



Thematic Evolution of Artificial Intelligence in Financial Engineering: A Bibliometric Analysis

التطور الموضوعاتي للذكاء الاصطناعي في الهندسة المالية: تحليل بيبليومتري

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Abstract

Keywords

This study conducts a bibliometric analysis of research on Artificial Intelligence in financial engineering over the period 2015–2025. Employing performance analysis and science-mapping methodologies, including co-citation, co-authorship, and co-word analysis, this study analyzes 995 peer-reviewed publications sourced from the Scopus database. The findings reveal a swift expansion of the literature, particularly pronounced following 2022, which is attributable to developments in machine learning and deep learning techniques. The predominant research areas encompass market forecasting, risk management, and bankruptcy prediction, with models such as LSTM, Random Forest, and XGBoost exhibiting considerable predictive accuracy. China, India, and the United States are identified as the principal contributors to global collaborative networks. Furthermore, recent research increasingly highlights robo-advisory services and the necessity of explainable AI to improve transparency within financial decision-making processes. Consequently, these findings offer a structured overview of significant trends, influential sources, and prospective research avenues within the domain of AI-based financial engineering.

artificial
intelligence ;
financial
engineering ;
decision-making ;
bibliometric
analysis ;

JEL Classification Codes : G17 ; G32 ; O33 ; C63 ; C88 ; G23 ; G11

الكلمات المفتاحية

المخلص

تتناول هذه الدراسة تحليلاً بيبليومترياً للأبحاث المرتبطة بالذكاء الاصطناعي في الهندسة المالية خلال الفترة 2015–2025، بالاعتماد على تحليل الأداء ورسم الخرائط العلمية لعدد 995 منشوراً مفهراً في قاعدة سكوبس. وتكشف النتائج عن نمو متسارع في الإنتاج العلمي، خاصة بعد عام 2022، نتيجة التطورات في تعلم الآلة والتعلم العميق. وتركزت أبرز الموضوعات البحثية في التنبؤ بالأسواق، وإدارة المخاطر، والتنبؤ بالإفلاس، مع كفاءة عالية لنماذج مثل LSTM و XGBoost. كما تزايد الاهتمام بالاستشارة الآلية والذكاء الاصطناعي القابل للتفسير لتعزيز شفافية القرارات المالية.

الذكاء الاصطناعي؛ الهندسة
المالية؛ اتخاذ القرار؛ التحليل
البيبليومتري.

تصنيف JEL: G17 ؛ G32 ؛ O33 ؛ C63 ؛ C88 ؛ G23 ؛ G11

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I. INTRODUCTION:

The rising adoption of advanced information technologies by the worldwide financial system has made Artificial Intelligence and Machine Learning essential elements of current financial engineering practices (Ahmed et al., 2022). The current AI methods enable systems to learn from data while they also manage changing conditions, which allows financial systems to make decisions based on multiple data sources instead of fixed rules (Raj and Seamans, 2019; Martinelli et al., 2021).

The scientific research of Bresnahan and Trajtenberg from 1995 and Mosteanu and Faccia from 2020 shows that artificial intelligence has developed into a General-Purpose Technology which transforms financial economics and practice by 2025. The current scientific research shows that econometric modeling has moved away from traditional linear models to machine learning methods which use high-dimensional data and non-linear systems (Ahmed et al., 2022). AI technology now sees wider use in financial markets and institutions because of improved computing power and accessible data and increased spending on digital technologies (Ernst et al., 2018).

AI technology works best in the financial industry because this sector depends on processing large data volumes and requires automated business operations. Previous research demonstrates that artificial intelligence creates major economic effects which drive value creation and productivity increases throughout the financial services industry (Bughin et al., 2018; World Economic Forum, 2018). FinTech operates as a primary force for innovation in this field because AI technology enables the creation of financial relationship models which traditional analysis methods cannot handle (Dyba and Gernego, 2019).

AI applications in financial decision-making show their strongest impact through market prediction and algorithmic trading and risk management. The financial data analysis results show that machine learning and deep learning models including Multilayer Perceptrons and Long Short-Term Memory networks achieve better performance than classical linear methods when they need to detect non-linear relationships and temporal patterns in financial data (Agusta et al., 2024; Ferrara and Ciano, 2024). The developments helped algorithmic and high-frequency trading systems to grow while they also created a theoretical basis which moved market analysis from the Efficient Market Hypothesis to the Adaptive Market Hypothesis that treats markets as systems which develop and acquire knowledge (Dahal et al., 2024).

Recent developments in large language models (LLMs) now enable financial professionals to analyze customer sentiment and process information more effectively. Unstructured financial text becomes accessible for detailed examination through BERT and FinBERT systems, which also face reliability issues about their predictive power due to existing bias and transparency problems (Huang et al., 2023; Akpan, 2025). AI-based technologies exhibit superior efficiency in performing credit risk evaluation and bankruptcy forecasting and financial auditing and fraud detection activities when compared to conventional statistical methods (Doria et al., 2025; Dash et al., 2025). The growth of robo-advisors further illustrates AI's role in automating and expanding access to financial services, despite ongoing concerns about adaptability and accountability and regulatory requirements (Statista, 2022).

Current research shows divided results because different fields use different methods to study their particular geographical areas. The need for Explainable Artificial Intelligence and the European Union's AI Act and other regulatory frameworks arose because organizations face difficulties with AI systems that use black-box technology to maintain model transparency and meet

compliance requirements and uphold ethical standards (Burrell 2016; Adadi and Berrada 2018; Montagnani et al. 2024). Organizations need to conduct systematic research that combines their technological advancements with governance progress to address current issues.

Accordingly, this study employs a bibliometric analysis of 995 peer-reviewed publications indexed in the Scopus database between 2015 and 2025 to map the intellectual structure of research on AI-driven financial engineering and financial decision-making. The study objectives include three main goals which are to assess scientific output development in the field through its different phases of progress, to identify important journals and authors and institutions and countries, and to study major research topics together with new research areas which will help develop a clear research plan for the future.

This study addresses the following research questions:

- RQ1. The research study investigates three elements of artificial intelligence research in financial engineering and financial decision-making which include scientific output and growth pattern and citation impact from 2015 until 2025?
- RQ2. The research study identifies which journals and authors and publications have made the greatest contributions to developing the research foundation of artificial intelligence in financial engineering and financial decision-making?
- RQ3. The research study examines how research activities distribute themselves throughout different countries and institutions while international collaboration networks contribute to knowledge production and dissemination?
- RQ4. What is the conceptual and thematic structure of artificial intelligence–driven financial engineering and AI-based financial decision-making research, and how have dominant themes and emerging research fronts evolved over time?

The remainder of the paper is organized as follows. Section 2 reviews the relevant literature, Section 3 outlines the materials and methods, Section 4 presents the bibliometric results, Section 5 discusses the findings, and Section 6 concludes the study.

