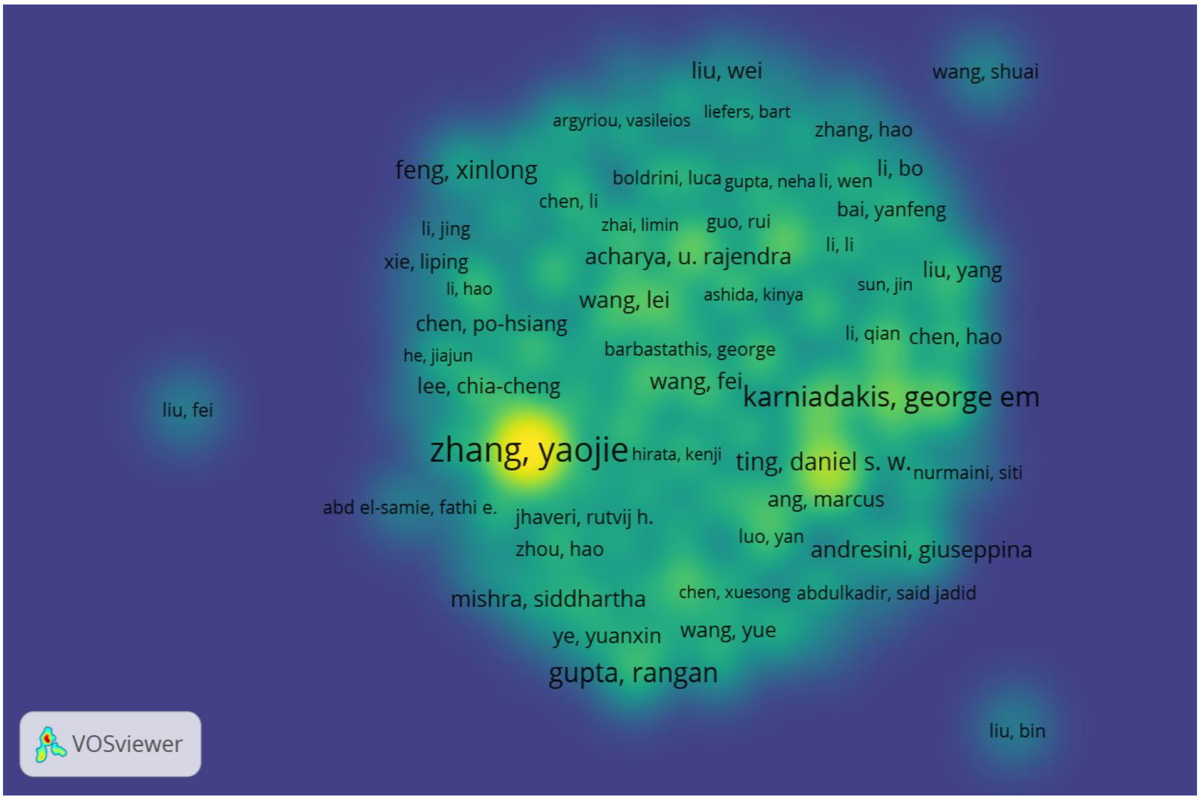

Figure 12. Density visualization of author collaboration network (VOSviewer output)

Based on the bibliometric analysis, the institutions that have made the most significant contributions to the field, according to the number of publications, citation levels, and total link strength, are presented in Table 4. The evaluation shows that the Chinese Academy of Sciences and the University of Chinese Academy of Sciences stand out, while institutions such as MIT, Brown University, and Monash University, despite having fewer publications, create a substantial impact through high citation levels.

