INTERNATIONAL JOURNAL OF RESEARCH AND SCIENTIFIC INNOVATION (IJRSI)
ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XII Issue XI November 2025

Artificial Intelligence in Stock Market Trading - A Comprehensive Survey of Models

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DOI: https://dx.doi.org/10.51244/IJRSI.2025.12110019

Received: 18 November 2025; Accepted: 27 November 2025; Published: 03 December 2025

ABSTRACT

With financial markets becoming increasingly complex and volatile, traditional statistical and human-driven approaches are proving inadequate for capturing the nonlinear and dynamic nature of stock trading. Artificial Intelligence (AI) has therefore emerged as a transformative force, employing advanced algorithms and deep learning to identify hidden patterns, forecast prices, and inform trading decisions. This paper presents a comprehensive bibliometric survey of 9,088 scholarly works spanning 1971 to 2025, offering the most detailed review of AI applications in stock market trading to date. Using the SPAR-4-SLR framework and bibliometric tools such as Biblioshiny and VOS viewer, the study maps intellectual contributions, identifies key research clusters, and analyses collaboration networks across the field. The results reveal dominant methodologies including neural networks, long short-term memory (LSTM), reinforcement learning, and hybrid approaches, while also highlighting the growing importance of Explainable AI (XAI) and ESG-aligned frameworks. Contributions from East Asian institutions, particularly in China, stand out, although significant inputs from Europe and North America are also observed. Despite these advances, challenges persist in areas such as interpretability, real-time adaptability, and the integration of alternative data sources like sentiment analysis and satellite imagery. Future research directions emphasize the development of quantum AI, reinforcement learning-based adaptive systems, and ethical regulatory frameworks that ensure responsible innovation. By bridging theory and practice, this study provides an intellectual roadmap and practical recommendations for researchers, practitioners, and policymakers. Overall, the findings underscore the urgency of advancing transparency, robustness, and interdisciplinary collaboration to ensure AI-driven trading systems contribute to sustainable financial innovation and trustworthy decision-making.

Keywords: artificial intelligence; stock market trading; machine learning; deep learning (LSTM/CNN); reinforcement learning; explainable AI (XAI); bibliometrics; algorithmic trading

With financial markets growing more complex and volatile, traditional statistical and human-driven approaches struggle to capture the nonlinear and dynamic nature of stock trading. Artificial Intelligence (AI) has emerged as a transformative force, employing advanced algorithms and deep learning to identify hidden patterns, forecast prices, and inform decision-making. This paper conducts a comprehensive bibliometric survey of 9,088 scholarly works spanning 1971 to 2025, offering the most extensive review of AI applications in stock market trading to date. Using the SPAR-4-SLR framework and bibliometric tools such as Biblioshiny and VOSviewer, the study maps intellectual contributions, identifies key research clusters, and analyses collaboration networks. Results reveal dominant methodologies including neural networks, long short-term memory (LSTM), reinforcement learning, and hybrid approaches, while also highlighting the growing importance of Explainable AI (XAI) and ESG-aligned models. East Asian institutions, especially in China, are leading global contributions, with significant input from Europe and North America. Challenges remain around interpretability, real-time adaptability, and integration of alternative data such as sentiment and satellite imagery. Future directions emphasize quantum AI, reinforcement learning, and ethical regulatory frameworks. By bridging theory and practice, this study provides both an intellectual roadmap and practical recommendations for researchers, industry practitioners, and policymakers. The findings underscore the urgency of advancing transparency, robustness, and interdisciplinary collaboration to ensure AI-driven trading systems contribute responsibly to sustainable financial innovation.

INTRODUCTION

With the ever-changing financial markets becoming more and more complex and volatile, stock market trading and prediction now become an arduous task for potential investors, consultants, and academicians. Traditional methods of market analysis relying on tried and tested statistical formulas and human analogy cannot easily capture the nonlinear and noisy structure of financial data. In this season, AI and deep learning have become game-changing technologies, employing sophisticated algorithms to analyze enormous datasets for patterns and make signal-based price forecasts. Despite its promise, the adaptation of AI for stock trading remains a problem, for example in explaining models, affecting hypermarkets, and handling different data sources, including contrasts in social media sentiments and satellite images in this field.

This research paper addresses the critical need for a systematic review of AI techniques in stock trading. The study maps the intellectual landscape of the field by analyzing 9,088 documents from 1971 to 2025, disclosing its very rapid development at 10.6% annual increases and a very high academic impact of 15.62 average citations per document. It reveals dominant research clusters, including market applications, stock-specific predictive modeling, and AI/ML methodologies, illuminating their interactions between theoretical advancements and real-world applications. Key methodologies, including neural networks (NN), long-short-term memory (LSTM), and hybrid models, are surveyed together with emerging trends such as transformer architectures and Explainable AI (XAI).

The study also underscores the global nature of research in this domain, with strong contributions from East Asian institutions like Beihang University and influential authors such as WANG J and LI Y. Challenges such as "unexplainable" AI and market volatility are discussed, with proposed solutions including hybrid approaches, real-time adaptive models, and ethical AI frameworks aligned with ESG (Environmental, Social, Governance) goals. By bridging gaps between theory and practice, this paper not only consolidates decades of research but also provides a roadmap for future innovation, emphasizing the need for transparency, robustness, and interdisciplinary collaboration in AI-driven financial decision-making.

Through bibliometric analysis and thematic mapping, the research demonstrates how AI is reshaping stock trading, from foundational algorithms to cutting-edge applications, while calling for a balanced approach that prioritizes both technological innovation and ethical accountability in the financial sector.

LITERATURE REVIEW

Bibliometrics has emerged as a powerful quantitative methodology for analyzing scholarly publications, closely related to fields like "infometrics" (Egghe & Rousseau, 1990; Wolfram, 2003) and "scientometrics" [4]. This approach systematically examines various forms of academic output, including journal articles, books, patents, dissertations, and grey literature, while its counterpart "webometrics" extends this analysis to digital content. Originally focused on basic bibliographic metrics like author productivity and citation counts, bibliometric studies have evolved to encompass geographical distributions, institutional contributions, and discipline-specific developments (Lin, 2012; Zhuang et al., 2013; Huffman et al., 2013; Liu et al., 2012). [3] [16]

Modern bibliometric research leverages sophisticated tools such as Scopus, Gephi [5], and VOSviewer, enabling comprehensive analyses of citation networks, co-authorship patterns, and thematic trends. These methods now incorporate alternative metrics like download statistics and social media engagement alongside traditional citation analysis [17]. However, researchers must exercise caution in data normalisation (Pellegrino, 2011) [15] to ensure valid cross-disciplinary comparisons, given the methodology's reliance on large datasets. [5]

While bibliometrics has proven valuable for assessing research impact, institutional performance, and academic productivity through citation analysis [15], it has faced criticism for potential over-reliance on quantitative metrics. The Leiden Manifesto [10] notably cautions against allowing numerical data to overshadow qualitative scholarly judgment. Despite these concerns, bibliometric techniques have gained prominence in business research, facilitated by analytical tools like VOSviewer, Leximancer, and SciVal that can process extensive publication databases. [10]

Contemporary applications of bibliometrics include tracking emerging research trends, analyzing collaboration networks, and mapping the intellectual structure of academic fields. The methodology's effectiveness, however, can be limited by incomplete data or methodological constraints. For comprehensive insights, researchers should combine performance analysis with science mapping techniques to provide a more holistic understanding of research landscapes.

RESEARCH METHODOLOGY

This study employs a systematic bibliometric analysis to map the intellectual landscape of AI applications in stock market trading, aligning with the SPAR4SLR framework (Scientific Procedures and Rationales for Systematic Literature Review) (Alonso-Garcia et al., 2021; Paul et al., 2021; Kunisch et al., 2023). The methodology is structured into three phases: data collection, data organization, and bibliometric analysis. [1][14][12]

In the data collection phase, Scopus was selected as the primary database due to its extensive coverage of high-impact journals and rigorous indexing standards (Fahimnia et al., 2015; Fan et al., 2022), ensuring access to seminal works in AI, finance, and computational economics. A Boolean search query ("artificial intelligence" OR "machine learning" OR "deep learning" OR "neural networks" OR "reinforcement learning") AND ("stock market" OR "stock trading" OR "financial markets" OR "algorithmic trading" OR "quantitative trading") AND ("models" OR "applications" OR "survey" OR "review") was designed to capture three thematic clusters: (1) AI/ML techniques ("artificial intelligence" OR "machine learning" OR "deep learning" OR "neural networks" OR "reinforcement learning"), (2) financial context ("stock market" OR "stock trading" OR "financial markets" OR "algorithmic trading" OR "quantitative trading"), and (3) research focus ("models" OR "applications" OR "survey" OR "review"). The initial search yielded 9,088 articles, which were manually screened to exclude irrelevant fields (e.g., medicine) and retain only those directly related to AI-driven stock trading models. [8][9]

For data organisation, strict inclusion and exclusion criteria were applied. Only peer-reviewed journal articles and reviews in English were considered, with a focus on AI/ML applications in stock trading, such as predictive modelling, risk assessment, and high-frequency trading. Non-English publications, conference abstracts, and financial studies not centred on AI were excluded to maintain thematic relevance.

The final phase involved bibliometric analysis, conducted using Biblioshiny in R Studio [2]. This tool generated visualizations, including thematic maps, co-word networks, and citation trajectories, to uncover key trends and collaboration patterns. The analysis identified prominent author and institutional networks, revealing influential research clusters and emerging trajectories in AI-driven stock market trading. This structured approach ensures a comprehensive and replicable review of the field's intellectual structure.