II. THE ORETICAL FRAMEWORK AND PREVIOUS STUDIES:

Financial engineering through banking and accounting and finance experienced a complete transformation during the period from 2015 until 2025 because organizations began to use Artificial Intelligence technology. The field has moved away from using traditional linear econometric models which depend on classical assumptions to adopt data-driven machine learning methods because financial data has become more accessible. The financial industry has demonstrated this transformation through its rapid rise of AI-related research papers and the implementation of AI technologies in its financial establishments (Ahmed et al., 2022; Muthukannan et al., 2021).

The combination of AI and deep learning with big data has enabled banking and financial services to improve their operational efficiency while achieving better transaction accuracy and controlling costs because this technology enhances their ability to predict credit assessment and financial decision-making (Dyba and Gernego, 2019; Mosteanu and Faccia, 2020). The systems decrease dependence on human judgment while they help to eliminate cognitive biases which results in greater analytical reliability (El Hajj and Hammoud, 2023).

There exists a significant amount of research which investigates how artificial intelligence technologies apply to market prediction and trading activities. Recent studies extend traditional

technical and fundamental analysis by incorporating enriched financial indicators, including recent accounting and market variables, which improve predictive accuracy when combined with machine learning models (Agusta et al., 2024; Beaver et al., 2020). Financial data analysis shows that deep learning systems which include LSTM and GRU networks deliver better results than traditional linear models because they can model complex financial patterns and time-based relationships (Ferrara and Ciano, 2024; Wang et al., 2024). Financial institutions expand their algorithmic trading systems because of these technological developments.

AI technology extends its functions from market applications to serve as an essential component for risk management and credit scoring and financial stability assessment. The study shows that machine learning methods which include Random Forests and Support Vector Machines outperform traditional statistical methods in their ability to predict financial distress and bankruptcy (Doria et al., 2025). AI-based monitoring systems in corporate finance and governance help organizations reduce agency problems while improving their oversight processes to achieve data-driven governance standards (Dibra and Sejdinaj, 2025).

AI systems in accounting and auditing fields provide organizations with continuous transaction monitoring and real-time anomaly detection capabilities, which enhance their ability to detect fraud and conduct effective audits. The banking sector requires artificial intelligence applications to maintain accurate accounting standards and meet regulatory obligations.

The expansion of robo-advisory services demonstrates how artificial intelligence technology impacts personal finance management and wealth management services. While robo-advisors increase accessibility and automation, empirical evidence reports mixed performance outcomes and raises concerns regarding adaptability during periods of market stress and legal accountability (Statista, 2022; Tahvildari, 2025).

Despite these advances, the opacity of many AI models presents challenges for transparency, regulation, and trust—particularly in banking and accounting contexts. Explainable AI techniques, which include both SHAP and LIME, have gained importance because they provide support for regulatory compliance and create systems that can be easily understood (Adadi and Berrada, 2018; Gunning, 2016). The regulatory frameworks which include GDPR and the new AI-specific regulations mandate organizations to provide explainable systems which operate with high-risk financial applications. The literature demonstrates that AI has become increasingly essential for banking and accounting and finance operations because different fields and research methods and geographical areas create various implementation challenges. The research field requires a dedicated bibliometric study because application-driven studies dominate the field and technological advancements do not match existing regulatory frameworks. Accordingly, this study employs a Scopus-based bibliometric analysis to map the intellectual structure of AI research in financial engineering and to identify key themes, contributors, and emerging research directions relevant to financial decision-making.

III. METHOD AND PROCEDURES:

This study employs a systematic bibliometric research design to quantitatively map the scientific literature on artificial intelligence in financial engineering and AI-based financial decision-making from 2015 to 2025. The analysis combines performance indicators and science-mapping techniques to examine the field's intellectual structure, collaboration patterns, and thematic evolution. Specifically, the study aims to identify dominant theoretical foundations, analyze collaboration networks among authors, institutions, and countries, and detect emerging research themes.

The research examines AI applications in financial engineering and financial decision-making through its review of peer-reviewed journal articles and review papers which include machine learning-based financial modeling and algorithmic trading and AI-driven risk assessment and FinTech and digital finance. Only English-language publications indexed in Scopus within the subject areas of Business, Management and Accounting, and Economics, Econometrics and Finance were included.

Bibliometric data were retrieved from the Scopus database on January 3, 2026, covering publications from 2015 to 2025. The search was restricted to titles, abstracts, and author keywords using the following query: (TITLE-ABS-KEY (“Artificial Intelligence”) AND TITLE-ABS-KEY (“financial engineering” OR “stock market” OR “financial markets” OR “financial derivatives” OR “financial management” OR “decision making” OR “digitalization of investment”)) AND PUBYEAR > 2014 AND PUBYEAR < 2026.

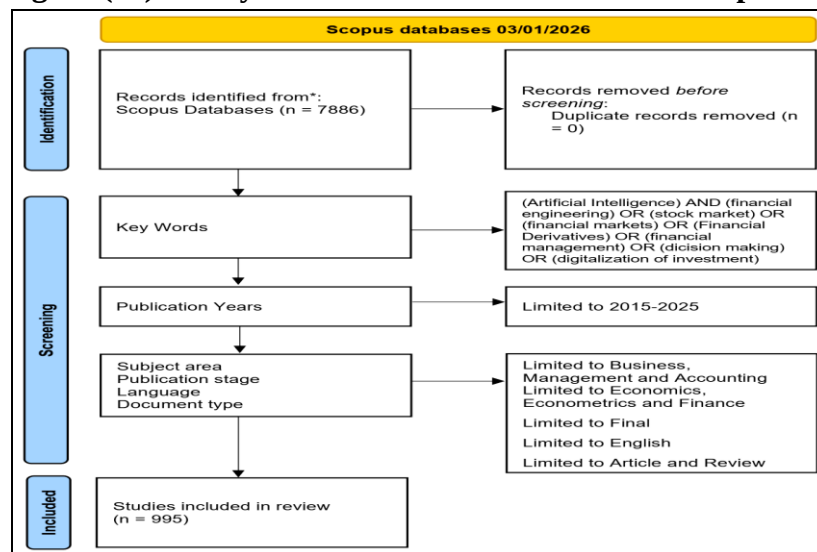
The initial search returned 7,886 records. After filtering by subject area, document type (articles and reviews), language, and publication status, and after removing duplicates and irrelevant records, the final dataset comprised 995 publications. This selection process adhered to the PRISMA guidelines, as illustrated in Figure 1.

Co-citation analysis was applied to identify the core knowledge base of the field, while co-authorship analysis examined collaboration patterns among authors, institutions, and countries. In addition, co-word analysis was conducted to detect dominant themes and emerging research topics based on keyword co-occurrence.

Bibliometric analysis was performed using the Bibliometrix package (Biblioshiny interface) in R for descriptive statistics, performance indicators, and trend analysis. Network visualization and clustering were conducted using VOSviewer. Microsoft Excel was used for preliminary data organization and basic validation.

The study relies exclusively on secondary data from publicly available sources and therefore required no ethical approval. The dataset contains no personal or confidential information. The search strategy is fully reproducible, and processed data and visual outputs are available from the corresponding author upon reasonable request.

