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Mapping the Research Landscape of Artificial Intelligence and Machine Learning in Finance: A Bibliometric Analysis

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Abstract

The rapid advancements in Artificial Intelligence (AI) and Machine Learning (ML) technologies have profoundly impacted the financial sector, offering significant improvements in areas such as risk management, algorithmic trading, fraud detection, credit scoring, and customer service. Using Scopus, this study conducts a bibliometric review of research on artificial intelligence and machine learning in finance. A BibTeX dataset of 103 English articles and reviews (1996–2026) from Economics/ Econometrics/ Finance and Business/ Management/ Accounting was analysed to map growth, impact, and collaboration. Output remained sparse until 2017, then expanded rapidly, peaking in 2024–2025. The literature is highly collaborative and influential. Dominant themes include digital finance, risk management, and sustainability-oriented finance.

Keywords: *Artificial intelligence; Machine learning; Finance; Bibliometric analysis; Digital finance*

1. Introduction

Artificial Intelligence (AI) and Machine Learning (ML) have transcended their status as mere buzzwords within the technology sector, emerging as transformative forces that are reshaping industries globally, with the financial sector being a primary beneficiary. Within the domain of finance, these technologies have progressed beyond theoretical applications to become integral components of daily operations, fundamentally transforming the interactions between financial institutions, investors, and consumers with the market. From algorithmic trading and fraud detection to credit scoring and customer service, AI and ML have unlocked unprecedented efficiencies, capabilities, and opportunities. As technology continues to

evolve, the financial sector is undergoing a digital transformation, with the rapid development of AI and ML playing a central role in this change.

The advent of AI in finance has been propelled by its capacity to analyze vast quantities of structured and unstructured data, discern patterns, and provide actionable insights in real time. Machine learning algorithms, a subset of AI, possess the ability to learn from historical data and adapt without explicit programming, enabling them to continually enhance and refine financial models over time (Brynjolfsson & McAfee, 2017). This adaptive capability is particularly valuable in the financial sector, where market conditions are in constant flux, necessitating swift and accurate decision-making.

One of the most significant areas in which AI and ML have impacted finance is in the domain of risk management. Financial institutions have long relied on data analysis to identify potential risks, but AI has elevated this practice to new heights. ML algorithms can analyze historical market data, financial statements, and even social media trends to predict market movements, identify emerging risks, and detect anomalies. For instance, in credit scoring, AI and ML models have enhanced the accuracy of risk assessments by incorporating a broader range of data points, including non-traditional sources such as social media activity, payment histories, and consumer behavior patterns (Chen & Zhang, 2019). This has enabled lenders to make more informed decisions, thereby reducing the risk of defaults and improving the accessibility of credit for underserved populations.

Artificial intelligence (AI) and machine learning (ML) have significantly advanced fraud detection beyond traditional risk management approaches. Conventional fraud detection systems predominantly relied on rules-based methodologies, which were limited to identifying known patterns of fraudulent activity. In contrast, AI-driven systems possess the capability to discern novel, previously undetected fraudulent behaviors by analyzing extensive datasets in real time and learning from historical fraud instances. This advancement has markedly improved the capacity of financial institutions to identify and avert fraud preemptively, resulting in substantial annual financial savings (Dastin, 2017). For instance, ML models can uncover subtle patterns in transaction data that might otherwise remain unnoticed, such as atypical spending behaviors or variations in transaction frequency, which may signal fraudulent activity. This proactive methodology proves considerably more effective than traditional approaches, which often detect fraud only post-occurrence.

Another significant domain where AI and ML have exerted considerable influence is algorithmic trading. Algorithmic trading entails the utilization of computer programs to execute buy and sell orders based on predefined criteria. AI and ML algorithms have furthered this concept by enabling machines to make real-time trading decisions through the analysis of vast datasets, encompassing market data, news articles, and even sentiment analysis from social media platforms. These algorithms can execute trades at speeds surpassing human capabilities, thereby capitalizing on transient market opportunities and optimizing trading strategies (Krauss, Do, & Huck, 2017). The outcome has been the enhancement of market efficiency, reduction in transaction costs, and improved investor outcomes. However, this development has also raised concerns regarding market stability, as

the rapid execution of trades can induce significant volatility, particularly during periods of market stress.

Customer service represents another sector where AI and ML have had a transformative impact. The introduction of AI-powered chatbots and robo-advisors has revolutionized customer service within the financial sector. These AI-driven tools can engage with customers continuously, providing answers to inquiries, offering financial advice, and even executing transactions, all without necessitating human intervention. This has substantially improved the customer experience, rendering financial services more accessible and affordable, especially for individuals lacking the resources to seek personalized financial advice from human advisors. For example, robo-advisors employ AI to assess an individual's financial situation, risk tolerance, and investment objectives to create personalized investment portfolios. This development has democratized access to investment services, previously exclusive to high-net-worth individuals, by offering affordable and automated financial advice to a broader demographic (Dastin, 2017).

Artificial intelligence (AI) and machine learning (ML) have significantly contributed to the emergence of financial technology (fintech) companies, which are increasingly challenging traditional financial institutions by offering innovative, technology-driven financial products and services. These companies utilize AI to deliver products that are more rapid, cost-effective, and personalized compared to those offered by conventional banks. By employing AI to optimize operations and minimize overhead costs, fintech companies are able to offer services that are more adaptable and accessible to consumers. This development has resulted in a proliferation of digital banking, mobile payment solutions, peer-to-peer lending platforms, and even blockchain-based applications that facilitate decentralized finance (DeFi). For example, AI is employed to evaluate credit risk in peer-to-peer lending platforms by analyzing alternative data sources that traditional banks may overlook, such as payment histories, social media activity, and utility bill payments. This approach has enabled individuals and small businesses to access loans and financial services that might otherwise be unavailable to them (Krauss et al., 2017). Despite the numerous advantages, the integration of AI and ML in the financial sector also presents several challenges. A primary concern is the ethical implications of utilizing AI in decision-making processes. AI algorithms are only as reliable as the data on which they are trained, and biased or incomplete data can lead to unfair or discriminatory outcomes. For instance, biased lending algorithms could result in discrimination against certain groups, such as women or minority communities, by denying them access to credit based on prejudiced data. Furthermore, the reliance on AI for financial decision-making raises issues of accountability and transparency, as decisions made by algorithms can be difficult to explain or audit. There is also the concern of job displacement, as automation and AI systems increasingly assume tasks traditionally performed by humans, potentially leading to significant job losses in the financial sector. This study investigates the impact of AI and ML on the finance industry, analyzing both the opportunities and challenges these technologies present. While AI has undoubtedly led to substantial improvements in operational efficiency, risk management, and customer service, it also poses important ethical,

regulatory, and employment-related questions that require attention. As AI and ML continue to advance, financial institutions must balance leveraging the capabilities of these technologies with ensuring that their applications are ethical, transparent, and compliant with regulatory frameworks.