Table 4. Organizational-level bibliometric indicators

Organization	Documents	Citations	Total link strength
Chinese Acad Sci	49	1509	109
Univ Chinese Acad Sci	34	1229	101
Hong Kong Polytech Univ	27	643	91
Singapore Natl Eye Ctr	14	343	85
Natl Univ Singapore	21	760	83
Nanjing Univ Sci & Technol	41	1778	73
Shanghai Jiao Tong Univ	33	821	71
Southwest Jiaotong Univ	54	2058	70
Sun Yat Sen Univ	18	343	69
Chinese Univ Hong Kong	15	210	67
Mıt	22	1051	65
Tsinghua Univ	30	534	64
Duke Nus Med Sch	9	368	61
Asia Univ	7	238	56
Wuhan Univ	19	712	50
Monash Univ	17	329	47
Zhejiang Univ	34	301	47
Univ Miami	6	247	45
Brown Univ	23	2847	43
Deakin Univ	11	398	43

According to Figure 13, which illustrates the institutional collaboration network, institutions are color-coded based on the number of publications, citations received, and total link strength, with the periods of most intense collaboration highlighted through distinct tones. Based on the data presented in Table 4, Brown University emerges as the institution with the highest number of citations. The corresponding density map, displayed in Figure 14, emphasizes the points of academic interaction between institutions through color intensity, where brighter regions indicate institutions characterized by both high productivity and strong collaborative linkages. According to this visualization, the highest concentration is observed for Brown University, followed closely by Southwest Jiaotong University.