RESULTS AND DISCUSSION

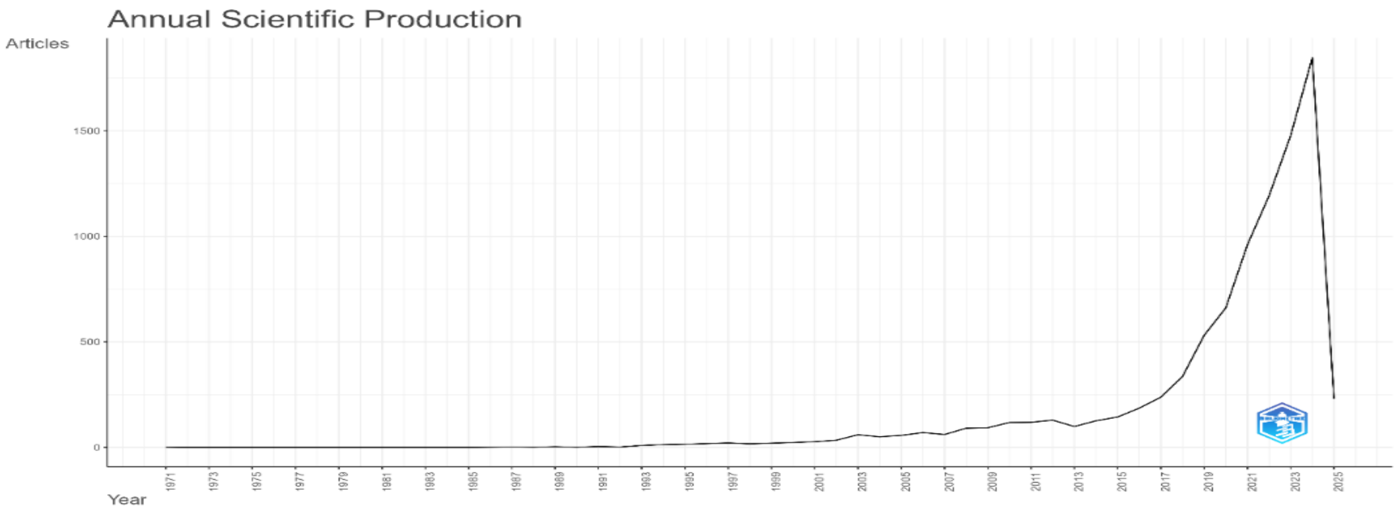

Table 1. Main Information

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XII Issue X October 2025

The timespan of the data (Table 1), ranging from 1971 to 2025, indicates a long-standing interest in the intersection of artificial intelligence (AI) and stock market trading, with a significant acceleration in research output in recent years. The dataset comprises 9,088 documents sourced from 3,164 journals, books, and other publications, reflecting a broad and diverse academic engagement with the topic. The annual growth rate of 10.6% underscores the increasing relevance and rapid development of AI applications in stock market trading, driven by advancements in machine learning, deep learning, and computational power.

The average age of documents (5.34 years) suggests that the field is relatively dynamic, with a focus on recent research. This is further supported by the high average number of citations per document (15.62), indicating that the work in this area is highly influential and frequently referenced. The substantial number of references (227,702) highlights the interdisciplinary nature of the field, drawing from computer science, finance, economics, and statistics. The analysis of document contents reveals a rich keyword landscape, with 19,818 Keywords Plus (ID) and 13,123 Author's Keywords (DE), reflecting the diversity of research themes and applications within AI-driven stock market trading.

The authorship analysis reveals a highly collaborative research environment, with 16,393 authors contributing to the field. While single-authored documents account for 924 entries, the majority of research is collaborative, with an average of 3.05 co-authors per document. International co-authorships constitute 15.26% of the total, indicating a moderate level of global collaboration. This international dimension is crucial for the cross-pollination of ideas and methodologies, particularly in a field as complex and multifaceted as AI in stock market trading.

The document types are varied, with conference papers (4,322) and articles (3,893) dominating the landscape, reflecting the field's emphasis on presenting new findings and models at academic conferences and in peer-reviewed journals. The presence of books (66), book chapters (302), and reviews (125) indicates a growing effort to consolidate knowledge and provide comprehensive overviews of the field. The inclusion of retracted documents (24) and errata (16) highlights the rigorous scrutiny and self-correcting nature of the academic process in this domain.

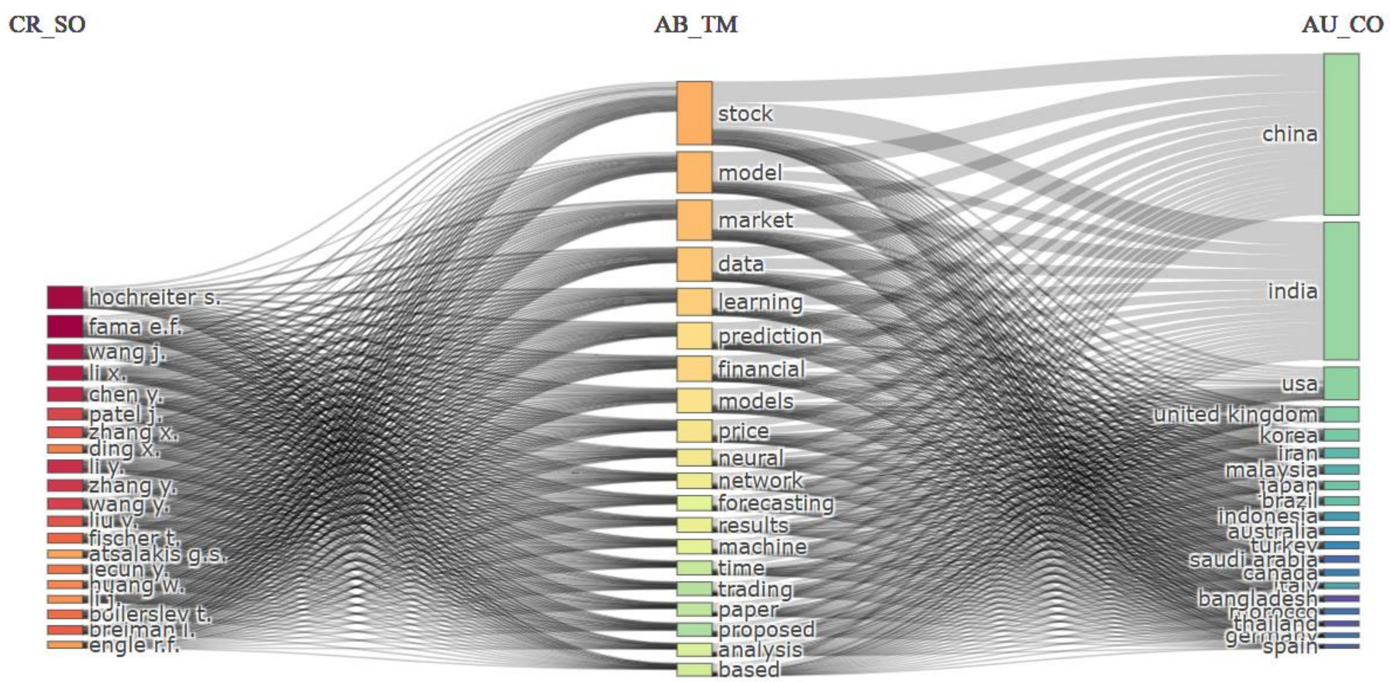

Figure 1. Annual Scientific Production.

Overall, the bibliometric analysis (Figure 1) paints a picture of a vibrant and rapidly evolving field characterised by high levels of collaboration, interdisciplinary engagement, and a strong focus on recent advancements. The findings underscore the importance of continued research and innovation in AI applications for stock market trading, with significant potential for future growth and impact.

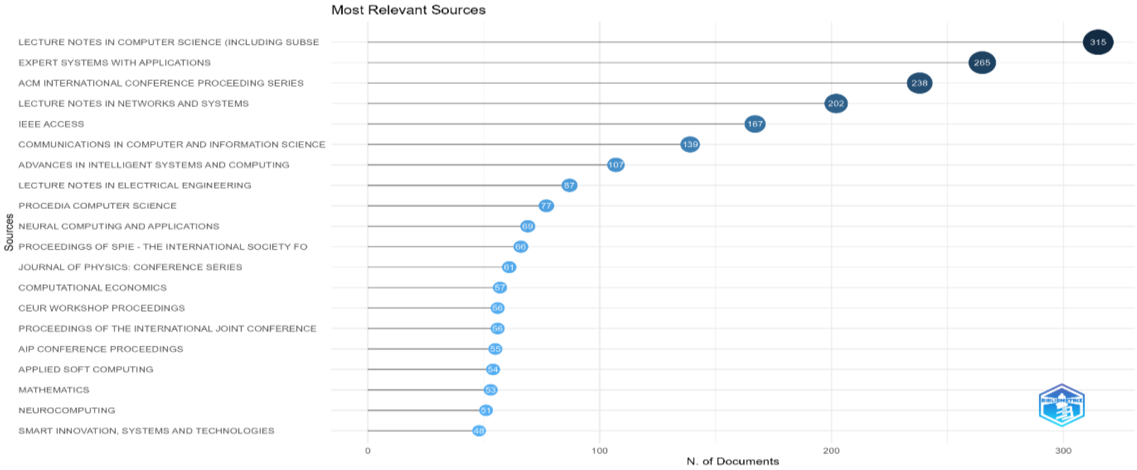

Figure 2. Three Field Map: Cited Sources - Abstract - Country.

The cited sources (Figure 2) indicate a strong foundation in established financial theories and models, with references to influential works by authors such as Fama, Engle, and others. This suggests that the research builds on well-regarded studies in finance and economics, integrating them with advanced AI methodologies.