Figure (01): Analytical framework and data selection process



Source: Prepared by the Authors

IV. STUDY RESULTS (ANALYSIS AND DISCUSSION):

1. Evolution of Scientific Production (RQ1):

Table 1 presents a synthesis of the fundamental bibliometric attributes of the Scopus-indexed literature concerning artificial intelligence (AI) within the domains of financial engineering and financial decision-making, spanning the years 2015 to 2025, thus directly addressing RQ1. The dataset encompasses 995 documents disseminated across 427 distinct sources, which suggests a wide-ranging and varied publication environment. The domain exhibits a remarkably strong growth trajectory, as evidenced by an annual growth rate of 45.87%. This signifies a rapid escalation in scientific production, particularly during the latter stages of the examined timeframe. This expansion underscores the increasing integration of artificial intelligence techniques, encompassing machine learning, deep learning, and intelligent optimization, within financial engineering applications and decision-support systems.

The collected works demonstrate substantial scientific influence, as indicated by an average of 21.74 citations per document, suggesting considerable academic prominence and impact for the research disseminated. Despite the field's relative novelty, as evidenced by the low average document age of 2.9 years, citation rates are nonetheless robust, thereby underscoring the strategic and methodological significance of AI-driven financial research. The 7921 cited references together establish both theoretical depth and accumulated knowledge base which underpins this research area. The existing scholarship on this topic demonstrates a significant prevalence of co-authorship, with an average of 3.29 authors per publication. The research shows that 29.65 percent of published works result from international partnerships which demonstrate how financial research using artificial intelligence operates across multiple countries and academic disciplines. The field depends on collaborative work because researchers produce single-authored publications at a low rate with only 137 documents existing as single-author works. The document type distribution shows an extreme imbalance because original research articles (935) outnumber review articles (60). The current research activity in the field shows active empirical research work which has not yet reached a stage of theoretical stability. Table 1 displays artificial intelligence research growth in financial engineering and financial decision-making which starts from 2015 and continues until 2025. The research experienced this expansion through an increase in international collaboration and a substantial rise in citation volume. These findings support the idea that this area of research is developing rapidly and maturing, which is what we expected based on RQ1.

Table (01): Descriptive statistics of the dataset

Description	Results
Timespan	2015:2025
Sources (Journals, Books, etc)	427
Documents	995
Annual Growth Rate %	45,87
Document Average Age	2,9
Average citations per doc	21,74
References	7921
Keywords Plus (ID)	2307
Author's Keywords (DE)	3121
Authors	2910
Authors of single-authored docs	129

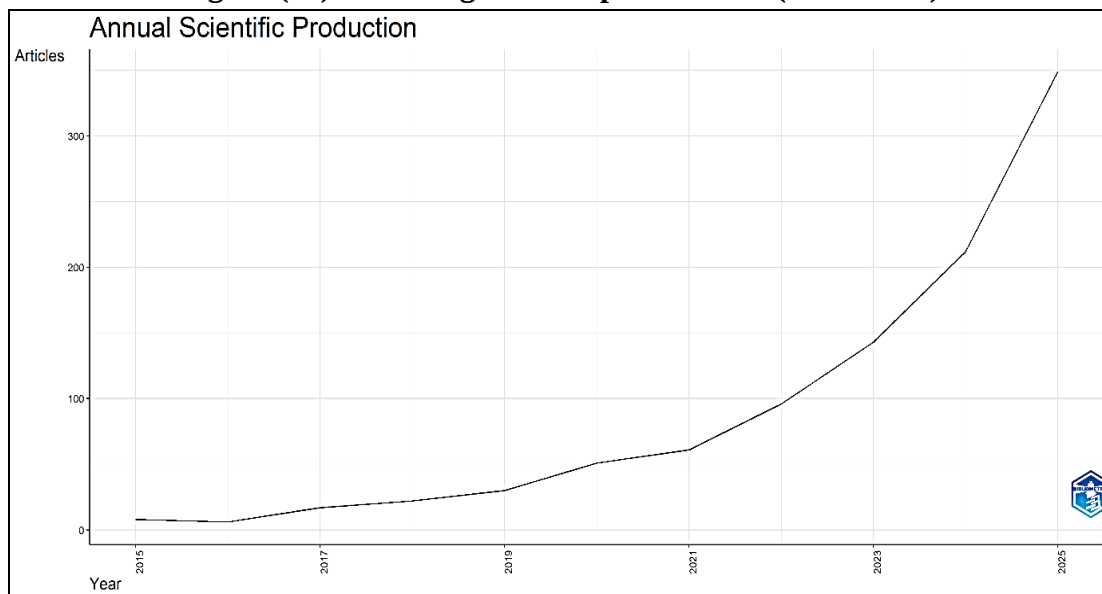
AUTHORS COLLABORATION	
Single-authored docs	137
Co-Authors per Doc	3,29
International co-authorships %	29,65
DOCUMENT TYPES	
Article	935
Review	60

Source: Extracted from Bibliometrix

Figure 2 provides clear empirical evidence of a strong and accelerating expansion in the scientific production on artificial intelligence applications in financial engineering and financial decision-making over the period 2015–2025, directly addressing RQ1. The publication trajectory reveals three structurally distinct phases. The years 2015 to 2018 are distinguished by a period of subdued and relatively constant output, indicative of an exploratory phase wherein artificial intelligence methodologies were only marginally incorporated into financial engineering research. From 2019 to 2021, production underwent a consolidation phase, marked by a steady, albeit slight, increase. This trend implies a growing methodological refinement and wider adoption of machine learning and data-driven approaches in financial research. Conversely, the field exhibits a significant inflection point beginning in 2022, transitioning into a phase of exponential growth, where annual publications show a substantial increase, peaking by 2025.

This rapid advancement signifies a substantial shift within the domain, as AI-powered models transition from niche applications to indispensable analytical instruments in financial decision-making, risk assessment, trading strategies, and financial forecasting methodologies. The ongoing research output which started in 2022 creates two main benefits because it increases the likelihood of academic citations and enhances visibility within scholarly circles. Figure 2 shows that artificial intelligence research in financial engineering has changed from a developing area to a rapidly growing, widely accepted field of study. The evidence demonstrates dynamic expansion through its upward trend which RQ1 describes.

Figure (02): Annual growth of publications (2015–2025)



Source: Extracted from Bibliometrix

2. Intellectual Structure: Core Sources, Authors, and Foundational Works (RQ2):

Table 2 shows actual research results which describe how academic journals measure productivity for their publications on artificial intelligence research in financial engineering and financial decision-making from 2015 until 2025. The publication distribution demonstrates a concentrated, yet interdisciplinary, core journal ecosystem, suggesting that scholarly understanding in this domain is primarily influenced by a small number of highly productive journals across finance, risk management, decision sciences, energy economics, and technological forecasting. The Journal of Risk and Financial Management is identified as the most prolific publication, thereby underscoring the significance of risk-focused and governance-related viewpoints in AI-driven financial engineering research. This prevalence reflects the field's strong connection to quantitative risk modeling, financial regulation, and the decision-support applications of artificial intelligence.

