REVIEW OF ANALYSIS ON ARTIFICIAL INTELLIGENCE IN STOCK PREDICTION: A CONCEPTUAL AND BIBLIOMETRIC SYNTHESIS

BANDI LAKSHMI M.COM, APSET
Lecturer in Commerce
Government Degree College, Sabbavaram
Anakapalli District, Andhra pradesh, India

Abstract

The stock market is volatile and complex. Clear trends are rare. This uncertainty challenges traders, investors, hedge funds, and portfolio managers. Artificial intelligence (AI) is reshaping investing, prediction, and trading. AI processes large, diverse datasets at speed and scale beyond human capacity, which can improve stock prediction.This study maps the AI methods, measures, and data sources used in stock market prediction. It uses a bibliometric analysis of publications indexed in Elsevier Scopus to track growth and application trends. The analysis reviews publication patterns, leading authors and institutions, top countries, time trends, citation impact, and source outlets. Results show a publication peak in 2021–2022, at about 40 papers per year. Knowledge-Based Systems has the most papers (over 35), followed by Decision Support Systems (about 20). The International Journal of Forecasting has more than 3,500 citations and is the most influential journal in the set. Discussion points to rapid growth in AI integration across financial tasks. Deep learning, richer data, and stronger methods offer new ways to support decisions and reveal market insights. Future work should combine advanced models with comprehensive datasets and rigorous evaluation to inform analysts, policymakers, and regulators.

1. INTRODUCTION

Stock markets usually represent an appealing investment avenue for capital growth. Recent advancements in communication technology have increased the popularity of stock markets among individual investors over the past few decades. As the number of shareholders and companies in the stock markets increases annually, many seek a method to forecast future market trends. This is a difficult topic with numerous intricate aspects affecting price fluctuations. The stock market is infamous for its intrinsic volatility and complexity, lacking a discernible trend, which poses a continual challenge for traders, investors, hedge fund managers, and portfolio management services in forecasting the unpredictable. In the current dynamic and shifting investing scene, stock prices are difficult to forecast due to various influencing factors, including investor attitude, global economic conditions, political events, unforeseen occurrences, and corporate financial performance. It also varies significantly due to numerous reasons, including shifts in market patterns, the emergence of new enterprises, and advancements in technology or politics.

Forecasting the stock market is difficult but essential for investors, traders, and scholars. Diverse methodologies, encompassing mathematical, statistical, and Artificial Intelligence (AI) tools, have been suggested to predict stock prices and surpass market performance. Artificial Intelligence methodologies, especially Machine Learning (ML) and Deep Learning (DL), have received heightened scrutiny. AI fundamentally permeates computer systems that perform numerous cognitive functions formerly executed by humans. They can also address creative challenges in the absence of explicit instructions. Historically, stock market prediction methodologies and instruments, despite numerous challenges, have enabled a significant number of investors, both individual and institutional, to engage in transactions where prospective profit is the primary objective. Insights gained from this type of asset-based investment can also delineate any approach a company may adopt for business recovery.

REVIEW OF LITERATURE

Bibliometric studies utilise already published research to analyse and investigate the patterns and trends of publications, hence facilitating the exploration, organisation, and comprehension of work conducted within a specific discipline or subject of study (Diodato, 1994; Ferreira, 2011). Alternative traditional methods for conducting a literature review may not provide an accurate understanding of the current state of knowledge on the subject, even though they may involve a more thorough analysis of the substance of each published work.

“Bibliometric studies utilise a quantitative analysis of written source documentation, such as academic articles, books, reports, theses, dissertations, and news media, as an objective method to examine a specific area or the entirety of a scholarly discipline. This approach is supported by various researchers” (Diodato, 1994; Nerur, Rasheed, & Natarajan, 2008; Ramos- Rodriguez & Ruiz-Navarro, 2004; Shafique, 2013).

Allen (2022) examines capital market research plan cluster performance elements. From 2020 to 2021, Scopus-indexed journal manuscripts were analysed with 400 manuscripts. High-credibility manuscripts were double-blind reviewed and classified by publishing type. VOS-Viewer analysis of 240 article titles and abstracts showed that the factors influencing stock market research during the COVID-19 pandemic were categorised into four clusters: a surge in cryptocurrencies, particularly bitcoin, due to oil and gold price spillovers, the response and behaviour of international stock markets, and significant stock market performance metrics.

Richerd (2022) examined cryptocurrency and the stock market. This study used bibliometric and content analysis on 151 articles from 2008 to November 2021. We examined important institutions, authors, countries, and periodicals using VOS-Viewer software. We analysed co-authorship, bibliographic coupling, and keyword co-occurrence to understand the network. The content analysis also addressed four major research streams' conclusions. We suggest seven exploratory research questions. The findings identify study gaps and future directions for bitcoin and stock market literature.

Darja Zabavnik (2023) uses bibliometric analysis to trace the evolution of research on the financial-real economy relationship and identify the most influential authors, journals, and articles. We also analyse the 50 most impactful papers, which may be scientific breakthroughs in the research domain.