This study investigates the influence of artificial intelligence (AI) and machine learning (ML) on the finance industry, analyzing both the opportunities and challenges these technologies present. While AI has undeniably enhanced operational efficiency, risk management, and customer service, it also poses significant ethical, regulatory, and employment-related questions that require attention. As AI and ML continue to advance, financial institutions must balance leveraging the capabilities of these technologies with ensuring their applications are ethical, transparent, and compliant with regulatory frameworks.

2. Review of Literature

The integration of Artificial Intelligence (AI) and Machine Learning (ML) into the financial sector has significantly transformed the interactions between financial institutions, investors, and consumers with financial markets and services. AI and ML facilitate remarkable advancements across various financial operations, including risk management, algorithmic trading, fraud detection, credit scoring, and customer service. However, while these technologies offer opportunities for enhanced efficiency, cost reduction, and improved decision-making, their adoption also raises substantial concerns regarding data bias, accountability, and job displacement. This literature review explores the diverse applications of AI and ML in the financial industry, emphasizing the advancements, challenges, and potential implications for the future.

The Role of AI and ML in Risk Management

Risk management is a pivotal function within financial services, and the integration of Artificial Intelligence (AI) and Machine Learning (ML) in this domain has resulted in more effective and efficient methodologies for risk assessment and mitigation. Historically, financial institutions have depended on historical data and manual processes for risk evaluation. However, the advent of AI and ML algorithms has markedly enhanced predictive capabilities. These technologies are particularly advantageous for the real-time identification of emerging risks through the analysis of extensive volumes of both structured and unstructured data, encompassing market data, economic indicators, and even social media sentiment (Brynjolfsson & McAfee, 2017). Machine learning algorithms possess the ability to discern patterns and trends within data that would be imperceptible to human analysts, thereby enabling financial institutions to implement proactive measures in response to potential risks.

Machine learning models are increasingly employed in the domain of credit risk assessment. AI-driven credit scoring models have the capability to integrate alternative data sources, including social media activity, payment histories, and behavioral data, thereby offering a more comprehensive and precise evaluation of an individual's or business's creditworthiness (Chen & Zhang, 2019). These sophisticated models mitigate the risk of credit

defaults and facilitate the extension of credit to individuals or businesses that may have been previously marginalized by traditional credit systems. Nonetheless, the application of AI in credit scoring raises significant concerns regarding fairness and transparency, as AI algorithms may inadvertently reinforce existing biases if they are trained on biased or incomplete datasets.

Fraud Detection and Prevention

Artificial Intelligence (AI) and Machine Learning (ML) have profoundly revolutionized the methodologies employed by financial institutions for fraud detection and prevention. Traditional approaches to fraud detection predominantly utilize rules-based systems, which are inherently limited in their capacity to identify novel, previously unrecognized patterns of fraudulent behavior. In contrast, AI and ML algorithms possess the capability to learn from historical instances of fraud, thereby continuously enhancing their proficiency in identifying emerging threats (Dastin, 2017). These algorithms conduct real-time analyses of transaction data, scrutinizing for anomalies or atypical patterns that may signify fraudulent activity, such as abrupt increases in transaction volume or irregular spending behaviors. By facilitating real-time fraud detection, AI-driven systems can avert financial losses prior to their occurrence, thereby offering significant cost savings to banks and financial institutions. Beyond traditional transaction fraud detection, AI is also being deployed to thwart fraud in digital and mobile banking contexts. As consumers increasingly utilize online platforms for banking purposes, the risk of cybercrime has escalated. Machine learning models that examine user behavior patterns and device fingerprints are capable of identifying suspicious activities, such as account takeovers or identity theft, and can promptly implement corrective measures (Krauss et al., 2017). These systems are also adaptable to evolving fraudulent tactics, ensuring that financial institutions remain safeguarded against increasingly sophisticated threats.

Algorithmic Trading and Market Prediction

The financial sector has historically employed automated systems for trading; however, the integration of artificial intelligence (AI) and machine learning (ML) has significantly advanced algorithmic trading. Traditional algorithmic trading systems operate based on predefined rules and models to execute buy and sell orders. In contrast, AI-driven systems possess the capability to analyze and adapt to market conditions in real-time, making decisions informed by extensive datasets, including historical market data, economic reports, and news articles (Krauss et al., 2017). These systems process information at speeds surpassing human capabilities, executing trades within fractions of a second and seizing transient market opportunities. AI has further facilitated the development of predictive models that assess market sentiment. By analyzing social media posts, news articles, and other unstructured data forms, AI algorithms can detect shifts in market sentiment that may not yet be evident in traditional market indicators. For instance, if AI identifies negative sentiment surrounding a particular stock through social media discussions, it may forecast a decline in stock price prior to the broader market's reaction. This capability has rendered AI-powered trading systems more agile, responsive, and capable of making highly informed investment decisions (Brynjolfsson & McAfee, 2017). Nevertheless, while AI and ML have enhanced trading

strategies' efficiency and effectiveness, their widespread adoption has also elicited concerns regarding market volatility. The rapid execution of trades by AI-powered systems has occasionally resulted in scenarios where automated systems induce swift market fluctuations, such as "flash crashes," characterized by sudden and severe stock price drops often triggered by algorithmic trading. Consequently, there is an increasing demand for regulatory frameworks to govern AI's use in trading to mitigate the risk of market instability (Chen & Zhang, 2019).

Customer Service and Personalization

AI and ML are transforming customer service through chatbots and robo-advisors. These AI-driven tools engage with customers 24/7, providing immediate responses to inquiries, processing transactions, and offering personalized financial advice (Dastin, 2017). Robo-advisors use AI to assess financial goals, risk tolerance, and investment preferences to recommend personalized portfolios, making financial advisory services more affordable and accessible. AI enhances customer experiences by delivering personalized marketing and financial products. By analyzing customer data, including transaction history, online behavior, and demographics, AI systems can tailor services to meet individual customer needs, helping financial institutions build stronger relationships and improve satisfaction.

Fintech Disruption and Regulatory Challenges

AI and ML have enabled fintech companies to disrupt traditional financial services. These companies use AI to offer innovative products, with AI-powered lending platforms assessing creditworthiness through alternative data sources (Krauss et al., 2017). AI is also developing blockchain-based financial services, enabling decentralized finance applications that bypass traditional intermediaries. The growth of AI in fintech has raised regulatory challenges regarding data privacy, fairness, and transparency. Regulators must ensure AI-driven financial services comply with existing regulations while managing potential risks. As AI evolves, regulatory bodies must adapt their frameworks to address these unique challenges in the financial sector (Brynjolfsson & McAfee, 2017).