Concurrently, the importance of journals such as Technological Forecasting and Social Change, IEEE Transactions on Engineering Management, and Decision Support Systems underscores the methodological and technological foundations of the discipline, thus demonstrating AI's role as an analytical and strategic tool for informed decision-making. The Energy Economics and Resources Policy program shows how AI-based financial engineering technology extends its applications to various sectors of the energy finance sector and sustainability investment field and resource decision-making analytics. The productivity patterns show that AI-based financial engineering intellectual systems exist beyond traditional finance publications because they combine financial theory with computational intelligence and practical decision-making methods. Consequently, Table 2 substantiates that the core journals shaping this research field act as institutional conduits for interdisciplinary knowledge integration, reinforcing the bibliometric evidence that AI-driven financial decision-making is evolving through cross-domain scholarly convergence rather than disciplinary isolation.

Table (02): Most Relevant Journals

Source Title	Articles
Journal of Risk and Financial Management	31
Technological Forecasting and Social Change	20
Energy Economics	18
Finance Research Letters	18
IEEE Transactions on Engineering Management	15
Computational Economics	13
Decision Support Systems	13
International Review of Financial Analysis	13
Resources Policy	12
Cogent Business and Management	11

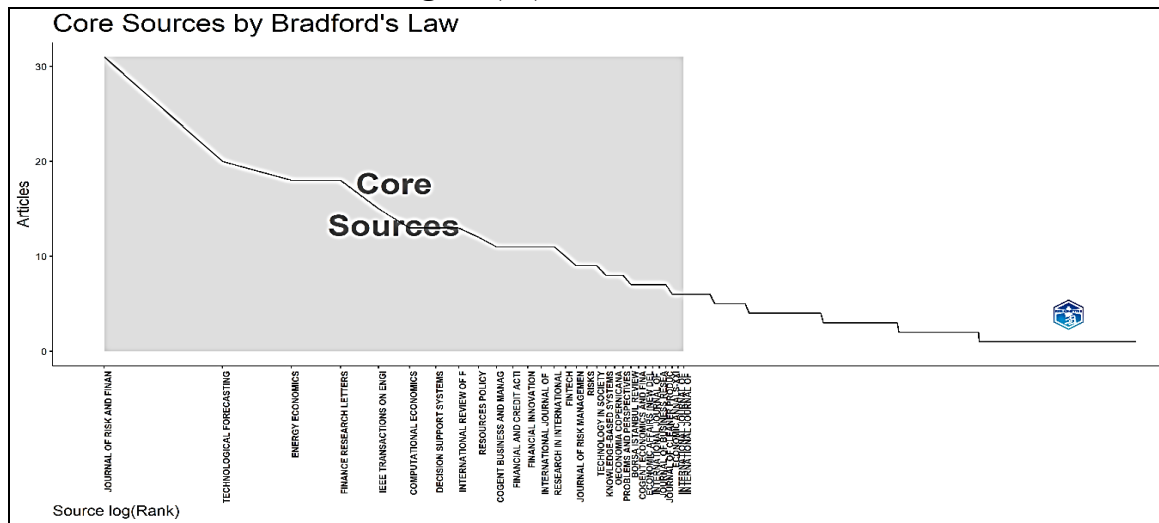
Source: Extracted from Bibliometrix

Figure 3 reports the application of Bradford's Law to identify the core publication outlets structuring the literature on artificial intelligence in financial engineering and financial decision-making over the period 2015–2025. The Bradford distribution demonstrates a significant concentration of academic publications within a restricted group of journals, thereby validating the presence of a clearly delineated core of sources that primarily drive knowledge creation in this field. The published articles in this study are based on a restricted set of journals which includes five specific journals. The Journal of Risk and Financial Management, Technological Forecasting and

Social Change, Energy Economics, Finance Research Letters, and IEEE Transactions on Engineering Management constitute a small part of available journals which produce most of the published articles. The other journals which exist outside this main group of journals produce minimal content which their publications spread out across multiple Bradford zones that show declining output rates. This unequal distribution suggests that research on AI-driven financial engineering is not widely dispersed across various publications; rather, it is concentrated in journals that integrate financial economics, risk management, forecasting, and computational decision systems.

Regarding RQ2, these key journals serve as the principal intellectual framework for disseminating seminal works and establishing citation-based connections among prominent scholars. As a result, the preeminence of these publications highlights their role in determining theoretical perspectives, methodological norms, and research priorities within the domain of artificial intelligence and financial decision-making; conversely, less central journals primarily act as secondary dissemination pathways, lacking the capacity to foster intellectual unity.

Figure (03): Bradford's Law



Source: Extracted from Bibliometrix

As reported in Table 3, the productivity distribution of authors reveals a highly concentrated and asymmetric authorship structure within the literature on artificial intelligence in financial engineering and financial decision-making. While a small number of researchers have published many papers, fractionalized authorship metrics provide a more accurate view of intellectual contribution, considering collaboration and co-authorship patterns. While LI Y and WANG Y have the most publications, their contributions, when considered fractionally, show different levels of impact. This suggests that academic influence in this field depends less on the number of publications and more on consistent, central involvement in collaborative research networks.

The presence of multiple authors exhibiting identical publication counts but disparate fractionalized scores implies an uneven distribution of authorship leadership and varying degrees of intellectual contribution throughout the publications. These findings, taken together, indicate that the intellectual foundation of artificial intelligence research within financial engineering is primarily shaped by a limited number of influential contributors embedded within interconnected co-authorship networks, rather than by individual authors with substantial output. The study found that prominent authors who produced work at higher productivity levels had significant influence on

field research and distribution of information through their academic work. The study found that authors who produced work at higher productivity levels had a major impact on establishing academic connections through their journal publications and citation patterns, which helped define the intellectual framework of the discipline.

Table (03): Most Relevant Authors

N	Authors	Articles	Articles Fractionalized	N	Authors	Articles	Articles Fractionalized
1	LI Y	11	2,73	6	LI X	5	1,45
2	WANG Y	9	2,95	7	LIU Y	5	1,42
3	GHOSH I	6	1,57	8	WANG S	5	1,32
4	CHEN Y	5	1,57	9	ZHANG L	5	1,68
5	KUMAR A	5	1,17	10	ZHANG X	5	1,21

Source: Extracted from Bibliometrix

Table 4 synthesizes the most highly cited documents within the Scopus corpus and provides citation-based evidence on the foundational publications shaping the intellectual structure of artificial intelligence (AI) in financial engineering and financial decision-making, thereby directly addressing RQ2. The results indicate that the discipline is fundamentally underpinned by a body of conceptually important research, primarily disseminated in high-impact Q1 journals from 2019 to 2022, thereby demonstrating both theoretical integration and methodological progress. Highly cited contributions such as Lu et al. (2020) and Sjödin et al. (2020), demonstrate the highest total citation counts, thereby highlighting their significance in establishing AI-enabled service systems, digital servitization, and organizational transformation—conceptual foundations that indirectly influence AI adoption within financial engineering settings.