Dr.Naveen Prasadula (2023) bibliometrically analysed 437 commodities connection journal papers from 1994 to 2022. The study employs bibliometrics, content analysis, and qualitative approaches. The analysis finds four key commodity connectedness research streams: commodity interconnectivity, traditional commodity-renewable energy-cryptocurrency links, oil-stock market relationships, and copula studies on oil-financial market interconnectivity. We proposed 15 commodity connectedness research topics on post-COVID global uncertainties, climate change, cryptocurrency growth, and Russia-Ukraine conflict implications.

2. METHODOLOGY OF THE STUDY

The analysis encompasses the period from January 1, 1991, to December 31, 2024, ensuring a minimum duration of 24 years for an extensive longitudinal study. The initial Scopus search yielded a diverse array of items, encompassing articles, conference papers, and reviews, published in English. This investigation concentrates solely on a selection of 710 published works, despite the vast amount of available data. This study specifically focusses on topic areas that fall under the subject area of "Economics, Econometrics and Finance" and "Business, management, and accounting," The analysis is limited to only 39 keywords that includes Forecasting, Commerce, Financial Markets, Artificial Intelligence, Investments, Finance, Decision Making, Stock Market, Prediction, Stock Market Prediction, Stock Price, Artificial Neural Network, Financial Forecasting, Stock Price Prediction, Stock Prediction, Financial Market, Artificial Neural Networks, Forecasting Method, Stock Predictions, Risk Management, Risk Assessment, Stock Market Forecasting, Marketing, Stock Price Forecasting, Investment, ANN, Stock Returns, Stock Price Movements, Stock Markets, Portfolio Management, Financial Data, Economic Analysis, Artificial Neural Network (ANN), Market Prediction, Investment Strategy, Investment Decisions, Fintech, Financial Analysis and AI.

The VOS-Viewer software has been utilised for bibliometric mapping and visualisation. It facilitated the analysis of co- authorship to uncover collaboration networks among scholars and institutions. Moreover, it enabled the analysis of term co- occurrence to identify principal research themes and emerging topics. Of the total 710 papers, only 263 articles have been used into this analysis. The listed papers were chosen based on a minimum citation criterion of 10.

The search results encompassed information regarding the titles of sources, document types, keywords, affiliations, and funding organisations. The collected data was evaluated to assess publishing patterns and identify significant contributors, prolific writers, influential institutions, leading countries, the temporal evolution of publications, citation trends, and the distribution of research across various sources.

3. FINDINGS AND ANALYSIS

The analysis of the paper has been divided into two parts:

A. Conceptual Study

(1). What AI methodologies and technologies are predominantly employed to predict stock market prices?

(2). Which informational sources are most commonly employed to forecast stock market prices?

(3). What measures are most frequently utilised to assess the success of predictive models?

B. Bibliometric Study

The bibliometric indicators utilised in this study are as follows:

- Analysis of Year-wise Published Documents
- Analysis of Top 12 Journal wise published documents
- Analysis of Top 12 Source documents through Network Map
- Analysis of Top 12 Journals Having Maximum Citation
- Analysis of Network Map of Top 12 Cited Journals
- Analysis of Top 12 authors having maximum citations
- Analysis of Network Visualization of Co-authorship among top 12 authors
- Analysis of top 12 keywords occurring maximum times.
- Analysis of network visualization of co-occurrence of keywords.
- Analysis of top 12 country wise publication
- Analysis of Network Map of Country-wise publications

A. Conceptual Study

1. Main AI Methods and Technologies used for Stock Market Price Prediction

Financial market forecast, especially stock market values, relies on AI and ML. These technologies let models process massive volumes of data, find hidden patterns, and anticipate price movements. The most common AI stock market forecast methods and technologies are:

A. Supervised Learning:

- Linear regression: One of the simplest algorithms is linear regression. This approach compares stock price to market indicators, trade volume, etc. This basic strategy may miss intricate linkages in volatile financial data.
- SVMs(Support Vector Machines): SVMs can predict stock price rise or decline and stock price regression. SVM finds the optimal hyperplane for classification or regression. This algorithm works well with high-dimensional data, common in financial markets.
- Random Forests: Decision tree ensembles forecast stock prices in random forests. These trees are less likely to overfit than single decision trees since they randomly select data attributes. Random forests can capture non-linear stock price connections in huge datasets.
- GBMs (Gradient Boosting Machines) like XGBoost and LightGBM are powerful ensemble

algorithms that iteratively create models to rectify earlier faults. The predictive power of these models makes them popular in finance.

B. Unsupervised Learning:

Unsupervised learning finds latent data patterns and structures without labelled outcomes. These strategies discover anomalies and group equities with similar behaviours in stock market analysis. Examples of unsupervised methods:

- The K-means clustering method: We use previous price movements to categorise equities with similar behaviour for portfolio optimisation and asset identification.
- PCA: Dimensionality reduction with PCA condenses huge datasets while maintaining most of their variance. PCA is used in stock market analysis to identify price-moving factors.