In conclusion, the impact of AI and ML on the finance industry is undeniable, with these technologies driving significant improvements in areas such as risk management, fraud detection, algorithmic trading, and customer service. However, the widespread adoption of AI also raises important ethical, regulatory, and operational challenges. As AI continues to evolve, financial institutions must strike a balance between harnessing the power of these technologies and addressing the potential risks they pose. The future of AI in finance will depend not only on technological advancements but also on the development of regulatory frameworks that ensure fairness, transparency, and accountability in the use of AI in financial services.

3. Statement of the problem

The rapid advancements in AI and ML technologies have significantly transformed various industries, including the financial sector. AI and ML are increasingly being integrated into financial processes, impacting areas such as risk management, trading algorithms, fraud detection, credit scoring, and customer service. However, despite their growing prominence,

the extent and nature of their impact on the financial industry remain insufficiently understood. Existing research at the intersection of AI, ML, and finance is dispersed across multiple disciplines, with studies addressing a broad range of applications, from algorithmic trading to regulatory compliance. A comprehensive, systematic evaluation of these studies is lacking. There is a need to consolidate and synthesize the existing literature to identify key trends, emerging themes, and areas that require further exploration. This bibliometric analysis aims to address this gap by systematically analyzing the academic literature on the impact of AI and ML on finance. By doing so, it seeks to provide an objective overview of the current state of research, highlight critical gaps, and offer recommendations for future research directions in this dynamic and evolving field.

4. Objectives

1. To systematically map, quantify, and synthesise the global research landscape on the impact and applications of Artificial Intelligence and Machine Learning in finance using bibliometric techniques.

5. Findings

Table 1 *MAIN INFORMATION ABOUT DATA*

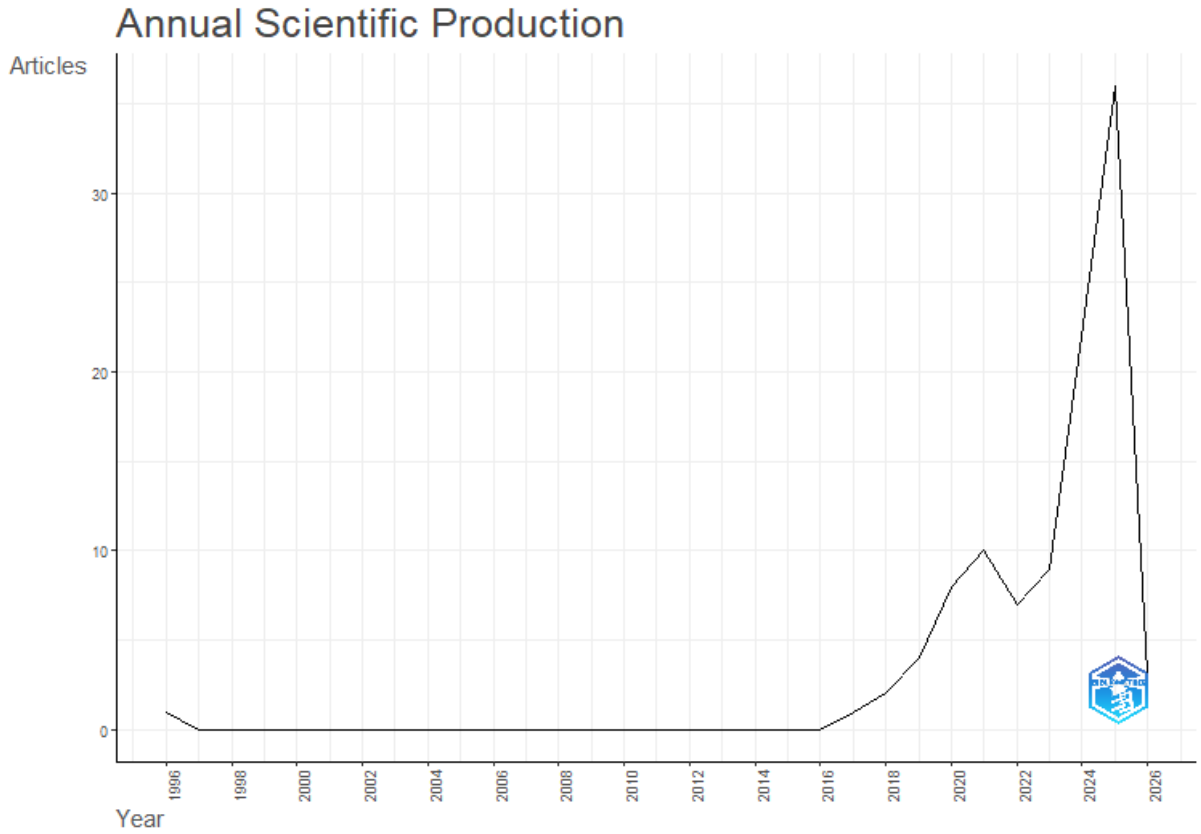
Timespan	1996:2026
Sources (Journals, Books, etc)	70
Documents	103
Annual Growth Rate %	3.73
Document Average Age	3.07
Average citations per doc	48.17
DOCUMENT CONTENTS	
Keywords Plus (ID)	335
Author's Keywords (DE)	316
AUTHORS	
Authors	311
Authors of single-authored docs	15
AUTHORS COLLABORATION	
Single-authored docs	15
Co-Authors per Doc	3.22
International co-authorships %	43.69
DOCUMENT TYPES	
Article	91
Review	12

The bibliographic dataset downloaded from the Scopus database comprises 103 documents published over a 30-year period (1996–2026), representing a focused yet impactful

body of scholarly work. Although the number of documents is relatively modest, the extended timespan allows for meaningful analysis of long-term trends and intellectual development within the research domain. The presence of 70 distinct sources for these publications indicates a high degree of dispersion across journals and other scholarly outlets, suggesting that the topic has strong interdisciplinary relevance rather than being confined to a limited set of core journals. The thematic richness of the collection is evident from the large number of keywords, with 335 Keywords Plus and 316 author-provided keywords. Given the relatively small document count, this diversity of keywords points to a wide range of perspectives, sub-themes, and methodological approaches within the field, reflecting both conceptual depth and topical variety. In terms of productivity and collaboration, the dataset demonstrates a highly collaborative research environment. A total of 311 authors have contributed to the 103 documents, resulting in an average of 3.22 authors per document. Single-authored works are limited to 15 documents, accounting for only a small proportion of the total output, which underscores the dominance of collaborative research. This pattern is further reinforced by a notably high international co-authorship rate of 43.69 per cent, indicating strong cross-country collaboration and global engagement. Such international collaboration often enhances research visibility, methodological robustness, and scholarly impact. The annual growth rate of 3.73 per cent reflects steady and sustained scholarly interest in the field over time. The most striking feature of the dataset is its exceptionally high citation impact. The average citations per document stand at 48.17, which is remarkably high, particularly when considered alongside the average document age of only 3.07 years. This indicates that the publications in this collection are not only recent but also highly influential, attracting significant scholarly attention in a short period. Such a pattern suggests that the research addresses timely, relevant, and high-priority issues, leading to rapid integration into ongoing academic discourse.