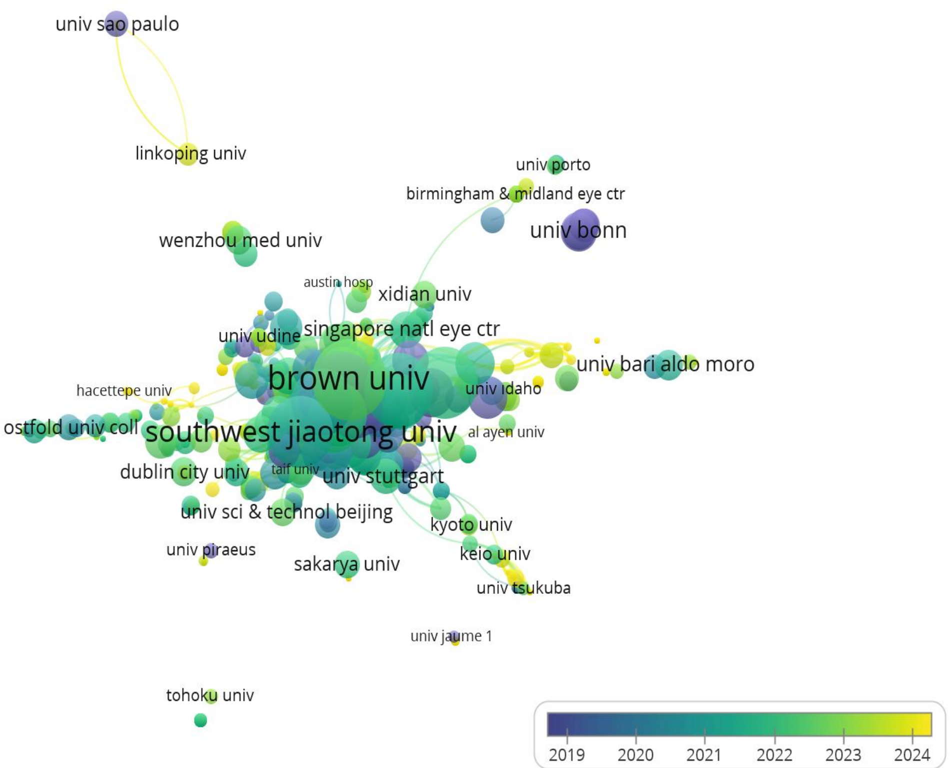

Figure 13. Overlay visualization of institutional collaboration network

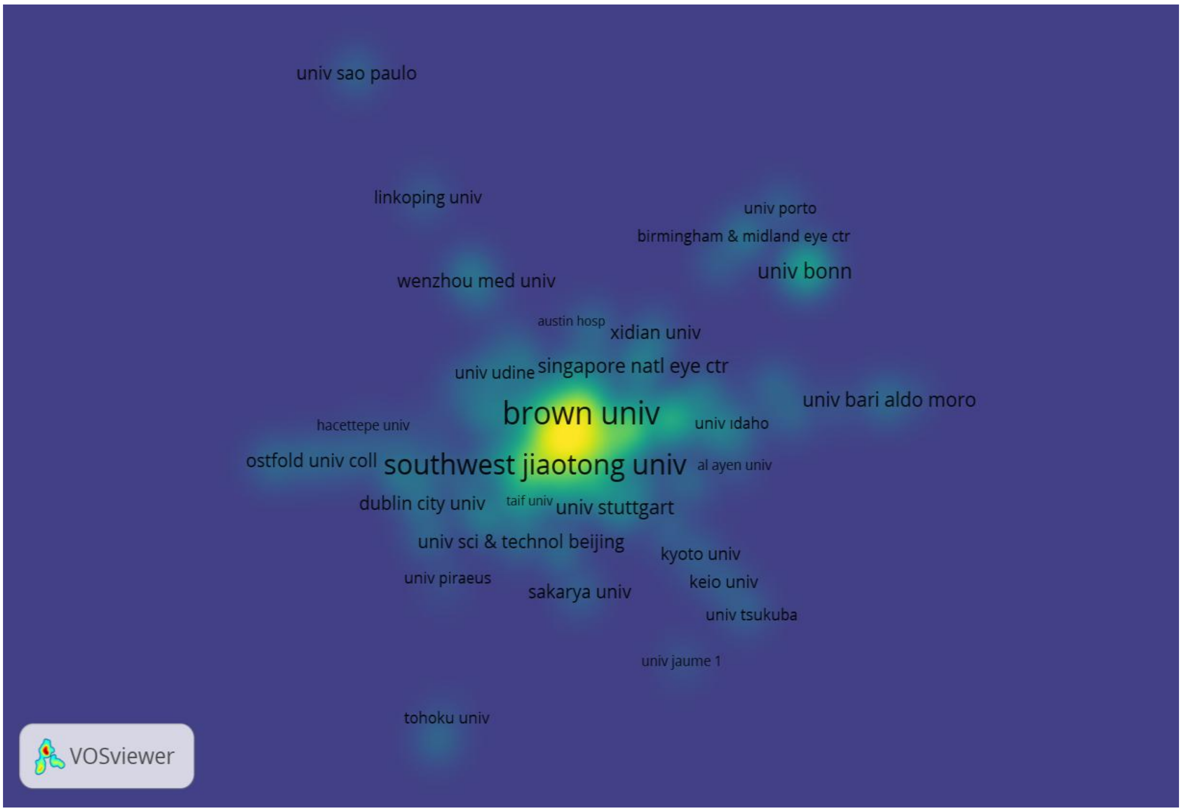

Figure 14. Density visualization of institutional co-authorship

Table 5. Top contributing countries by documents, citations, and total link strength

Country	Documents	Citations	Total link strength
Usa	473	24541	393
Peoples R China	853	18099	353
Australia	111	3628	193
England	143	6509	193
Canada	85	4124	145
Italy	81	1814	132
Germany	104	2724	121
France	66	2473	111
India	186	2389	111
Singapore	52	1909	100
Spain	66	1028	99
Saudi Arabia	53	941	96
South Korea	100	1682	81
Netherlands	37	1464	70
Pakistan	33	562	67
Taiwan	62	962	66
Switzerland	36	1278	65
Malaysia	36	549	60
Iran	32	883	52
Sweden	24	378	51

The bibliometric analysis conducted on the reviewed literature presents key findings at the country level in Table 5, highlighting scientific productivity, citation impact, and collaboration strength. Within this framework, China and the United States stand out with high publication volumes and citation metrics, while the United Kingdom, Australia, Canada, and several European countries also emerge as prominent actors within the collaboration network. Based on the findings, the temporal distribution of international scientific collaborations is illustrated through color mapping in Figure 15. Furthermore, Figure 16 displays a density map emphasizing the countries with the highest levels of interaction and collaboration clusters, where brighter areas represent nations with strong link strength and significant academic influence within the field.