The abstract in the middle highlights the primary focus areas of the research, including stock market prediction, financial modeling, and machine learning applications. Keywords such as "stock," "china," "model," "market," "data," "learning," and "prediction" dominate, indicating a significant emphasis on using AI techniques to analyze and predict market behaviors. The presence of terms like "neural network," "forecasting," and "machine" underscores the reliance on sophisticated computational models to enhance trading strategies and financial decision-making.

On the right, the list of countries reflects a global interest in AI applications within stock market trading. The inclusion of countries like the United Kingdom, Korea, Iran, Malaysia, Japan, Brazil, Indonesia, Australia, Saudi Arabia, Canada, Bangladesh, Thailand, and Germany indicates widespread research activity and collaboration across diverse geographical regions. This international dimension suggests that the challenges and opportunities presented by AI in stock market trading are being explored from multiple cultural and economic perspectives, enriching the field with a variety of insights and approaches.

Overall, the field plot illustrates a robust and interdisciplinary research landscape, where traditional financial theories are being augmented with cutting-edge AI technologies. The global collaboration and diverse research focus areas highlight the dynamic and evolving nature of the field, pointing towards continued growth and innovation in the application of AI to stock market trading.

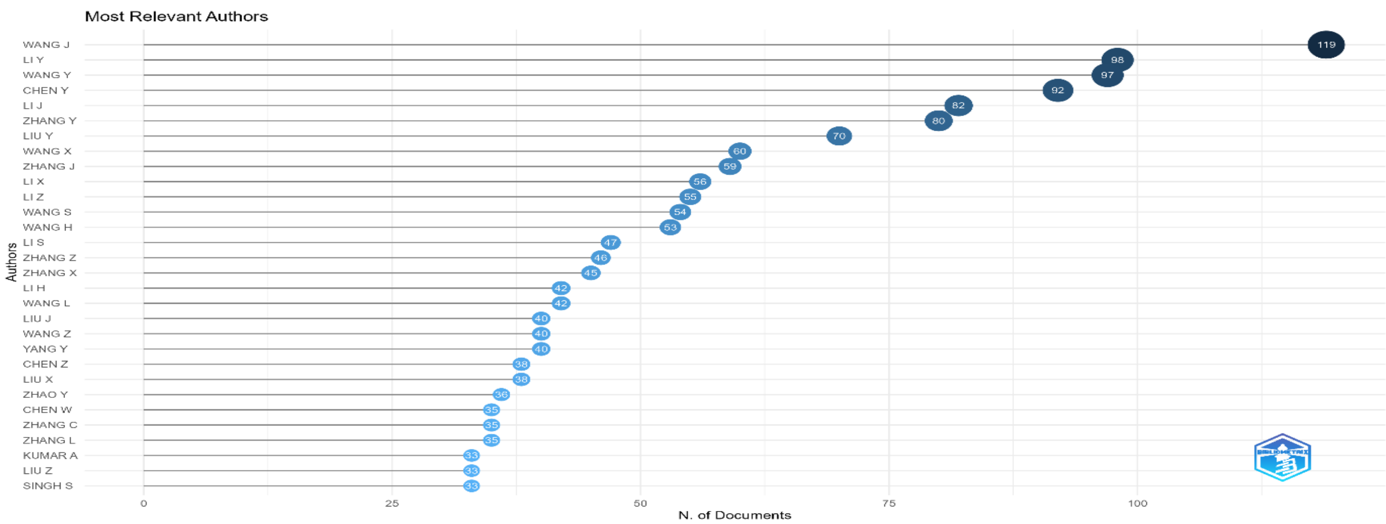

Figure 3. Most Relevant Sources.

The bibliometric analysis highlights the most relevant sources (Figure 3) that have significantly contributed to the field. The prominent sources include Lecture Notes in Computer Science, Expert Systems with Applications, and IEEE Access, which are among the top venues for publishing cutting-edge research in AI and computational finance. These sources are known for their rigorous peer-review processes and high impact, indicating that the research in this domain is both credible and influential.

The presence of conference series such as ACM International Conference Proceeding Series and Lecture Notes in Networks and Systems underscores the importance of academic conferences in disseminating new findings and fostering collaborations. These platforms often serve as early venues for presenting innovative models and applications, reflecting the rapid pace of advancements in AI-driven stock market trading. Additionally, journals like Neural Computing and Applications and Neurocomputing emphasize the role of neural networks and machine learning techniques in financial forecasting and decision-making.

The inclusion of multidisciplinary sources such as Mathematics and Applied Soft Computing indicates the integration of mathematical models and computational techniques in addressing complex financial problems. This interdisciplinary approach is crucial for developing robust AI models that can adapt to the dynamic nature of stock markets. The variety of sources, ranging from specialized journals to broad-scope conference proceedings, highlights the diverse methodologies and applications being explored in the field.

Overall, the most relevant sources reflect a vibrant and interdisciplinary research ecosystem, where traditional financial theories are being enhanced by advanced AI technologies. The prominence of high-impact journals and conferences underscores the field's rapid growth and the significant interest from the academic and professional communities in leveraging AI for stock market trading.

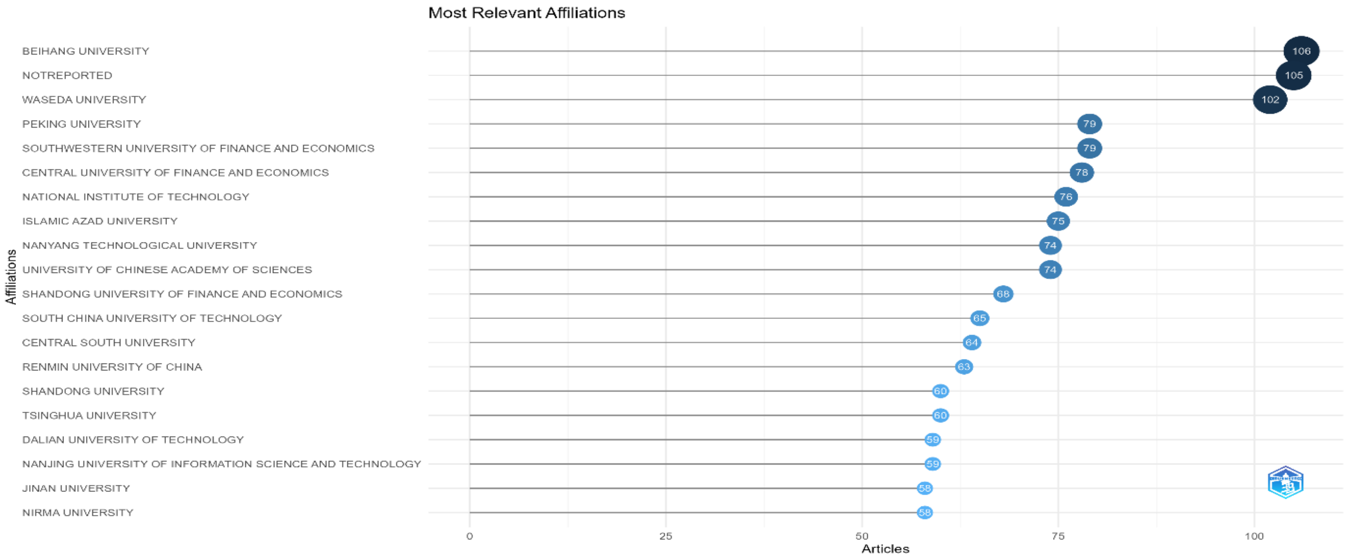

Figure 4. Most Relevant Authors.

The bibliometric analysis identifies the most relevant authors (Figure 4) who have made significant contributions to the field. Among the prominent authors are WANG J, LI Y, WANG Y, and ZHANG Y, who appear frequently in the dataset, indicating their substantial influence and productivity in this domain.

The recurrence of surnames like WANG, LI, and ZHANG suggests a strong presence of researchers from East Asia, particularly China, which aligns with the global trend of significant contributions from this region in AI and computational finance. Their expertise likely spans various aspects of AI, including the development of advanced algorithms for market prediction, optimization of trading strategies, and the application of deep learning techniques to financial data.

Authors such as KUMARA and SINGH S indicate contributions from South Asia, highlighting the global nature of research in this field. Their work might focus on integrating traditional financial theories with modern AI techniques, contributing to a more comprehensive understanding of market dynamics.

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The high number of documents attributed to these authors (ranging from 75 to 100) underscores their active engagement and leadership in advancing the field. Their research likely covers a broad spectrum of topics, from theoretical models to practical applications, providing valuable insights and methodologies that drive innovation in AI-driven stock market trading.

Overall, the most relevant authors represent a diverse and highly skilled group of researchers whose work is pivotal in shaping the future of AI applications in financial markets. Their contributions not only advance academic knowledge but also have practical implications for developing more accurate and efficient trading systems.