Mhlanga (2020), Angelis and Ribeiro da Silva (2019), Ahmed et al. (2022), and Bussmann et al. (2020), all of which are more finance-specific in their focus, exhibit considerable citation intensity and elevated normalized citation scores, thereby underscoring their significant intellectual impact, notwithstanding their relatively recent publication dates. Specifically, research centered on artificial intelligence applications in financial inclusion, the creation of value through blockchain technology, explainable machine learning methodologies, and AI-based credit risk management demonstrates heightened normalized citation values, indicating their crucial role in establishing methodological benchmarks and decision-support frameworks within the field of financial engineering.

The citation patterns presented in Table 4, when considered collectively, indicate that the intellectual framework of this domain is shaped by an interdisciplinary fusion of artificial intelligence methodologies, digital transformation theory, and finance-focused applications. The core knowledge base of the field depends on a central collection of journals which includes the Journal of Service Theory and Practice, Technology in Society, Long Range Planning, and Research in International Business and Finance. The research results show that authors and publications achieve distinction through two criteria which include their volume of work and their enduring effect on citation patterns. This highlights their importance in shaping the field of knowledge and guiding financial decision-making research, particularly through AI-based analytical methods.

Table (04): Most Cited Documents

Author (year)	Title	TC	TC per Year	Normalized TC
Lu et al., (2020)	Service robots, customers and service employees: what can we learn from the academic literature and where are the gaps?	479	68,43	6,11
Sjödin et al., (2020)	An agile co-creation process for digital servitization: A micro-service innovation approach	432	61,71	5,51
Mhlanga, (2020)	Industry 4.0 in Finance: The Impact of Artificial Intelligence (AI) on Digital Financial Inclusion	387	55,29	4,94
Brunetti et al., (2020)	Digital transformation challenges: strategies emerging from a multi-stakeholder approach	374	53,43	4,77
Galaz et al., (2021)	Artificial intelligence, systemic risks, and sustainability	349	58,17	6,43
Volberda et al., (2021)	Strategizing in a digital world: Overcoming cognitive barriers, reconfiguring routines and introducing new organizational forms	321	53,50	5,91
Angelis & Ribeiro da Silva, (2019)	Blockchain adoption : A value driver perspective	315	39,38	8,47
Cubric, (2020)	Drivers, barriers and social considerations for AI adoption in business and management: A tertiary study	301	43,00	3,84
Ahmed et al., (2022)	Artificial intelligence and machine learning in finance: A bibliometric review	296	59,20	9,60
Bussmann et al., (2020)	Explainable Machine Learning in Credit Risk Management	287	47,83	5,29

Source: Extracted from Bibliometrix

Figure 4 illustrates the co-citation network underlying the literature on artificial intelligence (AI) in financial engineering and financial decision-making, thereby addressing Research Question 2. Applying a minimum threshold of five citations, the analysis identified 69 influential references from a total of 7,921 cited works, which were organized into eight interconnected knowledge domains. The resulting intellectual structure demonstrates how foundational financial theories, computational methods, and application-oriented studies collectively shape the development of the field.

The largest cluster integrates classical financial economics with early computational finance research, combining foundational models such as Black–Scholes, GARCH, and factor pricing frameworks with emerging machine-learning and sentiment-analysis applications. Strong co-citation relationships among studies on volatility forecasting, market microstructure, and investor sentiment indicate that AI-based financial decision-making remains firmly grounded in established financial theory rather than constituting an isolated computational discipline.

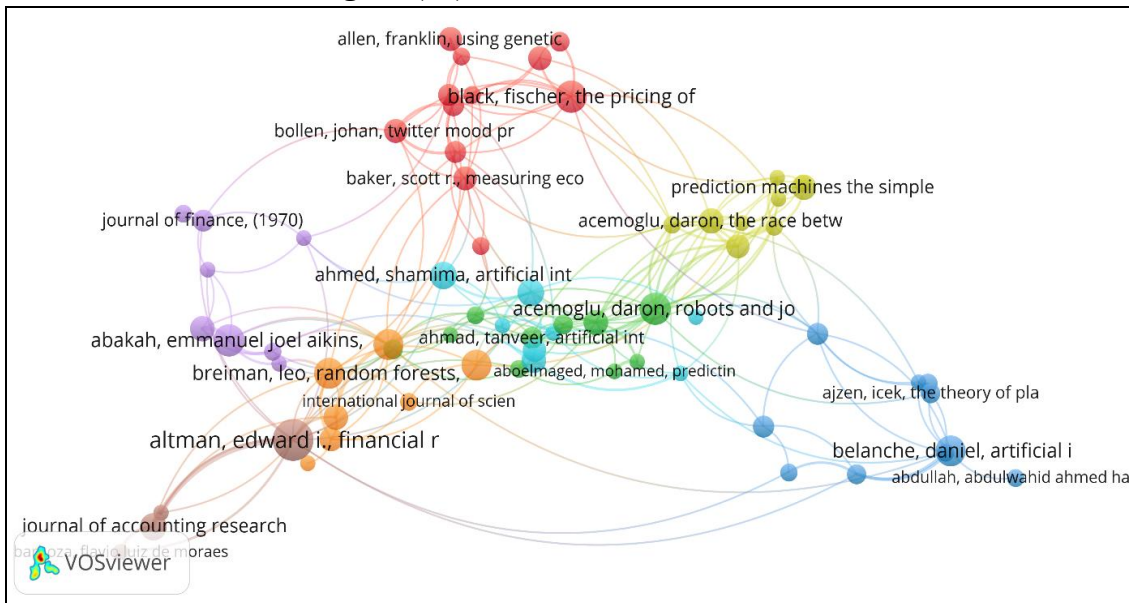
Clusters 2 and 4 focus on the economic implications of AI, drawing heavily on the contributions of Acemoglu and related macroeconomic and policy-oriented research. These clusters emphasize the integration of AI into analyses of productivity, labor markets, and economic growth, reflecting the expansion of financial engineering research beyond technical modeling toward broader socioeconomic considerations.

Clusters 3 and 6 address FinTech adoption, regulation, and institutional transformation. Influenced by behavioral frameworks such as the Theory of Planned Behavior, these clusters highlight the increasing relevance of robo-advisory systems, regulatory technology, and AI

governance, demonstrating a shift from purely technical applications toward decision-oriented and institutional perspectives.

Clusters 5 and 8 concentrate on AI-driven risk modeling and predictive analytics, including bankruptcy prediction, neural networks, and machine-learning-based asset connectedness. The frequent co-citation of Altman's bankruptcy model with modern AI methodologies suggests methodological continuity in which AI enhances traditional financial risk assessment tools. Finally, Cluster 7 emphasizes explainable and interpretable machine-learning frameworks, including Random Forest and XGBoost models, underscoring the growing importance of transparency and resilience in AI-supported financial decision-making.

Figure (04): Co-citation of references



Source: Extracted from VOSviewer

3. Social and Geographical Structure of Research Collaboration (RQ3):

As shown in Table 5, the institutional distribution of publications in Artificial Intelligence in Financial Engineering and Financial Decision-Making reveals a moderately concentrated yet internationally dispersed knowledge base. A small number of universities consistently contribute to this field, with University College London at the forefront (9 publications), succeeded by Lebanese American University and various institutions from Eastern Europe and Asia, each responsible for eight or seven articles. This distribution pattern suggests that research output is not monopolized by a single geographic or institutional entity; rather, it is spread across institutions situated in Western Europe, the Middle East, Eastern Europe, South Asia, and East Asia. Therefore, this distribution implies that the field is characterized by the creation of knowledge in multiple centers. These centers, located in different regions, contribute to both theoretical and practical advancements.