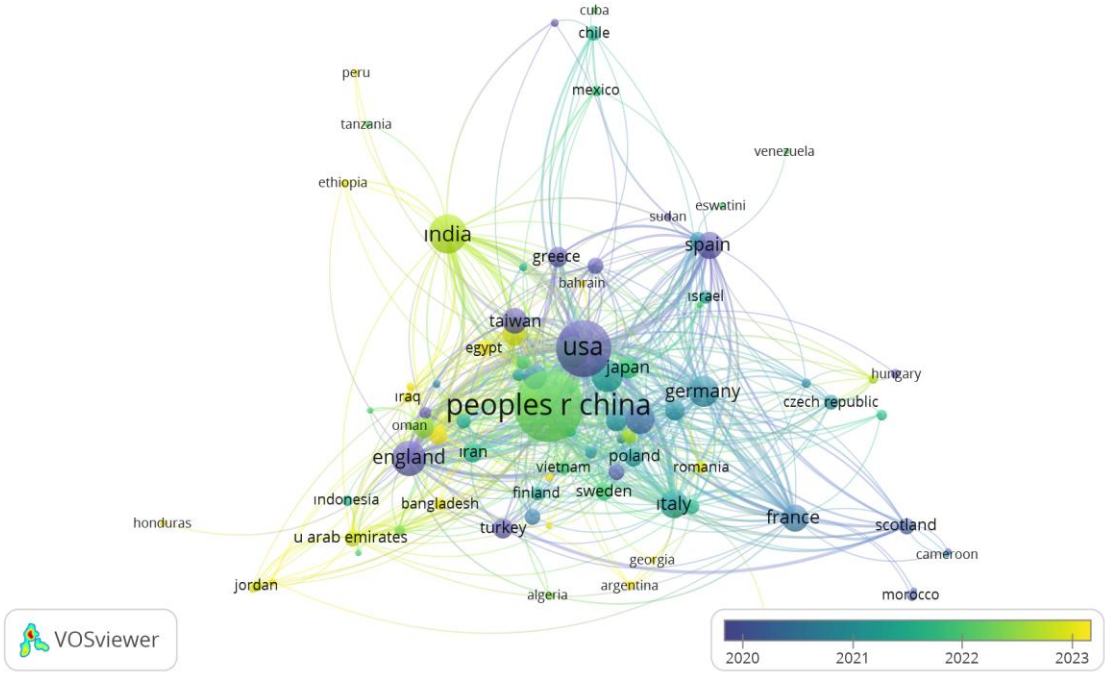

Figure 15. Overlay visualization of country collaboration network (VOSviewer output)