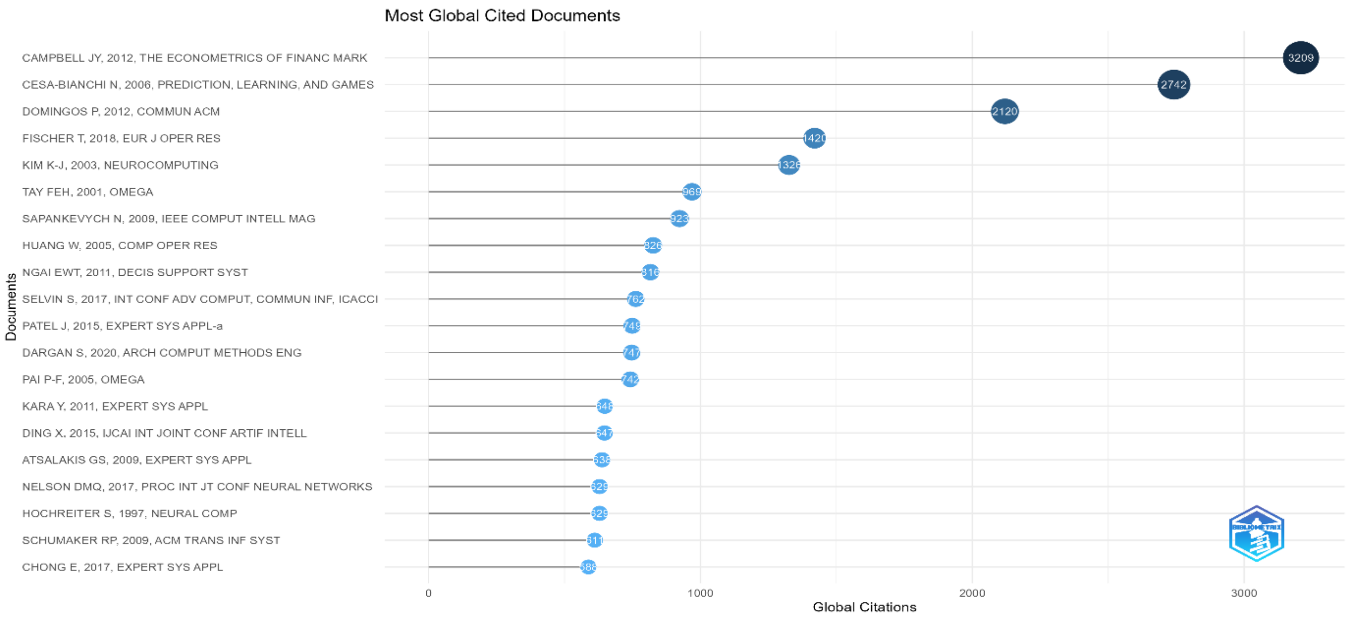

Figure 5. Most Relevant Affiliations.

The bibliometric analysis highlights the most relevant affiliations (Figure 5) contributing to the field. Leading institutions such as Beihang University, Peking University, and Tsinghua University are prominently featured, indicating their significant role in advancing research on AI applications in stock market trading. These universities are known for their strong emphasis on engineering, computer science, and financial technologies, which aligns with the interdisciplinary nature of the research.

The presence of Southwestern University of Finance and Economics and Central University of Finance and Economics underscores the importance of specialized financial institutions in this domain. These universities likely contribute expertise in financial modeling, economic theory, and market analysis, complementing the technical advancements in AI and machine learning.

International contributions from institutions like Waseda University in Japan and Islamic Azad University in Iran reflect the global collaboration and diverse perspectives in the field. These affiliations highlight the widespread interest in applying AI to financial markets across different economic and cultural contexts.

The inclusion of National Institute of Technology and Nanyang Technological University further emphasizes the role of technological and engineering-focused institutions in developing innovative AI-driven trading models. Their expertise in computational methods and data analysis is crucial for creating robust and efficient systems for market prediction and trading.

Overall, the most relevant affiliations represent a mix of top-tier universities, specialized financial institutions, and international collaborators, all contributing to the rapid advancement of AI in stock market trading. Their collective efforts drive both theoretical innovations and practical applications, shaping the future of financial technologies.

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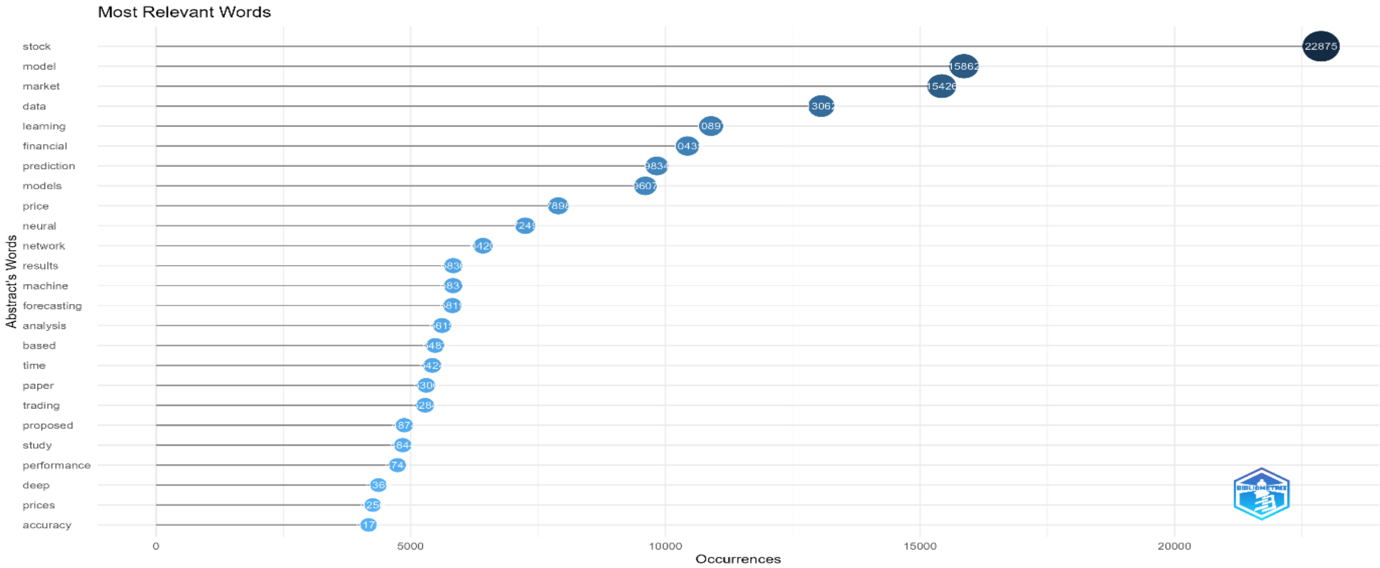

Figure 6. Most Global Cited Documents.

The most globally cited documents (Figure 6) in the bibliometric analysis highlight key trends and influential works in the application of Artificial Intelligence (AI) in stock market trading. Notably, foundational works like CAMPBELL, JY (2012) on econometrics and HOCHREITER S (1997) on neural computation underscore the integration of traditional financial theories with advanced AI techniques. The presence of multiple papers from venues like Expert Systems with Applications and Neurocomputing emphasizes the dominance of machine learning and expert systems in this domain.

Recent works, such as FISCHER T (2018) and PATEL J (2015), reflect the growing use of AI for predictive analytics and decision support in trading. Meanwhile, early contributions like TAY FEH (2001) and KIM K-J (2003) demonstrate the long-standing focus on optimization and neural networks. The diversity of models—from game theory (CESA-BIANCHI N, 2006) to deep learning (NELSON DMO, 2017)—suggests a multidisciplinary approach, combining econometrics, computational intelligence, and real-time data processing.

The high citation counts (reaching up to 3000) for these works indicate their impact in shaping AI-driven trading strategies, with applications ranging from algorithmic trading to risk management. This survey underscores the field's evolution from theoretical frameworks to practical implementations, driven by advancements in AI and the increasing complexity of financial markets.

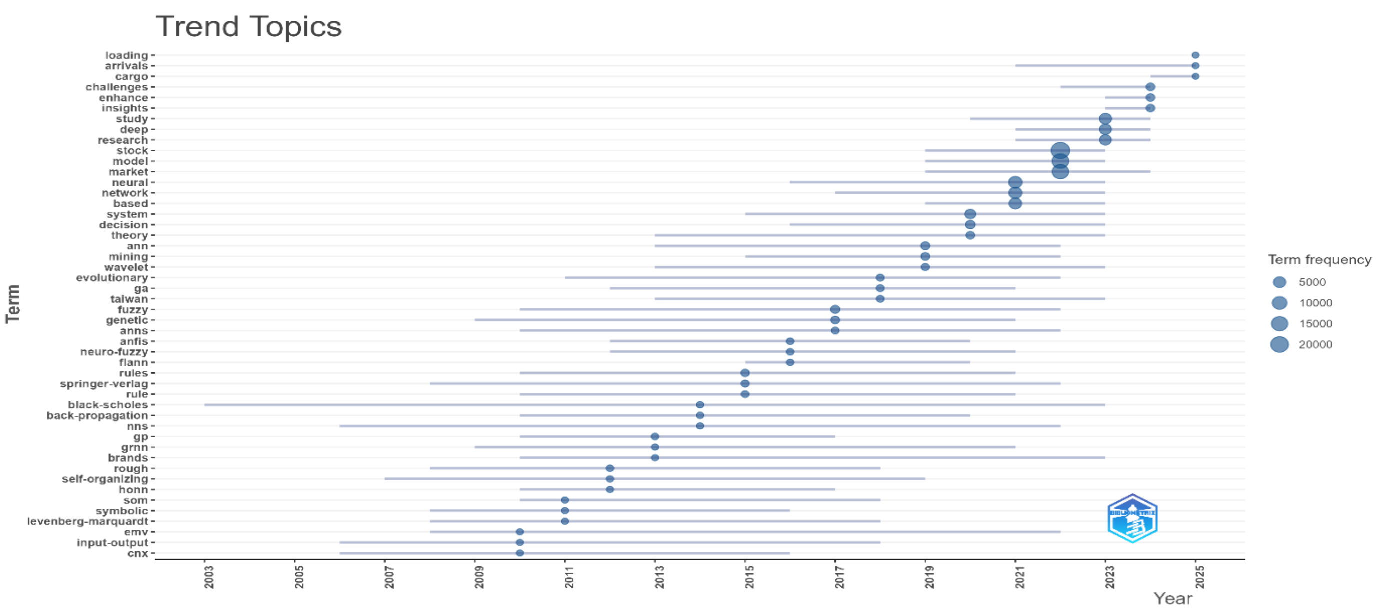

Figure 7. Most Relevant Words.