C. Deep Learning

The use of deep learning technologies, such as neural networks, is growing in stock market prediction due to their capacity to represent complicated data linkages. Popular deep learning models include:

- RNNs (Recurrent Neurals Networks): RNNs are ideal for sequential data like stock market time series. They can forecast stock values based on prior trends since they remember inputs.
- Long- Short terms Memory networks (LSTMs): LSTM is a type of RNNs avoid the vanishing gradient problem. LSTMs can capture long-term data dependencies, making them ideal for time series forecasting like stock price prediction.
- Convolutional Neural Networks (CNNs): CNNs may recognise financial data by treating time series data as 2D. CNNs can spot stock price trends.

D. Reinforcement Learning

RL, specifically Q-learning and Deep Q Networks (DQN), is used to construct trading techniques rather than direct price prediction. In reinforcement learning, an agent learns the best stock market behaviours (buy, sell, hold) to maximise profits over time. RL models are ideal for dynamic trading techniques where the agent adjusts to market changes.

- Natural Language Processing (NLP)

NLP is an AI area that studies computer-human language interaction. News, social media, earnings, and financial statements are analysed using NLP for stock market prediction. Sentiment analysis and topic modelling are used to anticipate how news sentiment may affect stock prices. Positive news items regarding a corporation may forecast stock price gains, while negative ones may indicate price reductions.

- Forecasting time series

Timing series forecasting is crucial to stock price prediction because it predicts future values based on past values. Stock prices and volatility are typically predicted using traditional time series models like

ARIMA and GARCH. These models presume past patterns will persist, which may not be true in volatile markets.

- Genetic Algorithms

Genetic algorithms optimise using natural selection and evolution. Over time, these algorithms can enhance stock market prediction by growing populations of viable solutions (such as trading strategies or feature picks). Genetic algorithms are employed with other machine learning models to determine the best tactics.

2. Most Common Stock Market Price Forecasting Sources

AI models must process massive data to anticipate stock prices. Data sources are roughly classified as:

- Historical Stock Data

Stock price prediction relies on past market data, including daily or minute-by-minute prices (open, close, high, low) and trading volumes. The temporal sequence of stock movements is used for technical analysis and time series forecasting.

- Technical Indicators

Many financial models use technical indicators based on past stock price and volume data. Some popular technical indicators are:

  - SMA, EMA Moving Averages: Some indicators smooth price data over a period and help spot trends. The Simple Moving Average (SMA) is the average stock price over a period, whereas the Exponential Moving Average (EMA) emphasises recent values.
  - The RSI measures relative strength. This momentum oscillator detects stock overbought or oversold conditions, indicating price reversals.
  - MACD: moving average convergence divergence This trend-following indicator detects stock price strength, direction, and duration.

- Fundamental Data

Financial statements (income statement, balance sheet, cash flow), earnings reports, and other company-specific measures are fundamental data. These data points determine a company's financial health, affecting stock prices. A solid earnings report may boost stock values.

- Market sentiment

Market sentiment can affect stock price, hence stock market prediction models use sentiment analysis from textual data sources.

- News and financial reports: News (good or negative) from news sources or earnings calls strongly influences market mood.

- Social media platforms

Platforms like Twitter, Reddit, and Stock-Twits give real-time crowd-sourced opinions and sentiment. Social media posts help models predict retail investor sentiment towards a stock.

- Macroeconomic metrics

Understanding metrics like GDP growth, interest rates, inflation rates, and unemployment rates is crucial for identifying market patterns and potential repercussions on specific stocks or sectors.

3. Most Common Predictive Model Success Measures

Stock market forecasting prediction models must be evaluated to determine their efficacy and reliability. These models are evaluated using several criteria:

(a). Accuracy

Accuracy measures how often predictions match results. Being a frequent statistic, it may not be the ideal for stock market predictions due to volatility and data imbalances (e.g., more downward moves than upward).

(b). Mean Absolute error (MAE)

MAE averages absolute errors between expected and actual values. In financial applications where exact predictions are needed, it shows prediction flaws directly.

(c). Root Mean Squared Error (RMSE)