Regarding RQ3, these results suggest that institutional productivity is indicative of internationally linked research hubs, as opposed to self-contained national research systems. The varied nature of highly productive affiliations additionally suggests that international collaborative networks probably serve a structuring function, allowing institutions beyond conventional financial research centers to actively engage in and disseminate knowledge within the domain. Therefore, the institutional framework presented in Table 5 corroborates the understanding that global

collaborative mechanisms promote both the geographical distribution and intellectual integration of AI-driven financial engineering research.

Table (05): Most Productive Affiliations

Affiliation	Country	Articles
University College London	UK	9
Lebanese American University	Lebanon	8
State University of Trade and Economics	Ukraine	8
Interregional Academy of Personnel Management	Ukraine	8
Xiamen University	China	7
Applied Science Private University	Jordan	7
Kyiv National Economic University	Ukraine	7
Symbiosis International Deemed University	India	7
PSB Paris School of Business	France	7
University of Johannesburg	South Africa	6

Source: Extracted from Scopus

Table 6 demonstrates that the global scientific production on Artificial Intelligence in Financial Engineering and financial decision-making is highly concentrated and unevenly distributed across countries. China leads the field with 320 publications, indicating a strong and sustained commitment to AI-driven financial engineering research between 2015 and 2025. India (207 publications) and the United States (197 publications) also represent major contributors, confirming the dominant influence of both emerging and advanced economies in shaping the intellectual structure of this research area.

The findings further reveal that AI-related financial research is not limited to traditional scientific centers. Countries such as Ukraine and the United Kingdom have also established a notable presence in the field. Meanwhile, Australia, Italy, Turkey, France, and Spain contribute fewer than 65 publications each, reflecting comparatively lower research intensity while still offering meaningful scholarly contributions.

These results directly address Research Question 3 by showing that knowledge production in AI-enabled financial engineering is concentrated within a limited number of influential countries functioning as international research hubs. The leadership of China, India, and the United States suggests that these nations not only dominate publication output but also shape research priorities, methodologies, and international collaboration patterns. Consequently, global collaboration networks appear hierarchical rather than evenly distributed, with leading countries serving as central nodes for knowledge dissemination across peripheral research systems.

Table (06): Countries' Scientific Production

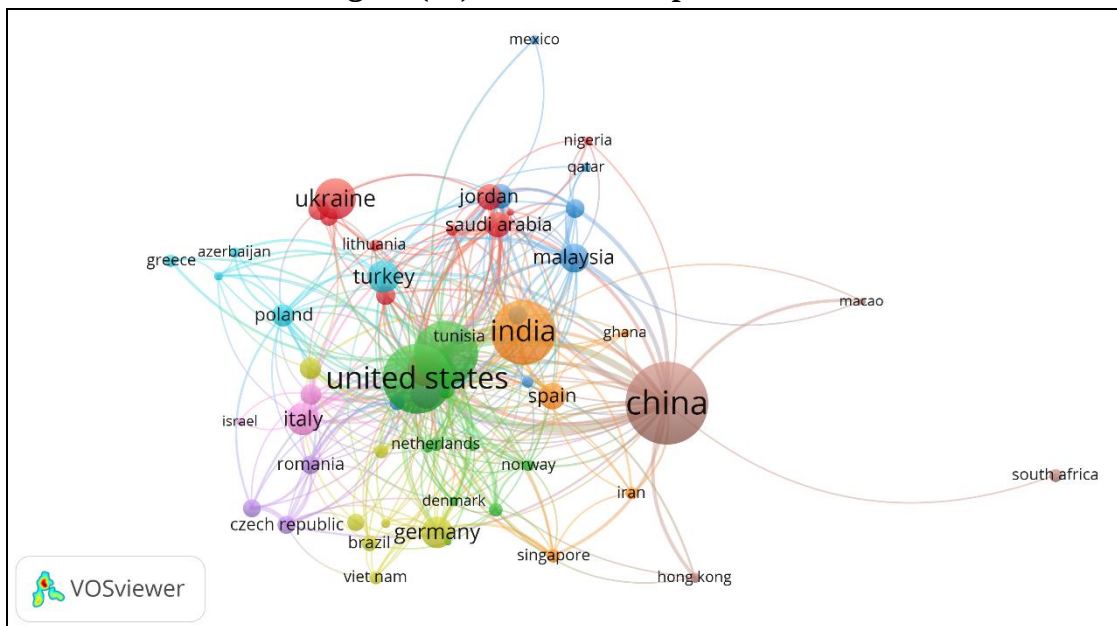
N	Country	Freq	N	Country	Freq
1	China	320	6	Australia	62
2	India	207	7	Italy	61
3	USA	197	8	Turkey	60
4	Ukraine	172	9	France	59
5	UK	163	10	Spain	55

Source: Extracted from Bibliometrix

To establish the country-level collaboration network, a minimum of five documents per country was required, while citation counts were not limited (minimum citations = 0). Consequently, 60 of the 98 countries satisfied the inclusion criteria. Figure 5 illustrates the resulting country-level co-authorship network within Artificial Intelligence in Financial Engineering research from 2015 to 2025, thereby offering direct empirical support for RQ3, which investigates the geographical and institutional distribution of knowledge and the organizational function of international collaboration networks. The results indicate a highly internationalized and network-dependent knowledge structure, characterized by an uneven distribution of research output and an organization centered around a small number of globally central hubs, alongside numerous regionally clustered collaboration blocs. The United States, China, India, and the United Kingdom, among others, function as key structural players, acting as essential connectors that integrate disparate regional groups and promote the spread of knowledge across regions. The United States, in particular, plays a significant role in brokering, connecting research communities in Europe, the Middle East, and Asia, which highlights its strong institutional ability to bring together diverse research areas. China creates a special worldwide connectedness through its connections with Asian countries and developing nations which lead to its twofold approach of building regional ties and expanding worldwide.

The presence of multiple medium-sized clusters across Europe, the Middle East, Southeast Asia, and Africa demonstrate that transnational thematic similarities now drive collaboration in this field more than geographical proximity does. The participation of developing and emerging economies across various clusters is particularly noteworthy, highlighting the significance of international co-authorship networks as essential instruments for research visibility and integration. These networks facilitate the active involvement of nations with comparatively limited domestic research capabilities in the global knowledge framework. Figure 5 proves that international collaboration networks determine how AI-based financial engineering research work is shared and organized. The networks provide access to prestigious publication outlets which enhance institutional partnerships and enable institutions to share their research methods and practical developments across the globe. The networks provide a final solution which addresses RQ3.