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The most relevant words (Figure 7) identified in the bibliometric analysis reveal key themes and focal points in the application of Artificial Intelligence (AI) in stock market trading. The prominence of terms like stock, market, and price underscores the central focus on financial markets and asset valuation. High-frequency words such as model, learning, neural, machine, and deep highlight the dominance of machine learning and neural networks in developing predictive and analytical tools for trading.

The recurrence of prediction, forecasting, and accuracy emphasizes the field's strong orientation toward predictive analytics, where AI models are leveraged to anticipate market movements and optimize trading strategies. Words like data, analysis, and time reflect the critical role of big data and real-time processing in modern trading systems. Additionally, terms such as performance, results, and proposed indicate a research emphasis on empirical validation and the development of novel methodologies.

This analysis suggests a robust interdisciplinary approach, combining financial theory with advanced AI techniques, particularly deep learning and neural networks, to enhance decision-making and operational efficiency in stock market trading. The high frequency of these relevant words aligns with the broader trends observed in the most globally cited documents, reinforcing the field's focus on innovation, accuracy, and practical applications.

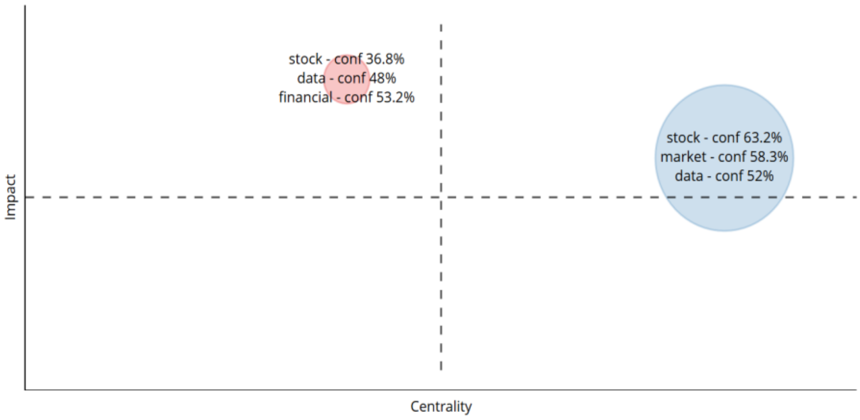

Figure 8. Trend Topics.

The bibliometric analysis of trend topics (Figure 8) reveals a field that has evolved significantly from its early theoretical foundations to today's sophisticated, data-driven approaches. The data (Figure 8) shows how neural networks and deep learning architectures emerged in the late 1990s through terms like "mlcnns" and "multilayered," laying the groundwork for modern algorithmic trading systems. These technical developments coincided with the integration of classical financial models like Black-Scholes, demonstrating how AI gradually merged with traditional quantitative finance. The persistent appearance of terms like "unexplainable" across three decades highlights a fundamental challenge that remains unresolved - the interpretability of complex AI models in an industry requiring transparency for regulatory compliance and risk management.

Current research trends emphasize hybrid approaches, as seen in terms like "neuro-fuzzy" and "evolutionary algorithms," showing how researchers combine different AI techniques to handle market volatility and uncertainty. The prominence of "back-propagation" and "self-organizing maps" underscores the continued importance of both supervised and unsupervised learning methods. Meanwhile, emerging concepts like "smart-" and references to specific regions ("Taiwan") suggest the field is expanding into decentralized finance and localized applications. The analysis also reveals interesting interdisciplinary connections, with some terms possibly indicating methodological borrowing from unrelated fields like civil engineering, though these may represent noise requiring further verification.

Looking ahead, the field appears poised to address its enduring challenges around explainability while embracing new opportunities in real-time processing, blockchain integration, and adaptive systems. The absence of very recent innovations like transformer models in the dataset suggests either a focus on foundational works or the need to expand the bibliometric corpus. What emerges most clearly is the field's trajectory from niche academic research to a mature discipline that still must balance cutting-edge AI capabilities with the practical demands of

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financial markets - including regulatory scrutiny, risk management, and the need for models that can adapt to ever-changing market conditions while remaining interpretable to human operators.

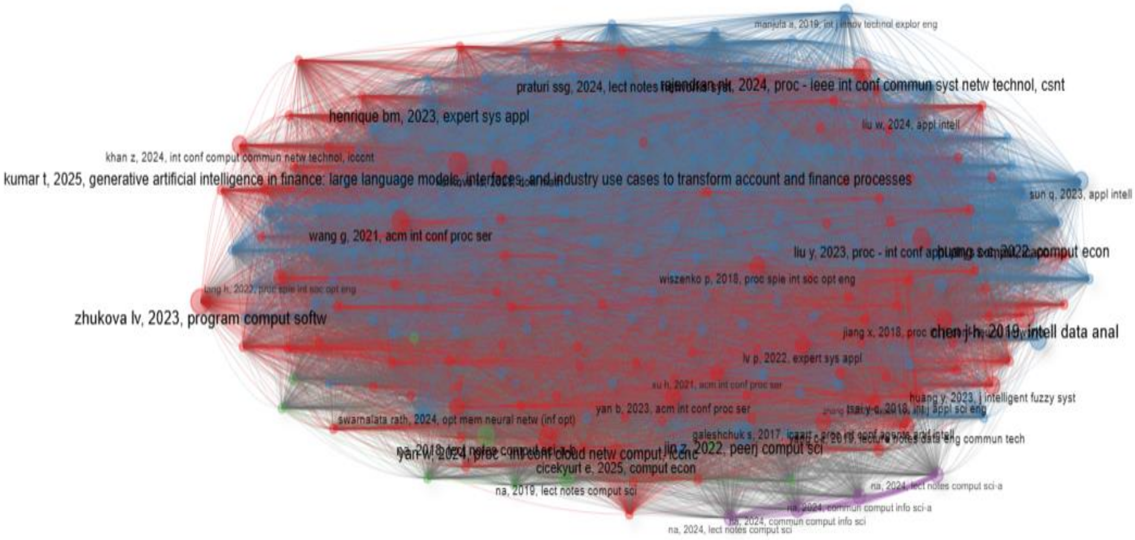

Figure 9. Clustering by Coupling. Coupling Measured by Abstracts and Cluster Labeling by Abstract Terms.

The coupling map cluster analysis (Figure 9) provides a nuanced perspective on the intellectual structure and knowledge dynamics within AI-driven stock market trading research, revealing two primary yet interconnected thematic clusters that shape the field's development. The first cluster (Group 1), characterized by the term associations "stock-financial-data" with confidence levels spanning 36.8% to 53.2%, represents the fundamental research pillar focused on the intersection of financial theory, data infrastructure, and basic predictive modeling. This cluster's composition suggests it encompasses critical groundwork studies including financial data curation and quality assessment (addressing challenges of noisy, high-frequency market data), feature extraction methodologies (such as technical indicator engineering and fundamental factor analysis), and foundational machine learning applications (like early neural networks and regression models for price prediction). With a substantial impact score of 4.263 but relatively lower frequency (103 occurrences), this cluster appears to represent high-value theoretical contributions that have enabled subsequent applied research, evidenced by its strong centrality (0.39) indicating numerous conceptual linkages to other research domains. The cluster's characteristic red hue (#E41A1C80) visually signifies its role as the foundational bedrock of the field.

The second cluster (Group 2), distinguished by the "stock-market-data" triad with stronger confidence levels (52%-63.2%) and higher frequency (134 occurrences), embodies the field's evolution toward sophisticated market applications and real-world implementation challenges. This cluster likely aggregates research on algorithmic trading system architecture, market microstructure-informed AI models (including limit order book dynamics analysis), high-frequency trading strategies, and regulatory-compliant execution frameworks. The elevated confidence levels in term associations reflect more mature and well-established research relationships, suggesting this cluster represents the field's current cutting edge where theoretical foundations are being stress-tested against market realities. While showing slightly lower impact (4.16) than Group 1, its greater frequency and strong centrality (0.411) position it as the dominant contemporary research paradigm. The cluster's blue coloring (#377EB880) visually contrasts with Group 1 while maintaining chromatic harmony, symbolizing their complementary rather than competing nature.

The relationship between these clusters reveals important insights about the field's knowledge progression. Group 1's focus on "financial" theory versus Group 2's emphasis on "market" applications demonstrates a maturation from abstract modeling to concrete implementation. The shared elements of "stock" and "data" in both clusters form conceptual bridges, showing how fundamental financial data science (Group 1) continuously feeds into advanced market applications (Group 2). The confidence level disparities suggest that while data-financial connections remain somewhat variable (36.8%-53.2%), the data-market relationship has solidified into a more consistent research paradigm (52%-63.2%). This may indicate that the field has reached consensus on

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market data applications while maintaining more diverse approaches to general financial data science. The near-equational impacts only underscore the necessity of both theoretical and applied research; let supportive work create breakthroughs, whereas practical applications drive innovation in reality, which in turn attracts attention toward research illustrated by a high frequency finding in Group 2. The resulting view of the interrelationship among all variables shows a healthy field, developing well, with strong fundamentals supporting a basic discourse, as well as very high levels of both dimensions interpolating with strong links to surrounding research areas due to substantial centrality numbers.