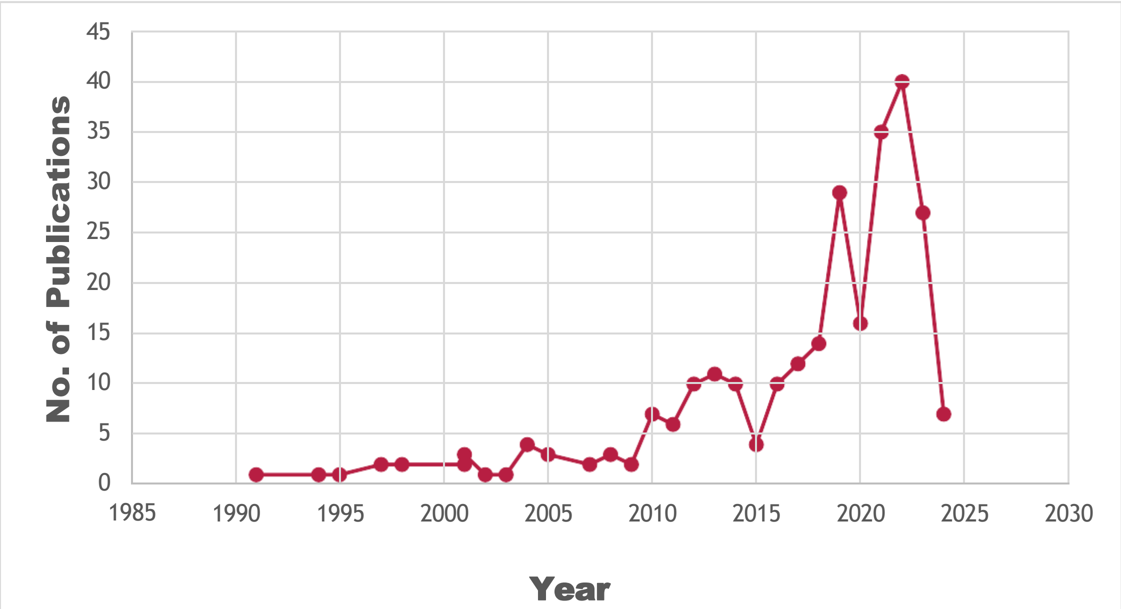
Error metrics like RMSE square errors before averaging. RMSE is more sensitive to higher errors, which is useful when predicting volatile stock prices because huge deviations might have greater financial effects.

(d). R-Squared (R^2)

R^2 indicates the percentage of variance in stock prices explained by predictive features. It evaluates model fit to data. Although a greater R^2 indicates a better fit, it cannot guarantee accurate stock price predictions owing to the unpredictability of financial markets.

B. Bibliometric Study

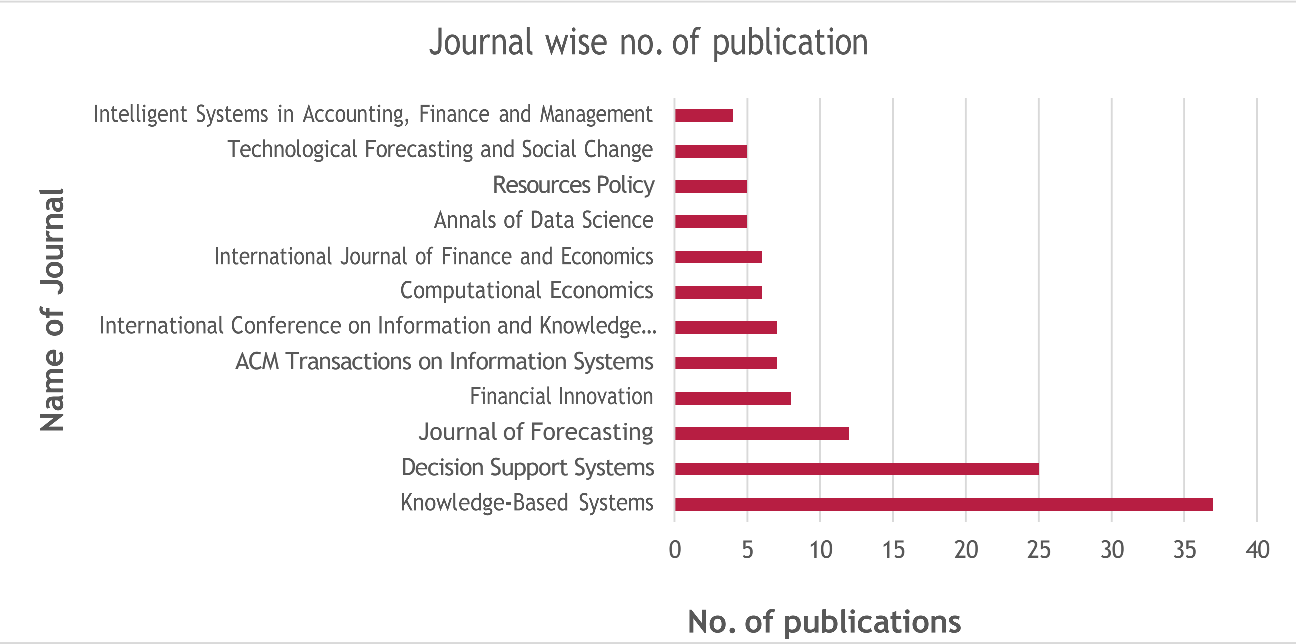
1. Analysis of Year-wise Published Documents



This line graph illustrates the number of publications with time, spanning approximately from 1990 to