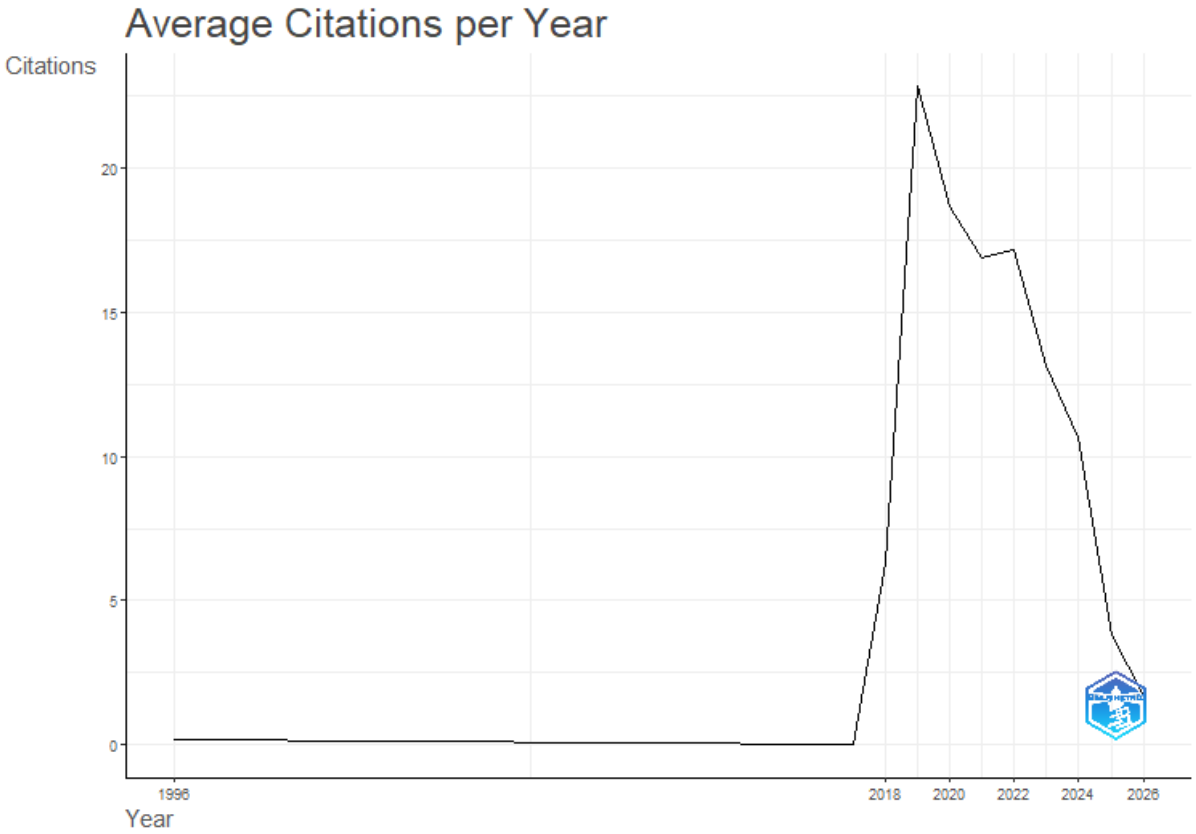
Overall, the bibliometric profile of this Scopus-based collection reveals a dynamic, globally collaborative, and high-impact research field. Despite its relatively limited size, the literature demonstrates strong scholarly influence, thematic richness, and international engagement. These characteristics collectively point to a research area that is both intellectually vibrant and rapidly evolving, providing a solid foundation for deeper bibliometric exploration and subsequent empirical or conceptual research.

Figure 2 *Annual Scientific Production*



The annual scientific production pattern reveals an uneven and time-concentrated growth trajectory. During 1996-2016, scholarly output remained limited, with one publication in 1996 and no publications for nearly two decades thereafter. This period of inactivity indicates the research area was nascent, underdeveloped, or lacked practical relevance. A clear emergence phase begins in 2017 with a single publication, followed by increased output in subsequent years. Publications rose from 2 in 2018 to 4 in 2019, signalling growing academic interest. Growth accelerated from 2020, with publications increasing to 8 in 2020 and 10 in 2021, reflecting a transition to more systematic studies. The most striking feature is the explosive growth in recent years. Despite a slight dip in 2022 (7 publications), momentum resumed in 2023 (9 publications) and intensified in 2024, with 22 publications, reaching 36 publications in 2025. This surge suggests the field gained significant relevance, likely driven by technological advancements, industry adoption, policy attention, or global events. The decline in 2026 (3 publications) should be interpreted cautiously, as it likely reflects partial-year data rather than decreased scholarly interest. Overall, the pattern demonstrates the field has undergone rapid expansion, with knowledge production concentrated within a recent time window. This compressed growth cycle highlights the field's contemporary relevance and momentum, while indicating a transition toward consolidation and deeper engagement.