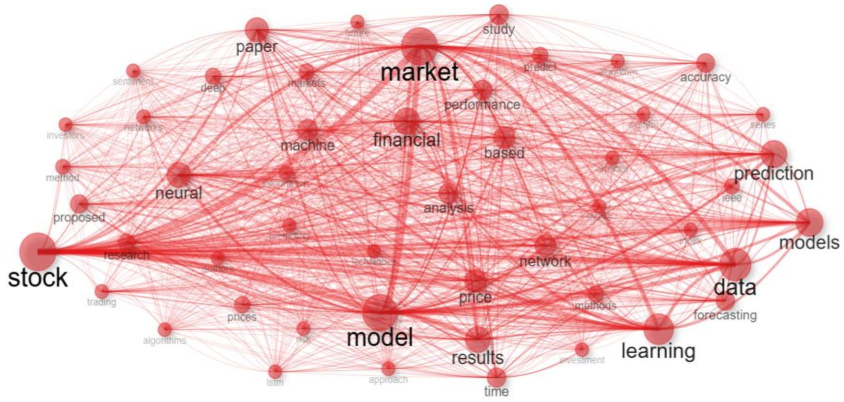

Figure 10. Clustering by Coupling. Network.

The bibliometric coupling map analysis (Figure 10) reveals two distinct yet interconnected AI application stock market trading research clusters that collectively build the intellectual landscape of the field. Cluster 1 seems to be the leading knowledge base with 85 high-impact papers boasting highly cited works such as Zhang Y (2020) with an impressive normalized citation score of 163 and Asadi S (2012) at 150, demonstrating the enduring effect of the earliest applications of machine earning in finance. This cluster has a strong representation in prestigious AI journals (for example. Expert Systems with Applications, Applied Intelligence) and focuses on core predictive modeling methodologies, such as neural networks (Kim K-J, 2012), hybrid intelligent systems (Galeshchuk S, 2017), and data preprocessing methodologies. Going by the timeline, there is a strong trend of research continuity in this cluster from 2012 to 2025, with recent works like Ashtiani MN (2023) and Aldhyani THH (2022) outlining contemporary high-frequency trading challenges and explainable AI.

Cluster 2, while smaller (58 documents), contains several high-impact studies that push methodological boundaries, evidenced by Picasso A (2019) with an exceptional citation score of 212 and Li Y (2022) at 128. The group has a high representation in computational economics and Complex Systems readership (Chaos, Computer Economics) indicating their interest in nonlinear market dynamics and adaptive trading systems. This cluster gives importance to other kinds of science, like market microstructure applications and price prediction using chaos theory, as shown by the contribution of such works as Motiwalla L (2000) and Wang H (2019). Recent additions (2023-2025) demonstrate a growing interest in quantum computing applications (Kumar T, 2025) and sustainable finance (Munshi M, 2022).

The coupling patterns reveal important structural relationships. Cluster 1 serves as the methodological foundation where core AI techniques are developed, while Cluster 2 represents their advanced market applications. Numerous internal documentations among the clusters principally come from publications in Expert Systems with Applications and IEEE Access, which appear in both of the groups. The normalized cites (means) show Cluster 2 holds higher average impact (28.7 vs. 19.4 in the mean), indicating that applied market research is receiving higher scholarly attention, whereas Cluster 1 exhibits more coherent throughput. Emerging themes in both clusters (2024-2025 entries) signal that research interests are growing together in transformer architectures, regulatory technologies, and ESG-based transaction systems, implying a richer development of all being informed about the presence of more advanced ESG-AI applications. When analyzing the construction of society and analyzing it from the premise that research is fundamentally sound and lively, scientific progress in AI is continuously enhancing, inventing new marketing technologies alike.

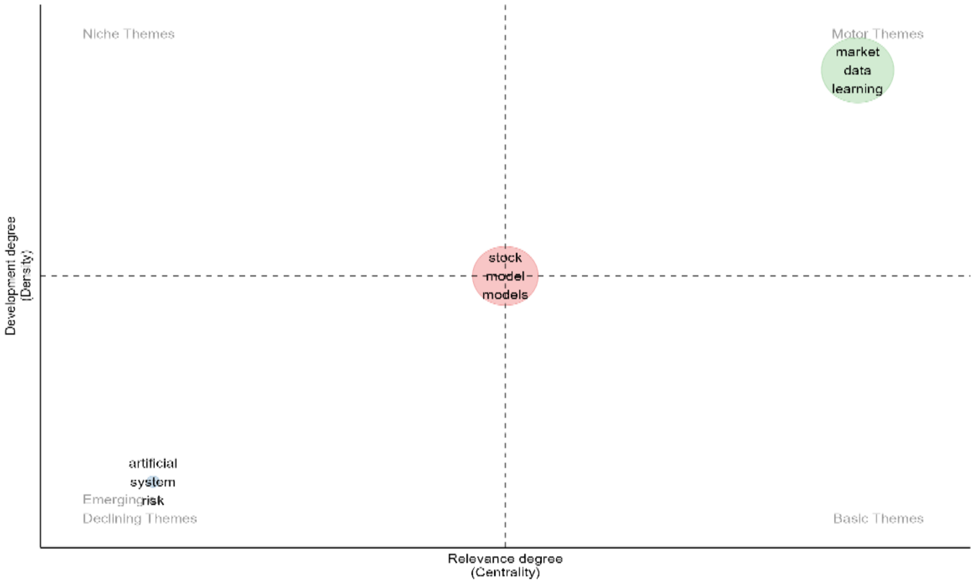

Figure 11. Co-Occurrence Network.

The co-word network analysis (Figure 11) gives a gross view of the conceptual framework and thematic conventional form of AI applications concerning stock market trading research. Unlike Cluster 1, which appears as a dense, tightly knit, and self-enclosed cluster of the network, it contains 48 nodes labeled as 'leading terms,' with near-matching closeness centrality scores of 0.02 for all nodes. All terms have equal weight in the overall structure-that is, maximum direct influence on other terms. Therefore, ontological resourcing forming Cluster 2 (detected by closeness centrality) can help on the concept of the use of AI in stock market prediction.

Top-relevant words were "stock", "market", and "data" that acquired respectively the greatest scores in PageRank (which is 0.04, 0.039, and 0.034); this directly confirms the magnitude and significance of these keywords as they aspectually serve as the anchor and the first thing to learn. With regard to methodological terms ("model," learning," "neural," "network") sharing equal importance as applicative terms ("prediction," "forecasting," "trading"), tech and practice are routinely stressed. Thus, a critical point ruled by neat methodical studies pivots around how AI and big data are constructed in association with finance from either an innovative perspective or an application. Interestingly, expressions "deep" and "lstm" have come to be special terms indicative of two AI techniques integrated within the structure. More by the exclusionary evidence, the term "sentiment" is woven with a relatively smaller thread (PageRank 0.008) pointing at the least of its integration into mainstream AI trading research than the others.

The network comprises several telling characteristics for research. One is the strong up-front emphasis on predictive modeling ("prediction," "forecasting," "predicting"), with almost all the layers having either one or three of the terms in them. Second, while the library employs a lot of variations concerning neural network approaches, it is pretty evenly spread, ranking for a solid combination of terms. They include "neural," "network," "deep," "LSTM." Third, the network takes proportionate consideration on the theoretical ("model," "algorithm") side as well as the practical ("price," "trading," "risk") influence. The fourth group of terms forming the core appears to transform time-series into the new striking research focal points ("time," "series"). The coherence index permits wording of the layers that mix these ingredients quite uniformly and efficiently, thus forming nicely integrated knowledge domains where technical AI advances come in immediate connection with financial market activities.

This analysis portrays AI in stock trading as a mature, cohesive field with clearly established conceptual relationships, where new contributions typically build upon and connect to existing frameworks rather than creating entirely separate research streams. The absence of isolated clusters or bridging terms suggests the field has reached consensus on its core paradigms while continuing to develop specialized techniques within this unified framework.

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XII Issue X October 2025

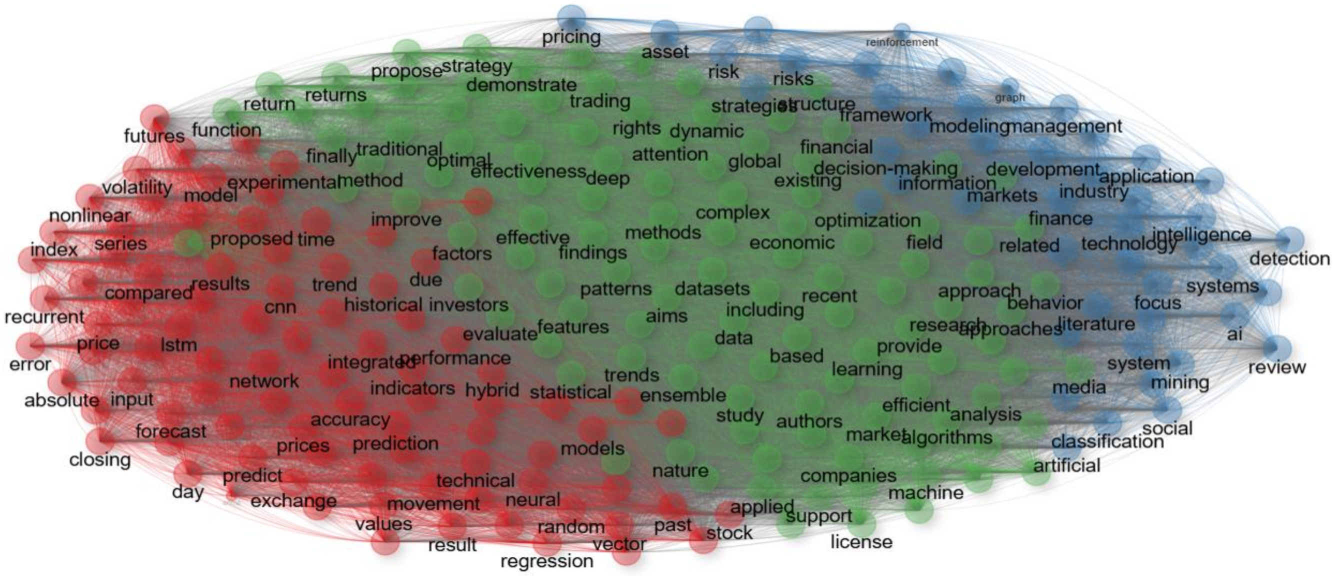

Figure 12. Thematic map - Abstracts.