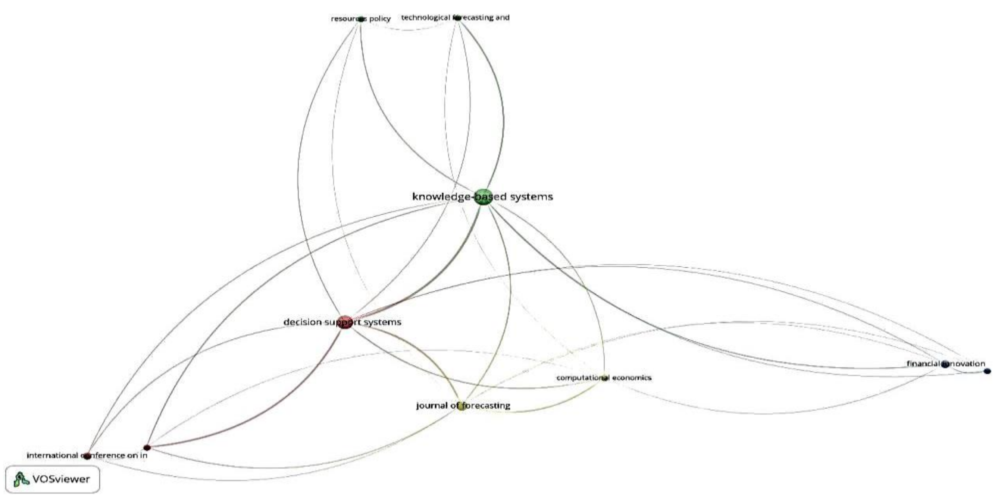
2025. The data reveals a steady escalation in publications from 1990 to 2010, succeeded by a substantial surge in the quantity of articles from 2010 to 2020. The highest level is noted between 2021 and 2022, with the maximum number of publications approximating 40. Subsequent to 2022, the graph indicates a considerable decrease in publications, significantly declining by 2025. The graph indicates a significant escalation in research activity during the past decade, maybe attributable to heightened interest in the topic or progress within the discipline. The abrupt decrease following 2022 may suggest diminished financing, alterations in research priorities, or external influences such as world events. This trend indicates a swift increase in research interest in the early 2020s, succeeded by a significant decline in publications in recent years.

2. Analysis of Top 12 Journal wise published documents



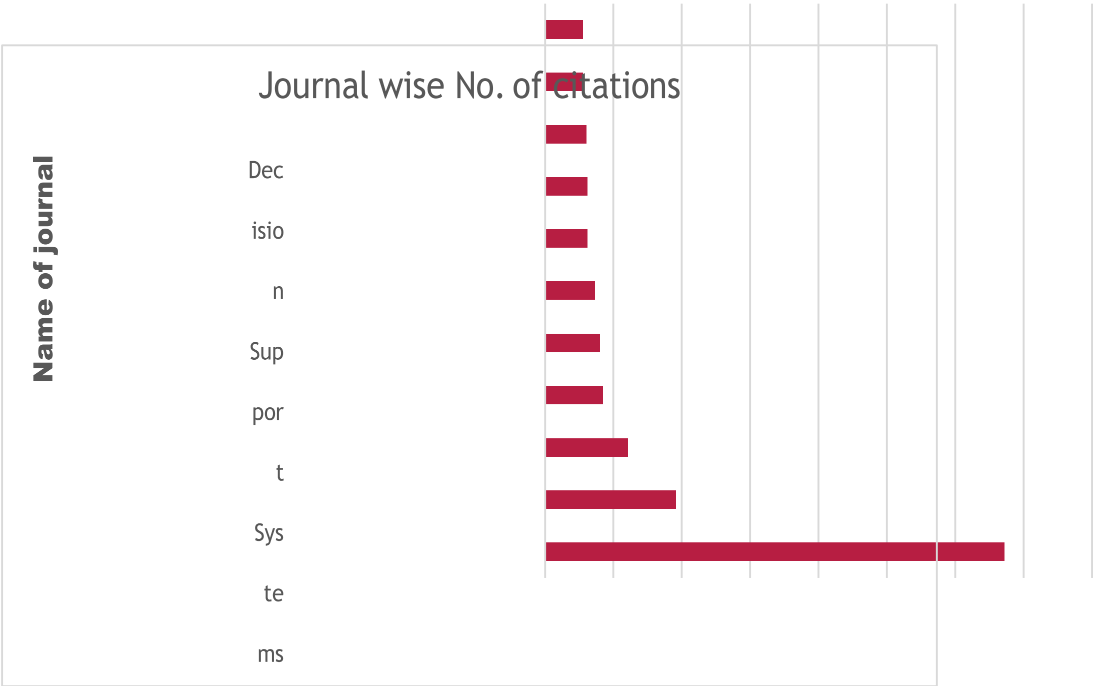
The bar graph illustrates the number of publications categorised by journal. It underscores the allocation of publications among diverse periodicals. The journal Knowledge-Based Systems has the most publications, surpassing 35, followed by Decision Support Systems with around 20 publications. The Journal of Forecasting has moderate contributions, with approximately 10 publications. Journals such as Financial Innovation, ACM Transactions on Information Systems, and the Proceedings of the International Conference on Information and Knowledge Management have a relatively smaller volume of publications, ranging from 5 to 8 articles. The remaining journals, such as Technological Forecasting and Social Change, Computational Economics, and Intelligent Systems in Accounting, Finance, and Management, each have fewer than five publications. This pattern demonstrates that the majority of research is focused on Knowledge-Based Systems and Decision Support Systems, underscoring their pivotal importance in the domain.