Figure (05): Co-authorship Network



Source: Extracted from VOSviewer

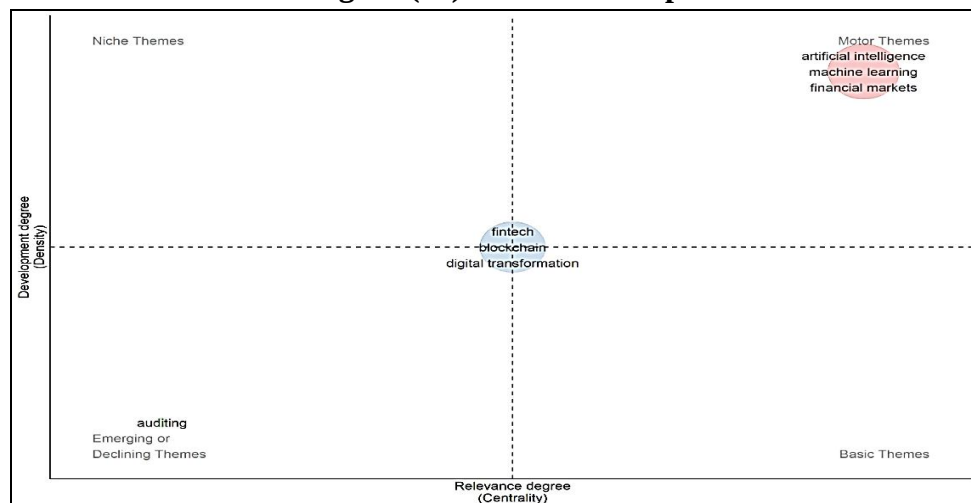
4. Conceptual and Thematic Evolution of the Field (RQ4):

Figure 6 synthesizes the conceptual and thematic architecture of artificial intelligence–driven financial engineering and AI-based financial decision-making research through a thematic mapping of keyword co-occurrence, revealing a clearly stratified knowledge structure aligned with research maturity and intellectual centrality. Addressing RQ4 directly, the map illustrates that the field is presently organized around a central motor theme cluster. This cluster is comprised of artificial intelligence, machine learning, and financial markets, and it demonstrates both high centrality and high density. Thus, this configuration implies that in financial markets, artificial intelligence enabled modeling, prediction, and optimization form the core intellectual base of the literature. Furthermore, it functions as a theoretically mature research stream and a structural driver that integrates and influences related thematic areas.

At the nexus of centrality, yet exhibiting relatively modest internal advancement, the cluster encompassing fintech, blockchain, and digital transformation occupies a transitional space, serving as a conduit between fundamental AI methodologies and practical financial engineering applications. This thematic positioning implies a continuing consolidation phase, wherein technological infrastructures and digital financial ecosystems are gradually integrating AI-driven decision-making principles, although full conceptual maturity has not yet been achieved. In contrast integration into the emerging or declining quadrant, which is characterized by lower density and lower centrality, implies a peripheral but potentially evolving research frontier. In this context, the application of AI remains fragmented and underdeveloped when contrasted with the dominant financial engineering discourse.

The absence of well-defined niche themes, which are marked by considerable internal cohesion yet minimal centrality, implies a restricted level of thematic specialization, somewhat distanced from the core of the discipline. This finding reinforces the understanding that research concerning AI's role in financial decision-making currently demonstrates a tendency toward convergence, as opposed to fragmentation. Overall, Figure 6 evidences a structural evolution from technology-driven experimentation toward a more integrated, market-centric and decision-oriented paradigm, thereby confirming that dominant themes have stabilized around AI-enabled financial markets, while emerging fronts are primarily associated with institutional, regulatory, and assurance-related applications of artificial intelligence in finance.

Figure (06): Thematic Map

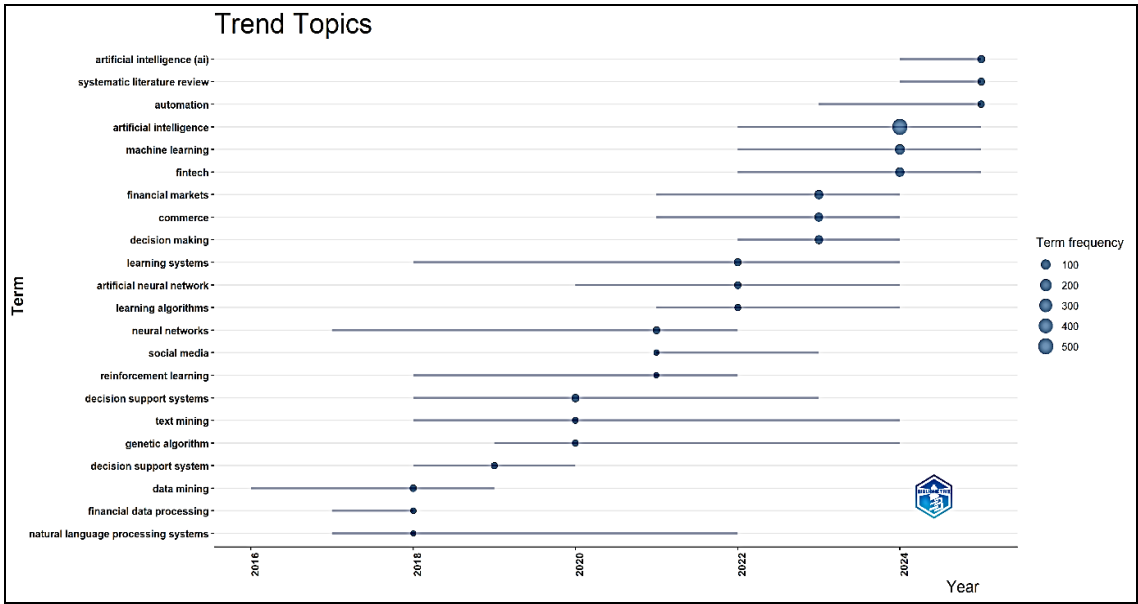


Source: Extracted from Bibliometrix

The evolving conceptual and thematic development of artificial intelligence research through financial engineering research between 2015 and 2025 shows established research frameworks and new research fields. The research results show that financial decision-making processes use advanced AI systems more than basic computational intelligence methods which include data mining and genetic algorithms and decision support systems and early neural network applications. From roughly 2019 onwards, the literature exhibits a significant increase in the prominence of machine learning, artificial neural networks, and learning algorithms as core methodological foundations, indicating a maturation phase in which AI techniques are shifting from exploratory modeling to decision-focused implementation within financial settings.

The recent surge in artificial intelligence, machine learning, fintech, financial markets, and decision-making underscores a convergence of methodological innovation and application-driven financial engineering, thereby emphasizing a transition towards real-time, automated, and intelligence-enhanced decision frameworks. Furthermore, the emergence of topics such as automation, systematic literature review, and AI-based learning systems suggests a reflexive and meta-analytical consolidation within the field, which is indicative of scholarly maturity and paradigm stabilization. These trends, taken together, confirm a shift in the research landscape. It has moved from a focus on algorithmic experimentation to a unified, decision-making AI system in financial engineering. Within this system, intelligent technologies are becoming the core infrastructure for financial analysis, market operations, and strategic decision support. This supports the evolving thematic development suggested in RQ4.