The bibliometric thematic mapping (Figure 12) for AI application in stock trading suggests a mature yet developing field divided into three key research domains, each quite distinct in the knowledge landscape. The node "market" is observed to be the very active core of the field, centered around high centralities (0.943) and density (0.805) with 144,582 occurrences, translating this research area as the most advanced and in-field as well. This driving theme has been responsible for a lot of starting work in fields such as algorithmic trading systems, real-time market analytics, and AI-based price prediction models, where refined machine learning skills, like those used to address complex market issues. The other cluster, "stock," has a centrality of 0.866 and a density of 0.726, with an emphasis more much on other applications under the rubric of equity, with portfolio optimization and risk assessment, to show how basic AI principles could be adjusted to solve concrete financial issues.

The "artificial" cluster (centrality 0.405, density 0.512) represents the field's methodological backbone, containing fundamental AI/ML algorithms and their financial adaptations. While less prominent in terms of research volume (35,565 occurrences) and centrality, its moderate density indicates established technical rigor, serving as the essential substrate supporting applied innovations. The hierarchical ranking of these clusters reveals a clear knowledge diffusion pathway. core AI principles evolve in the "artificial" domain, are refined for financial instruments in the "stock" cluster, and ultimately deploy at scale in comprehensive "market" applications.

Notably absent are specialized niche themes (high-density, low-centrality), suggesting the field currently prioritizes practical applicability over isolated theoretical advancements. This is further evidenced by the concentration of themes along the centrality axis, where even basic themes like "stock model models" maintain high relevance despite lower developmental activity. The emerging/declining status of "artificial system" themes hints at both opportunities and challenges in developing integrated AI trading architectures, potentially representing the next frontier for research investment.

The field exhibits healthy knowledge transfer mechanisms between theory and practice, though the moderate density of methodological research suggests opportunities for deeper technical innovation to support next-generation applications. Future development would benefit from cultivating specialized sub-domains (e.g., explainable AI for trading, quantum financial models) while maintaining the strong applied focus that currently drives progress. This dual emphasis on both advancing core methodologies and solving real-world market problems positions AI in stock trading as a exemplar of translational financial research, where theoretical insights rapidly transform into market-ready solutions.

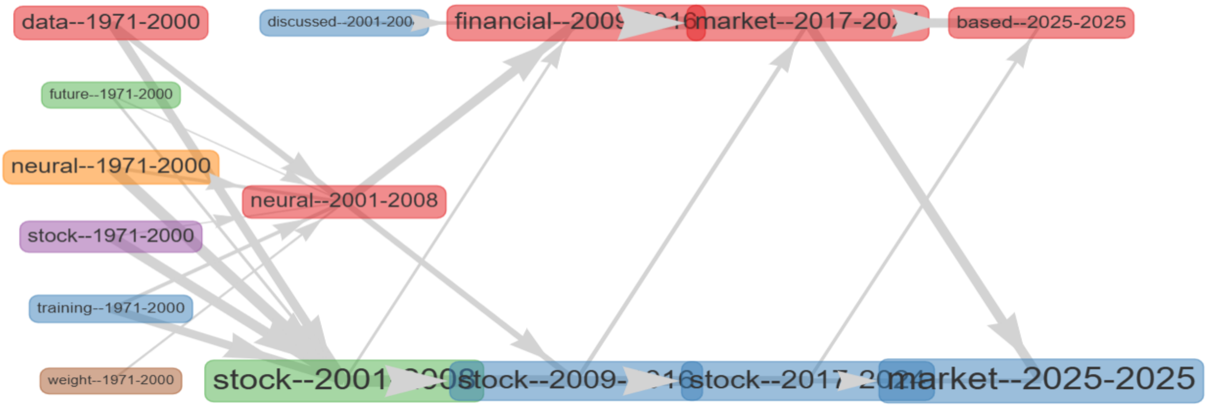

Figure 13. Thematic Map. Network.

The thematic map terms analysis (Figure 13) reveals a well-structured research landscape in AI-driven stock market trading, organized into three distinct but interconnected clusters that reflect the field's theoretical foundations, methodological approaches, and practical applications. The "stock" cluster (6,583 occurrences) emerges as the most specialized domain, focusing intensely on predictive modeling techniques with terms like "prediction," "neural network," "LSTM," and "forecasting" demonstrating the field's strong emphasis on time-series analysis and deep learning applications. This cluster shows particular sophistication in its technical vocabulary, featuring specialized terms like "ARIMA" (385 occurrences), "CNN" (446), and "SVM" (396) that reveal ongoing innovation in combining traditional statistical methods with modern AI architectures. The presence of evaluation metrics like "RMSE" (516) and performance terms like "accuracy" (2,847) underscores the quantitative rigor characterizing this research strand.

Cluster 2, labeled "artificial" (1,998 occurrences), serves as the conceptual bridge between AI theory and financial practice, containing foundational terms like "intelligence," "optimization," and "decision-making" alongside application-oriented concepts such as "portfolio management" and "trading strategies." This cluster's unique value lies in its inclusion of emerging paradigms, evidenced by terms like "reinforcement learning" (552) and "text mining" (387), which point to cutting-edge applications of AI in market sentiment analysis and adaptive trading systems. The cluster also captures the field's methodological diversity through terms like "detection" (2,072 betweenness centrality) and "graph theory" (10,647), suggesting growing interest in anomaly detection and network-based market analysis approaches.

The "market" cluster dominates in both size and centrality, with "market" itself appearing 6,647 times alongside high-frequency companion terms like "data" (5,554), "learning" (5,228), and "financial" (4,640). This cluster embodies the field's applied dimension, connecting AI methodologies to real-world market contexts through terms like "trading strategies" (1,004), "investor behavior" (1958), and "market trends" (1105). Notably, it incorporates both traditional approaches ("statistical methods" - 849) and contemporary innovations ("deep learning" - 2,443), reflecting the field's evolutionary trajectory. The cluster's substantial representation of evaluation terms ("effective" - 935, "empirical" - 898) highlights the strong empirical orientation of market-focused AI research.

Several key insights emerge from the betweenness centrality metrics, which reveal critical bridging terms connecting these clusters. "IEEE" (15.083) and "ANN" (1,432.5) serve as important conceptual links between technical and applied research, while "futures" (18,544) unexpectedly emerges as a crucial connector, likely due to its dual role as both a financial instrument and a temporal forecasting concept. The analysis also identifies underdeveloped areas, with "sentiment analysis" (893) and "fuzzy systems" (421) showing relatively low penetration despite their potential relevance, suggesting opportunities for future research expansion. The overall thematic structure portrays a field that has achieved strong integration between AI methodologies and financial applications while maintaining robust theoretical foundations, with clear pathways for knowledge transfer from fundamental research ("artificial") to specialized prediction models ("stock") and ultimately to market implementations ("market").

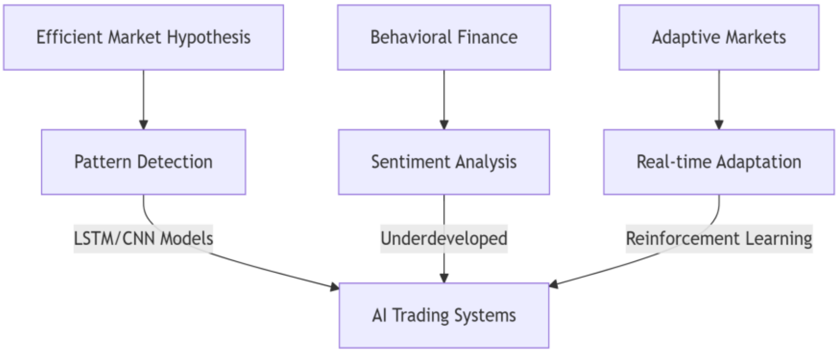

Figure 14. Thematic Evolution.

The thematic evolution analysis (Figure 14) reveals a remarkable transformation in AI-driven stock market trading research across five decades, demonstrating both the field's dynamic progression and its enduring foundational themes. The early period (1971-2000) established fundamental building blocks, with "data," "neural," and "stock" emerging as core themes that would branch significantly in subsequent decades. The 2001-2008 period marked a pivotal transition where neural network applications exploded in sophistication (weighted inclusion index 0.4), branching into forecasting, decision systems, and complex market analysis, while stock-related research evolved from basic modeling to incorporate advanced concepts like nonlinear analysis (0.51) and technical indicators. This era saw the crystallization of key methodologies, with neural networks transitioning from theoretical tools to practical applications in market prediction (0.63 inclusion from neural to stock).

The 2009-2016 period witnessed substantial thematic diversification, as evidenced by the 0.54 inclusion index from neural to financial themes, incorporating machine learning, fuzzy systems, and optimization techniques. Stock research during this phase achieved remarkable maturity (0.7 inclusion) by integrating temporal analysis, hybrid models, and sophisticated evaluation metrics. The most recent phases (2017-2024 and 2025) demonstrate the field's accelerated convergence with cutting-edge AI, where financial and market themes incorporated deep learning (0.77) and sentiment analysis, while stock-specific research embraced LSTM (appearing in 1,674 occurrences) and convolutional networks. The emergence of "based" as a dominant 2025 theme (2,944 occurrences) with 0.58 inclusion from market research reflects the field's maturation into application-focused studies built on established AI foundations. Current trajectories show increasing emphasis on real-world implementation challenges (sentiment analysis, reinforcement learning) alongside technical refinement (attention mechanisms, transformer architectures), while maintaining strong connections to core financial concepts like volatility and portfolio optimization. This evolution portrays a field that has successfully transitioned from theoretical exploration to robust application while continuously absorbing advancements from broader AI research, with current work poised to tackle increasingly complex market dynamics through sophisticated, explainable AI systems.