3. Analysis of Top 12 Source documents through Network Map



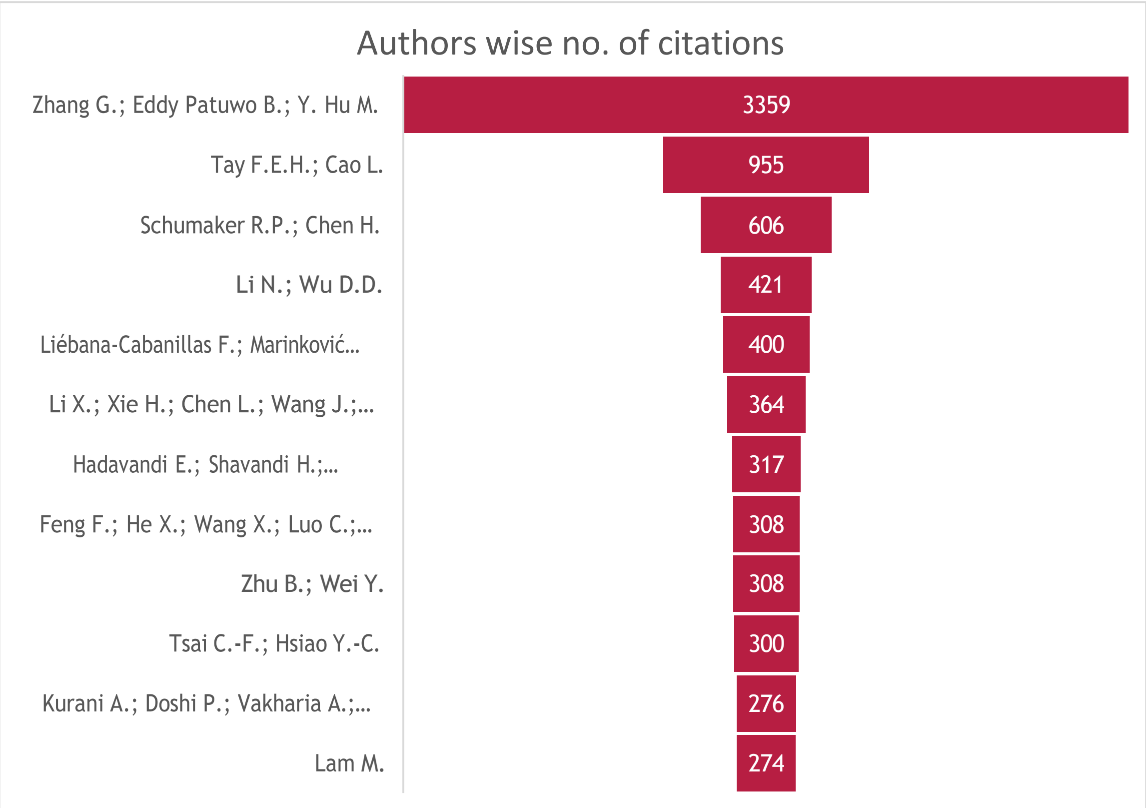
The VOS-viewer has created a journal-wise publication network map. The map shows journal co-occurrence by publication count. Each node represents a journal, and its size indicates its publication volume. The lines or edges linking the nodes signify journal collaborations, and their thickness indicates their strength. The most prominent journal is Knowledge-Based Systems, with the greatest node size and most publications. It has significant links to Decision Support Systems, Journal of Forecasting, and Technological Forecasting and Social Change, indicating that their research commonly overlaps or mentions each other. The blue cluster represents financial innovation research. The network map shows the dominance of Knowledge-Based Systems in research and the collaboration of journals on decision-making systems, forecasting methodologies, and technology applications.