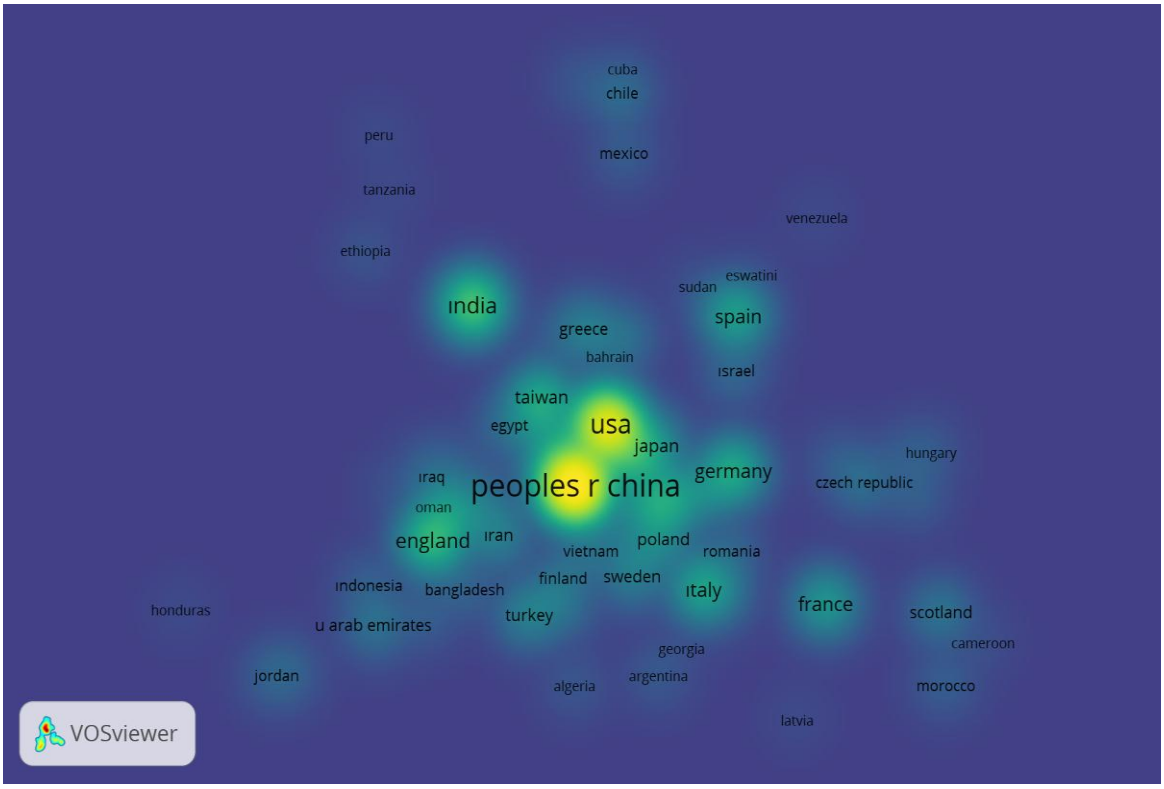

Figure 16. Density visualization of ınternational research collaboration (VOSviewer output)

Conclusion

This bibliometric study provides a comprehensive examination of how ML and DL techniques have evolved in the context of volatility forecasting between 2000 and 2025, highlighting key emerging trends. The findings indicate that hybrid models integrating traditional econometric methods with AI algorithms—particularly

LSTM, SVM, and related approaches—have gained prominence. Network visualizations generated through VOSviewer reveal that the majority of research outputs are concentrated in China and the United States, with notable collaboration networks also present across parts of Asia, North America, and Europe. In parallel with the increasing use of deep learning-based models in financial time series analysis in recent years, the keyword "deep learning" has appeared with growing frequency in the literature.

Furthermore, thematic and keyword co-occurrence analyses suggest a growing interest not only in well-established areas such as financial econometrics and time series modeling, but also in emerging topics like meta-learning and transformer-based models. The network maps visually capture the structural evolution of the literature and clearly reflect which themes have gained prominence over time.

By mapping the scientific landscape of ML applications in volatility forecasting, this study sheds light on the interdisciplinary nature and shifting methodological foundations of the field. The results emphasize the increasing success of ML models in addressing the nonlinear structures, uncertainty, and structural breaks inherent in financial time series, thereby offering both conceptual insight and future research directions.

Recommendations

Future research could enhance modeling accuracy and applicability by focusing on advanced AI techniques that remain underexplored in the volatility forecasting literature, such as transformer architectures, meta-learning, and other cutting-edge approaches.

Scientific Ethics Declaration

The author declares that the scientific ethical and legal responsibility of this article published in EPSTEM journal belongs to the author.

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