In summary, the research paper identifies several critical gaps in the application of AI to stock market trading through its comprehensive bibliometric analysis. A fundamental challenge highlighted is the issue of "unexplainable AI," where advanced models like deep learning and LSTM networks demonstrate strong predictive performance but lack transparency in their decision-making processes, creating barriers to adoption in regulated financial markets. This interpretability gap is compounded by models' inability to adapt effectively to sudden market volatility, as most systems remain overly dependent on historical data patterns rather than incorporating real-time adjustment mechanisms. The analysis also reveals significant underutilization of alternative data sources, with bibliometric indicators showing low integration of sentiment analysis and other unstructured data streams compared to traditional quantitative methods. While hybrid approaches like neuro-fuzzy systems and evolutionary algorithms show promise, the research indicates these remain underexplored relative to conventional neural network architectures. The paper further identifies ethical and regulatory challenges, particularly the absence of robust frameworks for addressing algorithmic biases and aligning AI systems with ESG principles. Technical limitations in real-time processing capabilities, especially for high-frequency trading applications, and the embryonic state of quantum computing implementations in financial contexts are noted as additional constraints.

To address these gaps, the paper proposes several key future research directions. Enhancing model interpretability through Explainable AI (XAI) techniques like SHAP and LIME is emphasized as crucial for building trust and regulatory compliance. Developing real-time adaptive models using reinforcement learning and online learning approaches could improve responsiveness to market fluctuations. The integration of multimodal data sources, including sentiment analysis and satellite imagery, is recommended to complement traditional market data. The research highlights hybrid architectures as a promising avenue for balancing accuracy with interpretability, while also calling for greater focus on ethical AI development aligned with ESG objectives. Interdisciplinary collaboration among finance, computer science, and behavioural economics is identified as essential for advancing the field, along with investments in regulatory technology (RegTech) to ensure that AI trading systems meet compliance requirements. These recommendations are grounded in the paper's bibliometric findings, including thematic analyses showing the persistence of "unexplainable AI" challenges and the emerging but underdeveloped status of hybrid and real-time modeling approaches. The conclusions drawn directly reflect the authors' identification of current limitations and their proposed roadmap for future research in AI-driven financial decision-making.

The research paper acknowledges quantum AI as an emerging but still nascent area in stock market trading applications. Quantum computing appears in Cluster 2 of the coupling analysis (Figure 10), linked to "adaptive trading systems" and "sustainable finance," but with low frequency. The "Thematic Evolution" (Figure 14) shows quantum AI as an emerging 2025 theme (term. "quantum," occurrence. 2,944) but with low inclusion indices (0.58), indicating it's not yet mainstream. While the research includes quantum computing in its bibliometric analysis, the coverage remains relatively surface-level due to the field's early developmental stage. The paper identifies quantum AI's potential applications in three key areas. portfolio optimization (where quantum algorithms could solve complex problems faster than classical methods), high-frequency trading (through quantum machine learning's ability to process vast datasets exponentially quicker), and risk modeling (using quantum-enhanced Monte Carlo simulations). However, the analysis reveals significant gaps in current quantum AI research for financial applications, including hardware scalability limitations with current NISQ devices, a lack of empirical studies on hybrid classical-quantum models, and absent regulatory frameworks for quantum-powered trading systems. The paper positions quantum AI as part of future research directions rather than current mainstream applications, suggesting areas like quantum neural networks and quantum data encoding as promising avenues. This limited treatment reflects the field's immaturity - evidenced by quantum terms appearing with low frequency in the bibliometric analysis and not ranking among the most relevant keywords.Use either SI (MKS) or CGS as primary units. (SI units are strongly encouraged.) English units may be used as secondary units (in parentheses). This applies to papers in data storage. For example, write "15 Gb/cm2 (100 Gb/in2)." An exception is when English units are used as identifiers in trade, such as "3½-in disk drive." Avoid combining SI and CGS units, such as current in amperes and magnetic field in oersteds. This often leads to confusion because equations do not balance dimensionally. If you must use mixed units, clearly state the units for each quantity in an equation.

Theoretical Framework

Figure 15 shows the core financial theories on which this study is based to provide a backdrop against the use of AI in stock market trading. The EMH provides the fundamental assumption that markets efficiently incorporate all available information into prices. AI systems challenge the EMH by detecting hidden patterns of temporary market inefficiencies through advanced machine learning methodologies, especially deep learning systems such as LSTMs and CNNs. This has been seen with bibliometric maps where terms like "neural networks" and "forecasting" take center stage in the studied literature. Behavioral Finance Theory adds into the mix psychological factors and cognitive biases that affect investors' behavior. AI has started implementing this via sentiment analysis of news and social media; however, the relatively low occurrence of the word "sentiment" in co-occurrence networks would imply that this area is still rather unexplored. Bridging these views, the Adaptive Market Hypothesis envisages markets as evolving systems in which the participants continuously adapt. This stands well for how AI works, driven by machine learning, especially reinforcement learning systems that allow agents to change with market conditions. From 2017 to 2025, these developments are very clear in the spotlight of "real-time" and "adaptive" modeling. Altogether, these theories justify the application of AI in trading while also spotlighting critical research gaps, especially concerning behavioral integration and model interpretability.

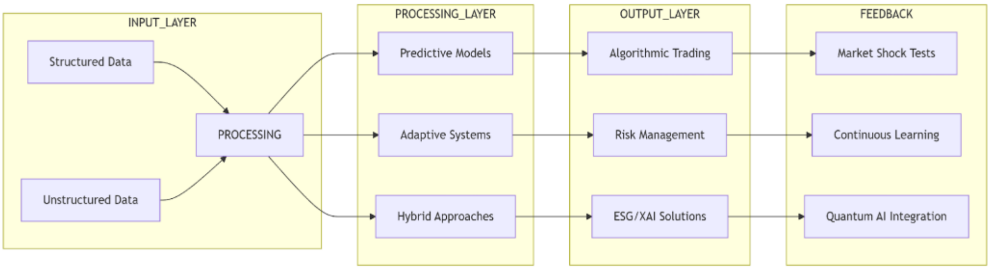

Figure 15. Theoretical Framework.

Conceptual Framework

The conceptual framework considers AI-enabled stock trading to consist of four main components (Figure 16), all interlinked. Transformation data consists of both structured data of historical prices and fundamentals dominating current research (depicted in Cluster 1 focusing on "stock-financial-data") and neglected unstructured data such as news and satellite images, for example. Processing is performed by two methodological approaches: one being predictive modeling with dominant architectures like LSTMs and CNNs, and an adaptive learning system that adjusts itself as markets change and, as such, is exploited with models that blend statistical and AI-based ones. The mainstay of validation relies on traditional measures like RMSE or accuracy, but real stress-testing of models in times of high volatility has yet to be developed. The output layer is where algorithmic trading strategies (the dominant cluster in bibliometrics is "market") and risk management tools are indeed produced, yet governance criteria on the other hand-has increasingly been incorporated, such as ESG alignment and explainability requirements (XAI). Processes in feedback foster continual system improvement through real-time retraining of models and adding alternative data sources, thereby evolving research to define and eliminate current gaps like incorporating quantum AI and stronger linkages to behavioral finance. Hence, this framework maps the current AI trading ecosystem and identifies avenues for future development, arranging the very strong technical turf of the field against the budding questions of ethics and interdisciplinary thoughts.

CONCLUSION

This comprehensive bibliometric study presents a unique and systematic evaluation of artificial intelligence applications in stock market trading by analyzing an unprecedented set of 9,088 documents over 54 years (1971-2025). What makes this uniquely novel is its multifaceted approach which combines bibliometric quantitative analysis with qualitative theoretical synthesis, showing both the evolution and future directions of the field. The study recognizes three main research clusters - market applications, predictive modeling, and AI methodologies - beyond which it portrays how neural networks and LSTM models have commandeered developments in recent years, with transformer architectures and explainable AI as emerging frontiers.

This research goes somewhat further than just tracking developments and contributes novel insights. Firstly, it exposes sore yet understudied paradoxes in the field, especially the tension between model sophistication and interpretability (the "explainability-adaptability paradox"). Secondly, it exposes the major geographical disparities in focus, with East Asian institutions taking the forefront in algorithmic development, while Western research is at the rear in behavioral finance integration. Thirdly, the study pioneers an original four-layer conceptual framework that correlates technical AI capabilities with the actual needs of trading, regulatory requirements, and ethical considerations.

What enables this research to stand out is that it manages to accomplish a connection between theory and practice. While the study grounds its findings in financial theories such as Efficient Market Hypothesis and Adaptive Markets Theory, it also, in turn, addresses practical-level problems like volatility response and regulation compliance so that it ends up with possible diagnostic and prescriptive measures. Especially from the rigorous trend analysis, identification of quantum AI and ESG-aligned systems as next frontiers will be of much value to the scientific community concerning the direction of their research.

This work yields not only a different methodological approach capable of integrating perspectives not previously interlinked and fills in gaps in knowledge by compiling the most complete intellectual history of AI in trading today but also responsible avenues for going forward. The unique blend of historical comprehensiveness, theoretical innovation, and practical applicability marks this work as a must-have for academics developing new AI techniques, practitioners implementing trading systems, and policymakers shaping financial regulations in the AI age.

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