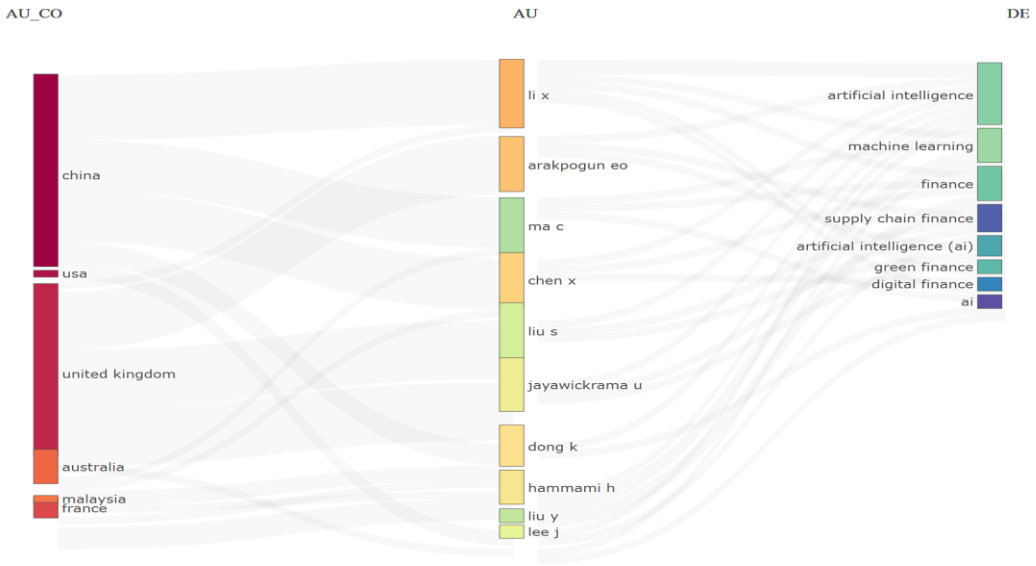
Figure 3 *Average Citations per Year*



The pattern of average citations per year provides insights into research impact over time. During the early period, citation activity was minimal due to low publication numbers and the long gap before field momentum. In 1996, the single publication had modest citations, while in 2017, the lone article received none, reflecting the field's dormant stage. A clear shift occurs from 2018 onwards with the field's rapid expansion. In 2018, average citations per article rose sharply, with a mean total citation of 57 and an annual rate of 6.33, indicating recognition of new studies. This trend peaked in 2019, where average citations per article reached 182.5, and mean citations per year peaked at 22.81, highlighting highly influential studies.The period from 2020 to 2022 shows a gradual decline in average citations per year, though levels remain high. Annual rates of 18.64 in 2020, 16.9 in 2021, and 17.17 in 2022 indicate sustained academic interest and continued referencing during the field's expansion phase. These publications played a significant role in shaping research directions. From 2023 onwards, average citations per year declined more noticeably, decreasing to 13.14 in 2023, 10.64 in 2024, and 3.81 in 2025. The reduction in 2026 (1.67) should be interpreted cautiously, as these publications are recent with limited citation time. This downward trend reflects a typical citation life-cycle effect, where newer publications receive fewer citations due to shorter exposure. The analysis shows the field experienced high-impact scholarly contributions between 2018 and 2022, when key studies rapidly influenced academic discourse. The subsequent decline in citation rates primarily reflects publication recency

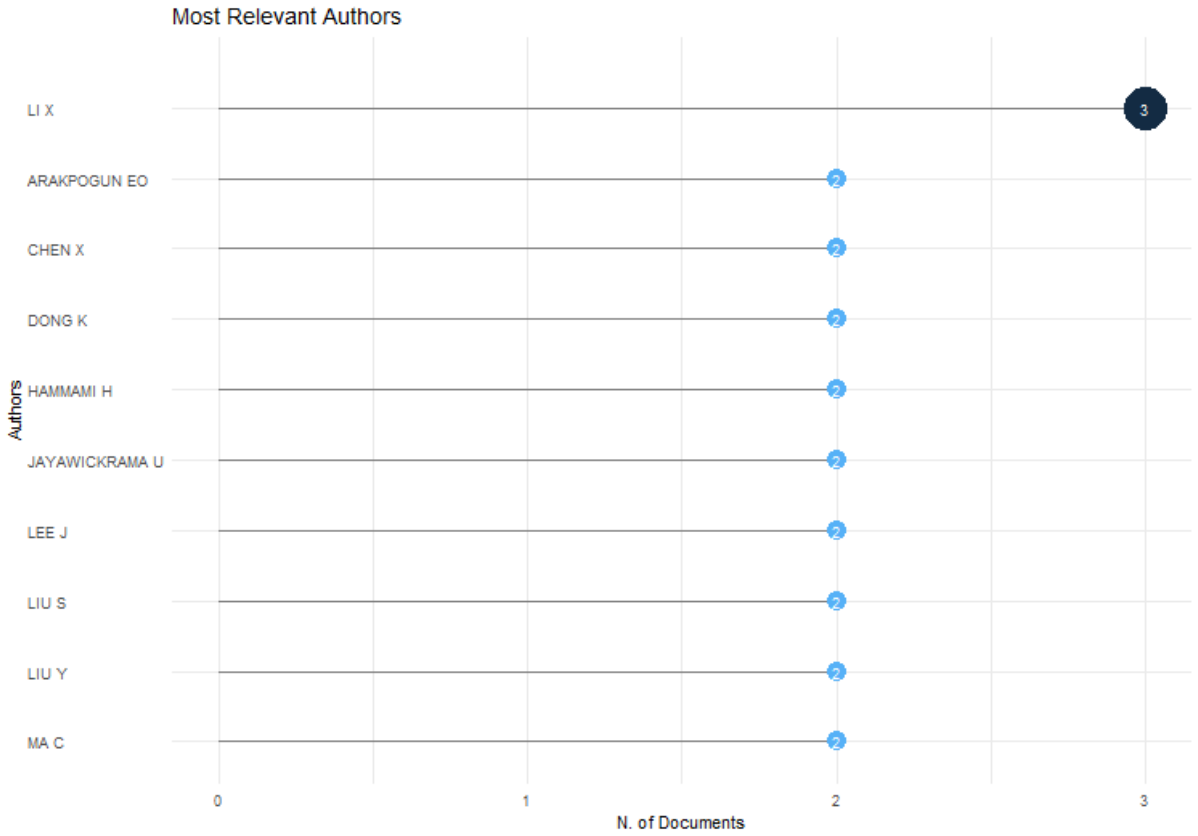
rather than reduced relevance, indicating an active field transitioning toward consolidation and incremental advancement.

Figure 4 *Three Field Plot*



The three-field plot illustrates relationships among contributing countries (AU_CO), leading authors (AU), and research themes (DE) in literature on AI and Machine Learning in Finance. This visualization shows how geographical origins, scholars, and themes interconnect within the field. China, the United States, and the United Kingdom emerge as the most influential contributors. China shows strong linkages, indicating high research output in AI- and ML-driven financial studies. Australia, Malaysia, and France reflect growing international participation, though major research hubs dominate the field. Key authors include Li X., Arakpogun E.O., Ma C., Chen X., Liu S., Jayawickrama U., Dong K., Hammami H., Liu Y., and Lee J., who link countries to research themes. Their recurring presence indicates sustained engagement in applying AI and ML in financial contexts. The most prominent keywords include artificial intelligence, machine learning, and finance, forming the conceptual core. These connect to specialised themes such as digital finance, supply chain finance, green finance, and artificial intelligence (AI). The themes indicate the literature extends beyond generic AI applications to address sector-specific innovations and sustainability. The plot reveals a coherent knowledge structure, where select countries and authors shape the research agenda, while the focus centers on AI- and ML-enabled financial transformation. The linkages between economies and application areas suggest a field that is both technologically driven and contextually evolving.