4. Analysis of Top 12 Journals Having Maximum Citation



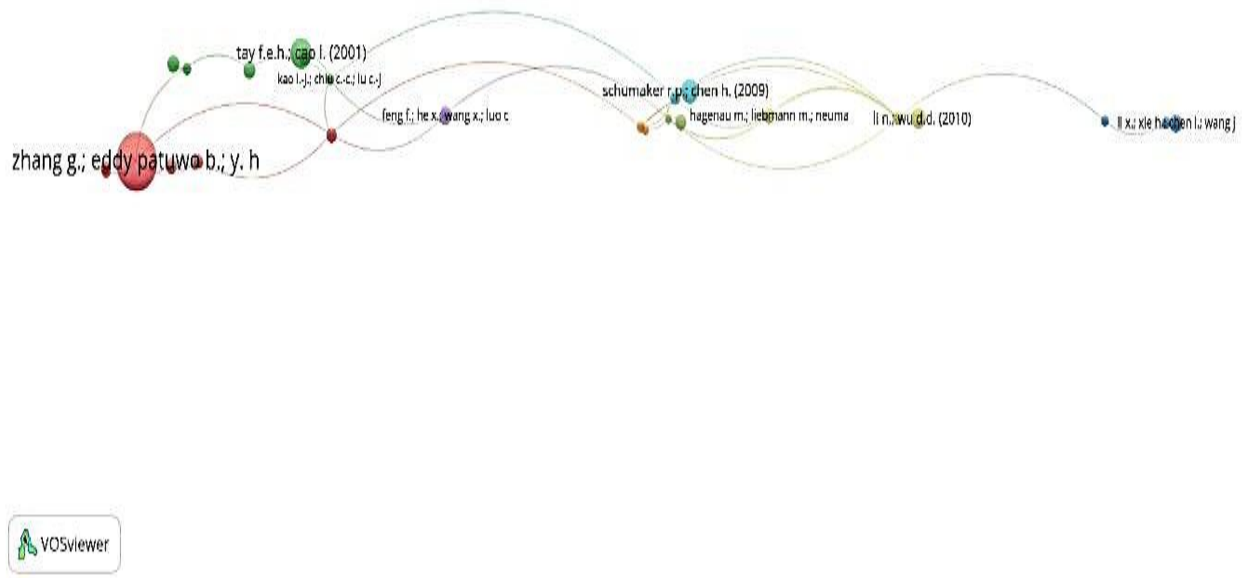
The bar chart shows academic journal citations by journal. The y-axis lists journal names and the x-axis shows citations. The chart shows the most prestigious and influential publications in each discipline. The International Journal of Forecasting has over 3500 citations, making it the most prominent journal in the dataset. The journal's writings are widely cited and have contributed to predicting research. Omega, the second most cited journal in management science and decision-making systems, is important. Following Omega, ACM Transactions on Information Systems has many citations, demonstrating its importance in information and decision support systems. Decision Support Systems appears many times, demonstrating its ongoing contribution to decision-making technologies. International Journal of Information Management and Knowledge- Based Systems is highly referenced, demonstrating their importance in information management and AI-based systems. Annals of Data Science and Omega (UK) have moderate citations, indicating their expanding significance in data science and operational research. The data shows that forecasting, decision support systems, and information management publications acquire more citations, indicating their growing importance in research. These journals' strong citation counts suggest they are important sources for decision-making, information management, and technological forecasting scholars and practitioners.

5. Analysis of Top 12 authors having maximum citations



The Author-wise citations across research publications are shown in the bar chart. The y-axis shows author names while the x-axis shows citations. The most cited writers are shown in this visualisation. Zhang G., Eddy Patuwo B., and Y. Hu M. had the most citations, 3359. They are the most influential writers in the dataset due to their high citation count, which shows their study has had a major impact. Tay F.E.H. and Cao L. with 955 citations, followed by Schumaker R.P. and Chen H. with 606 citations.

6. Analysis of Network Visualization co-authorship of Authors among 12 authors (Minimum no. of citations = 100)



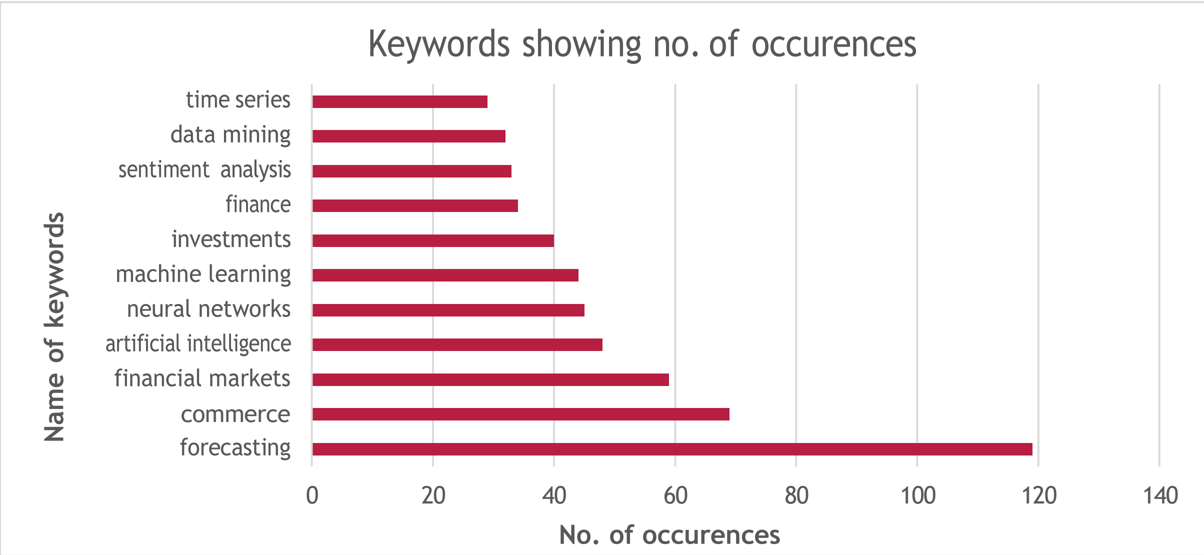
The visualisation shows a VOSviewer-generated author co-citation network. It shows how often two authors are cited in research papers. Each node's size symbolises an author's citations, while the connecting lines (edges) show co-citation relationships. Thicker lines indicate stronger co-citation relationships.