Figure (07): Trend Topics



Source: Extracted from Bibliometrix

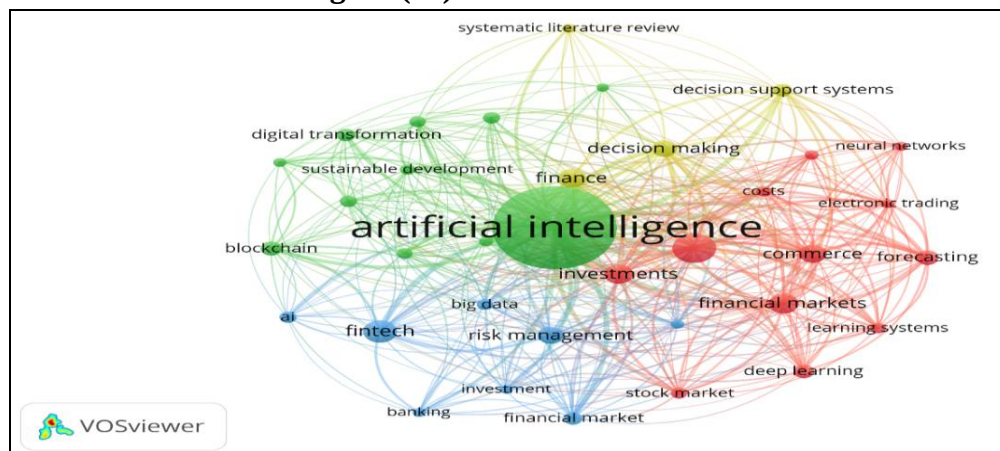
Figure 8 presents the co-word analysis network that maps the conceptual and thematic architecture of artificial intelligence-driven financial engineering and AI-based financial decision-making research during the period 2015–2025. Based on a threshold of 20 keyword occurrences, only 35 keywords out of 4768 met the inclusion criterion, indicating a high degree of thematic concentration and maturity in this research domain. The resultant network is organized into four distinct clusters, each of which signifies a unique, yet interconnected, knowledge domain that collectively informs the investigation of RQ4.

The initial cluster encompasses the methodological and application-focused essence of artificial intelligence within financial markets, primarily characterized by machine learning paradigms such as artificial neural networks, deep learning, and various learning systems. These methodologies are directly employed in forecasting, electronic trading, investment analysis, and the examination of stock market dynamics. This collection highlights how artificial intelligence has evolved, moving from early modeling to practical financial engineering solutions. It emphasizes the importance of accurate predictions, cost-effectiveness, and performance in the market. The second cluster encompasses the macro-level digital and sustainability-focused paradigm, wherein artificial intelligence is conceptualized as a versatile enabling technology. This technology is integrated with digital transformation, innovation, blockchain implementation, and sustainability results, encompassing both sustainable development and financial performance. The inclusion of "China" within this cluster indicates geographically specific research areas that substantially contribute to AI-driven digital finance and sustainability transitions.

The third cluster focuses on financial infrastructure and risk management which connects artificial intelligence with big data and financial technology to banking and financial markets through risk assessment and management practices. This cluster suggests a consolidation of AI applications within prudential finance, regulatory technology, and data-intensive risk analytics, representing a transition from solely predictive goals to a focus on system-wide stability and resilience. The fourth cluster, in contrast, represents the decision-oriented and reflective knowledge stream, incorporating decision-making processes, decision support systems, finance, and systematic literature reviews. This cluster highlights the increasing importance of explainable, decision-centric AI frameworks and the formalization of knowledge through evidence synthesis, thereby indicating a phase of maturation within the field.

The complete co-word structure which appears in Figure 8 demonstrates how research in AI-driven financial engineering has evolved through time. The research field has moved from its previous state of methodological separation into a coordinated system which uses multiple research themes. The prevailing themes are primarily concerned with machine learning applications in the market and digital transformation. Simultaneously, emerging research areas are increasingly incorporating sustainability, risk governance, and decision support viewpoints. These observations directly respond to RQ4 by elucidating the enduring conceptual foundations and the evolving research priorities that have influenced AI-based financial decision-making throughout the past ten years.

Figure (08): Co-word Network



Source: Extracted from VOSviewer

5. Discussion:

The bibliometric analysis demonstrates that artificial intelligence (AI) has evolved from a specialized computational instrument into a General-Purpose Technology (GPT) that is fundamentally transforming financial economics. Scientific production accelerated significantly after 2022, reflecting a shift from conventional linear econometric models toward advanced non-linear and high-dimensional AI techniques for complex financial decision-making. The intellectual structure of the field highlights the growing importance of Recent Fundamental Values (RFVs) and deep learning architectures, particularly Multilayer Perceptron (MLP) and Long Short-Term Memory (LSTM) models, which outperform traditional methods in capturing non-linear relationships and long-term market dependencies. This transformation has strengthened algorithmic and high-frequency trading practices and contributed to the transition from the Efficient Market Hypothesis (EMH) toward the Adaptive Market Hypothesis (AMH).

Thematic analysis further indicates that AI has become central to risk management, fraud detection, and bankruptcy prediction, with machine learning models such as Random Forests and XGBoost achieving predictive accuracies superior to traditional statistical approaches. Simultaneously, Explainable AI (XAI) techniques, including SHAP and LIME, have become essential for ensuring transparency and regulatory compliance. The study also reveals a geographically concentrated yet collaborative research structure dominated by China, the United States, and India, while international collaborations have enhanced global innovation capacity. Overall, AI-based financial engineering has evolved into an integrated decision-making ecosystem emphasizing sustainability, ethical standards, interpretability, and real-world financial applications.

V. CONCLUSION:

This study analyzed 995 Scopus-indexed publications to examine the evolution of artificial intelligence (AI) applications in financial engineering and financial decision-making between 2015 and 2025. The findings indicate that the field has transitioned from an exploratory stage prior to 2018 into a rapidly expanding research domain, characterized by an annual growth rate of 45.87% and an average of 21.74 citations per document, reflecting its growing academic and practical significance.

The intellectual structure of the field is centered around influential journals, particularly the Journal of Risk and Financial Management, and leading scholars such as LI Y and WANG Y. Foundational research integrates traditional financial models, including Black–Scholes and GARCH frameworks, with advanced computational intelligence and Explainable AI (XAI) techniques for applications such as credit risk assessment.

The global research landscape demonstrates a hierarchical yet collaborative structure, with China, India, and United States emerging as the leading contributors, while University College London represents a major institutional hub. International collaboration has also enabled peripheral research communities to participate more actively in knowledge production.

Thematic developments reveal a clear shift from traditional linear econometric methods toward high-dimensional and non-linear AI models. Deep learning architectures such as LSTM and MLP have strengthened forecasting and trading systems, while machine learning methods including Random Forest and XGBoost have significantly improved risk management and bankruptcy prediction accuracy. Despite these advances, the study emphasizes the necessity of transparent, resilient, and ethically governed AI systems through the adoption of XAI tools, systemic risk controls, and regulatory frameworks addressing forecasting bias and algorithmic instability.

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