Figure 5 *Most Relevant Authors*



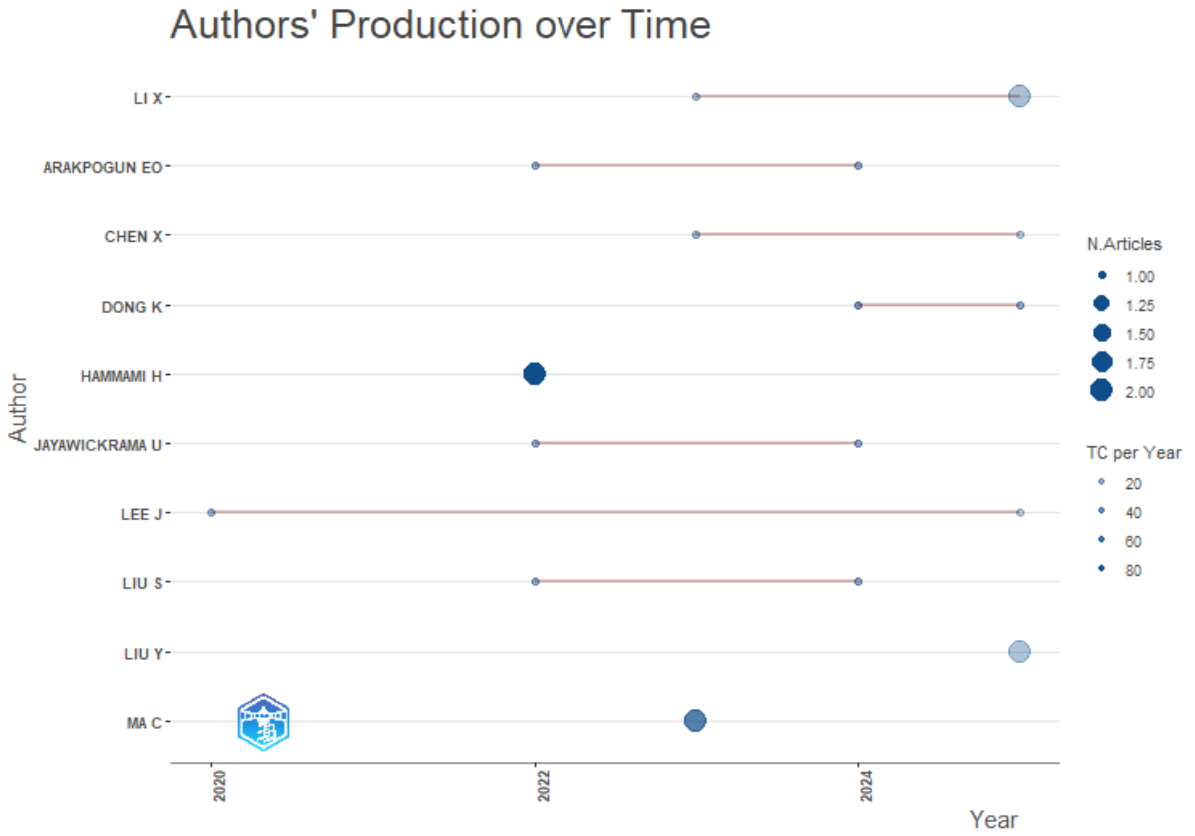
The figure presents the most relevant authors contributing to the literature on Artificial Intelligence and Machine Learning in Finance, ranked based on the number of documents published. The distribution indicates that authorship in this research field is relatively dispersed, with no single author dominating the literature, a characteristic often observed in emerging and interdisciplinary research areas.

Li X. emerges as the most prolific contributor, with three publications, indicating sustained engagement with the core themes of AI- and ML-driven financial research. This positions Li X. as a key contributor whose work helps shape the early intellectual structure of the field. The presence of a single author at the top suggests that while leadership exists, it is not yet highly concentrated. A group of authors, including Arakpogun E.O., Chen X., Dong K., Hammami H., Jayawickrama U., Lee J., Liu S., Liu Y., and Ma C., each contribute two publications. These authors collectively represent an important cohort of recurring contributors who are actively exploring diverse applications of artificial intelligence and machine learning in finance, such as digital finance, risk management, sustainability, and data-driven financial systems.

Overall, the author productivity pattern reflects a broad and collaborative research environment, where contributions are distributed across multiple scholars rather than being centralized around a small elite group. This dispersion suggests that the field is still in a formative and expansion phase, attracting researchers from different disciplinary

backgrounds. As the field continues to mature, it is likely that stronger author clusters and more pronounced scholarly leadership will emerge.

Figure 6 *Author's Production Overtime*



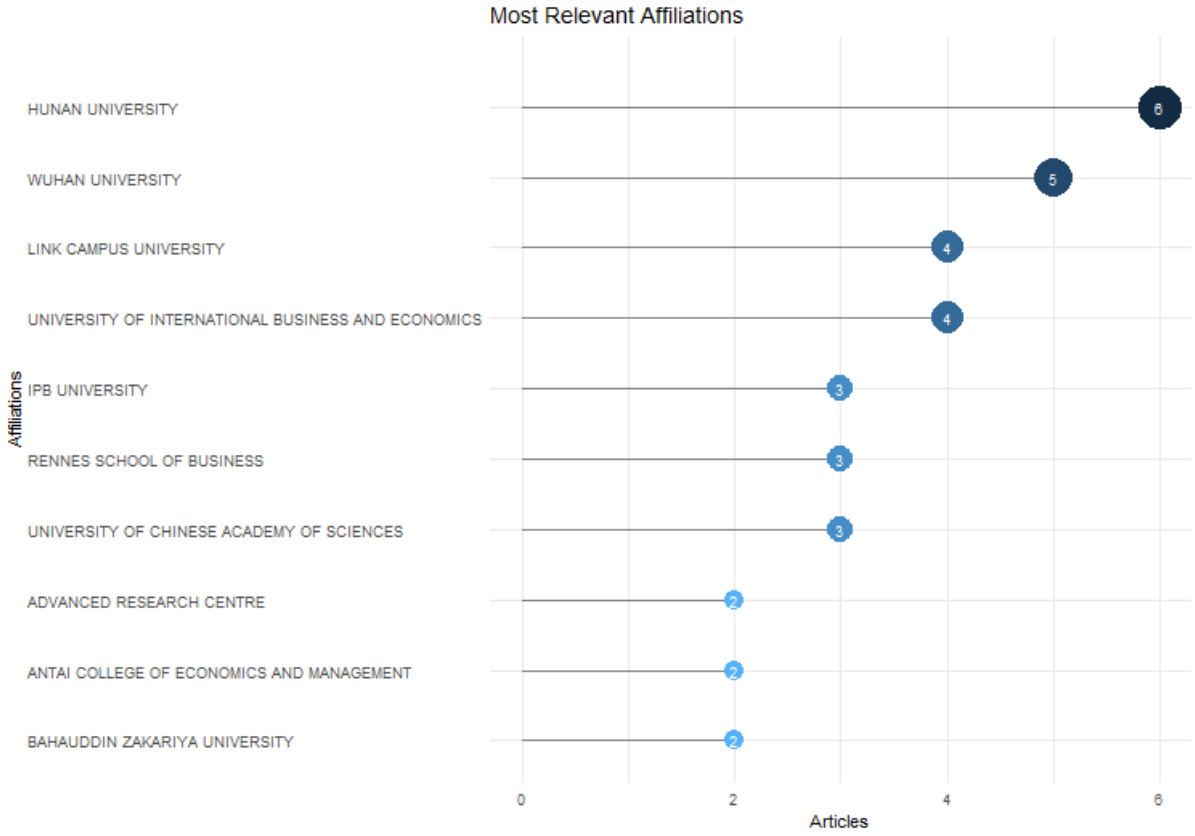
The figure illustrates the temporal distribution of publications by the most relevant authors in the research field of Artificial Intelligence and Machine Learning in Finance, highlighting both productivity and citation impact over recent years. A clear pattern emerges showing that author contributions are highly concentrated in the post-2020 period, confirming that this is a very recent and rapidly evolving research domain. Li X. stands out as the most consistently productive author, with publications spanning multiple recent years and relatively larger node sizes, indicating both higher output and stronger citation impact. This suggests sustained engagement and growing influence in AI- and ML-based financial research. Similarly, Chen X. and Dong K. demonstrate continued scholarly activity from around 2023 to 2025, reflecting active participation during the field's peak growth phase.

Authors such as Arakpogun E.O., Jayawickrama U., Liu S., and Lee J. show publication activity spread across two or more years, indicating intermittent but ongoing contributions rather than one-time involvement. Their publication timelines suggest collaboration-driven research, often aligned with emerging themes such as digital finance, sustainability, and AI-enabled financial systems. In contrast, Hammami H. and Ma C. exhibit more year-specific contributions, marked by larger bubble sizes in particular years, implying the publication of highly cited or impactful papers within a short timeframe.

The variation in bubble sizes across authors and years reflects differences in citation intensity, with some authors achieving high visibility despite fewer publications. This pattern is typical of emerging fields, where influential conceptual or methodological papers can rapidly accumulate citations. Overall, the figure reveals that the intellectual leadership of the field is still in formation, with no long-established author dominance but rather a set of emerging contributors gaining prominence simultaneously.

In summary, the authors' production over time confirms that research on AI and ML in finance is recent, dynamic, and collaborative, driven primarily by contributions in the last five to six years. The concentration of author activity in the most recent period aligns with earlier findings on rapid publication growth and supports the characterization of this field as one that is expanding quickly but has not yet reached full intellectual consolidation.

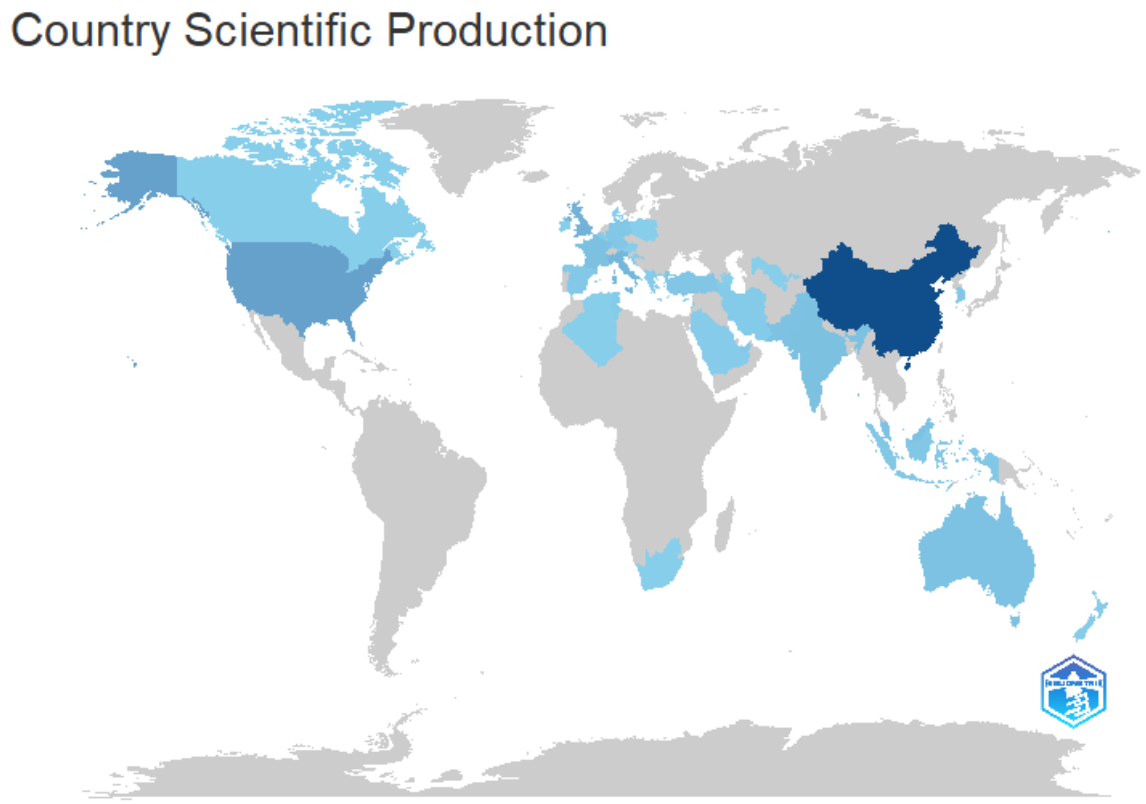
Figure 8 *Most Relevant Affiliations*



The figure presents the institutional affiliations contributing to research on Artificial Intelligence and Machine Learning in Finance, ranked by the number of articles published. The distribution highlights the institutional hubs shaping this emerging research field. Hunan University leads with six publications, indicating a strong research focus on AI- and ML-driven financial studies. Its position suggests dedicated research groups addressing applications of artificial intelligence in finance, such as digital finance, analytics, and risk

management. Wuhan University follows with five publications, reinforcing the significant role of Chinese academic institutions in this domain. Link Campus University and the University of International Business and Economics contribute four publications each, reflecting engagement from European and international business-oriented universities. Their involvement suggests emphasis on economic and policy implications of AI and ML adoption in financial systems. IPB University, Rennes School of Business, and the University of the Chinese Academy of Sciences each contribute three publications, indicating consistent scholarly output. These affiliations represent diverse geographical regions and disciplines, highlighting the field's global character. Other institutions, including the Advanced Research Centre, Antai College of Economics and Management, and Bahauddin Zakariya University, each with two publications, contribute to knowledge diffusion across regions. The affiliation analysis reveals that the field is driven by productive institutions, predominantly from Asia, alongside contributions from Europe and other regions. This pattern underscores institutional capacity in shaping AI- and ML-based financial research, while indicating opportunities for wider participation as the field evolves.

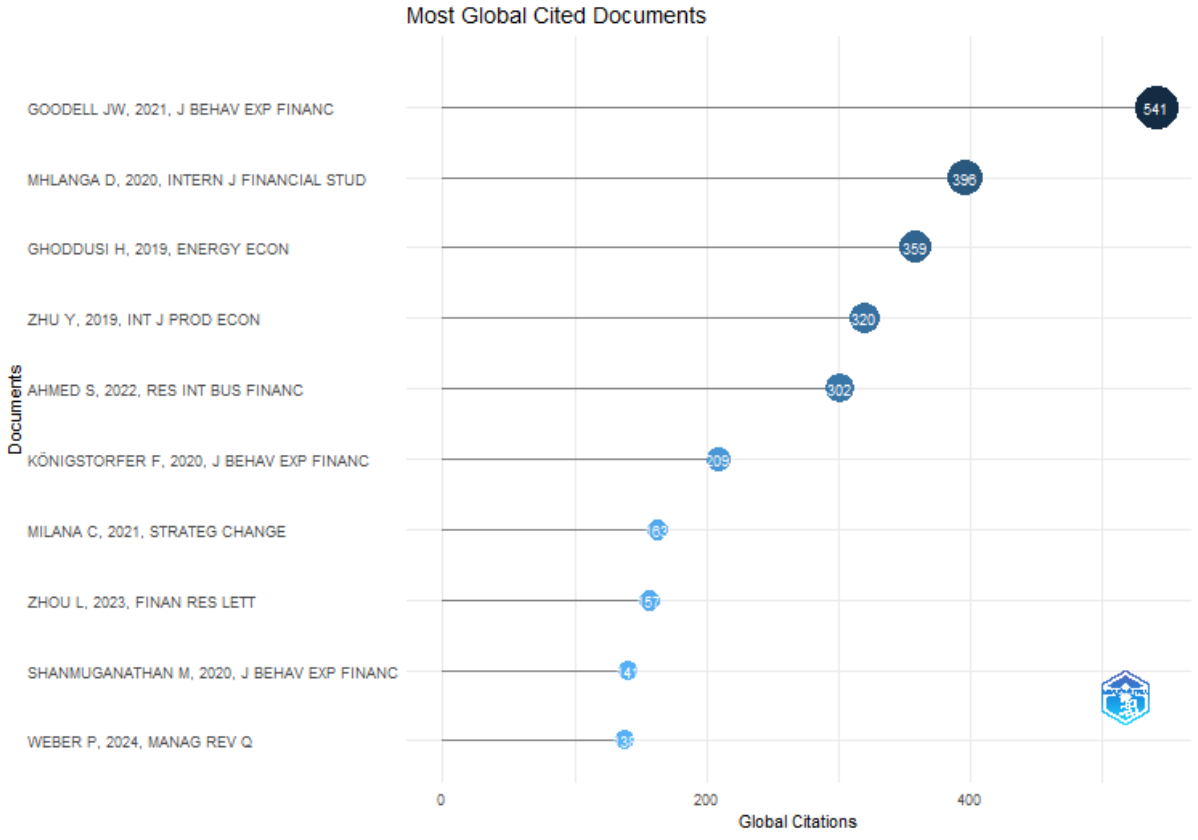
Figure 9 *Country Scientific Production*



The country-wise scientific production analysis reveals an uneven geographical distribution of research on Artificial Intelligence and Machine Learning in Finance, with dominance by key countries alongside broad international participation. China emerges as

the leading contributor with 83 publications, reflecting its national emphasis on artificial intelligence, digital finance, and data-driven innovation, supported by institutional capacity and policy initiatives. The United States ranks second with 28 publications, highlighting its importance in AI- and ML-based finance research. The United Kingdom follows with 18 publications, reinforcing its role in financial innovation and fintech research. European countries like Italy (15 publications) and France (9 publications) make notable contributions, showing growing interest in AI-enabled financial systems. Several emerging economies contribute to the literature. India and France record 9 publications each, while Australia, Malaysia, and Pakistan contribute 8 publications each, suggesting AI applications in finance extend beyond advanced economies. Countries like Turkey (6 publications), Germany, Indonesia, and South Korea (5 publications each) demonstrate the field's expanding global reach. A long tail of countries, including Spain, the United Arab Emirates, Belgium, Iran, and Tunisia, indicates broad international engagement. The scientific production pattern shows global distribution but regional concentration, with China as the principal research hub. The presence of both developed and emerging economies reflects the universal importance of AI and machine learning in modern financial systems, while publication imbalances suggest opportunities for greater cross-country collaboration as the field evolves.

Figure 10 *Most Global Cited Documents*



The analysis of globally cited documents highlights the foundational contributions shaping research on Artificial Intelligence and Machine Learning in finance. The citation distribution is skewed toward influential studies, indicating that seminal works have guided subsequent research. The most cited document, Goodell (2021) published in the Journal of Behavioral and Experimental Finance, stands out with high global citations, linking AI-driven financial analysis with behavioral perspectives, especially during uncertainty. Highly cited works by Mhlanga (2020) and Ghoddusi et al. (2019) signal the influence of studies examining digital transformation and machine learning applications in financial systems. These papers show how computational methods are applied to complex financial markets and forecasting. The presence of journals like Energy Economics, International Journal of Production Economics, and Research in International Business and Finance underscores the field's interdisciplinary nature, where AI intersects with operations and global finance. Recent contributions by Ahmed (2022) and Zhou (2023), achieving substantial citations quickly, indicate the rapid relevance of new research. Their citation performance suggests that studies addressing AI-enabled finance and risk modelling resonate with the academic community. The pattern of citations confirms that the field is anchored by landmark studies providing theoretical direction, while newer works gain traction rapidly, reflecting both mature core ideas and the dynamic nature of AI research in finance.

6. Conclusion

The research field has witnessed significant growth in recent years, with publications increasing sharply from 2020 onwards, signalling a growing academic interest in AI/ML applications in finance. The total number of publications, although relatively modest (103 documents), demonstrates that AI and ML are rapidly becoming integral to financial research, reflecting their increasing relevance to both industry and academia. This explosive growth, particularly after 2017, indicates a transformation in how AI and ML are perceived and applied within the financial sector. The field exhibits a high degree of international collaboration, with 43.69% of co-authorships being international. This global engagement underscores the interdisciplinary nature of AI/ML research in finance, which bridges technological, economic, and managerial expertise. The most prominent research themes, such as digital finance, risk management, and sustainability, reveal the breadth of AI/ML applications in the financial sector. Journals like *Finance Research Letters* and *Energy Economics* have played a central role in disseminating cutting-edge studies, showcasing the interdisciplinary intersection of AI, finance, and other sectors like energy and sustainability. Despite its rapid development, the field is still in a formative stage, with a wide dispersion of authors and institutions contributing to the research landscape. This indicates that the intellectual leadership of the field is yet to consolidate around a small group of scholars, though emerging contributors, such as Li X. and Arakpogun E.O., are already shaping the field. The impact of the literature is evidenced by a high average citation count, suggesting that recent works are making substantial contributions to the academic discourse. In conclusion, the research on AI and ML in finance is dynamic, collaborative, and influential. As the field continues to evolve, future studies should focus on addressing the emerging

challenges related to model transparency, ethical considerations, and the integration of AI with regulatory frameworks in finance.

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