The largest red node in the network represents Zhang G., Eddy Patuwo B., and Y. Hu M., the most cited writers. Their co - citation relationship with Tay F.E.H. and Cao L. (2001) is strong. Their work in similar disciplines like Artificial Neural Networks (ANN) and machine learning applications in financial forecasting may explain why they are often quoted together. Well-connected authors like Tay F.E.H., Cao L., and Kao L.J. are green nodes. Their high co-citation ties with Zhang G. and Eddy Patuwo B. indicate their forecasting and decision support system collaboration.

The blue nodes, including Schumaker R.P. and Chen H. (2009), are farther from the central cluster but still have high co - citation frequency, indicating their importance in financial text mining and sentiment analysis. Li N. and Wu D.D. (2010) and Li X., Xie H., Chen L., Wang J., and Deng X. create smaller clusters, indicating emerging financial forecasting and decision support system study topics. Colour groupings represent research themes.

The red cluster represents AI and machine learning, the green cluster forecasting models and hybrid methods, and the blue cluster text mining and sentiment analysis. In conclusion, the co-citation network shows how influential financial forecasting and decision support system authors are linked. It reveals the significant contributors who established the knowledge landscape and the collaborative nature of research in this topic. The visualisation shows how writers' works are related, providing a full view of field intellectual progress.

7. Analysis of Top 12 Keywords occurring maximum times

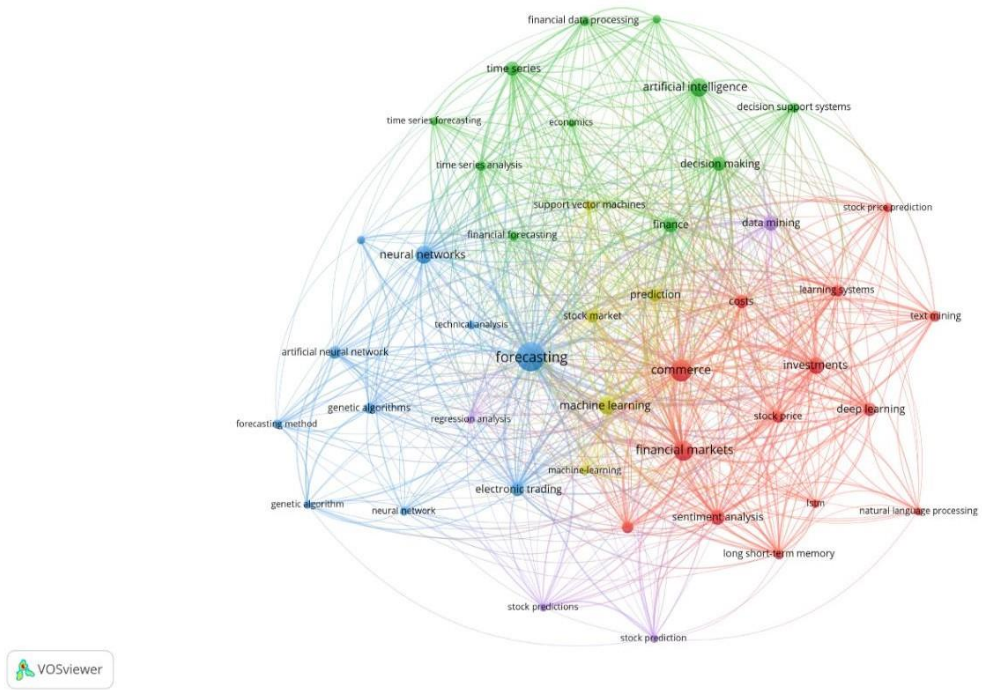


The bar graph shows the quantity of terms used in research publications, reflecting the main themes and interests. Vertical axis lists keywords, horizontal axis shows occurrences. The keyword "forecasting" appears 120 times, indicating its importance in study. Many research focus on forecasting techniques and their applications in banking, commerce, and investing. The second most common keyword is "commerce" with 70 occurrences, showing the importance of commercial applications in predictive models and decision support systems. Forecasting models are used in corporate operations and market analysis. "Financial markets" appears 60 times, indicating that financial market predictions are important. High keyword frequency indicates rising interest in predicting stock prices, exchange rates, and other financial indicators using advanced methods. The terms "artificial intelligence", "machine learning", and "neural networks" appear 40 to 50 times, indicating the growing use of AI in predictive modelling. These technologies are essential for forecasting accuracy and efficiency. Financial applications are highlighted in the literature by keywords like "investments", "finance", and "sentiment analysis". Sentiment analysis, used to evaluate financial news and social media, shows the growing interest in text mining for market forecasts.

There are also several references to "data mining" and "time series" to emphasise the necessity of finding patterns in vast datasets and analysing time-based data for forecasting. The graph shows that predicting, commerce, and financial markets dominate research, with a focus on AI-based methods.

The rise of machine learning, neural networks, and sentiment analysis shows that predictive modelling is moving towards advanced technology. This term distribution reveals domain research trends and primary focus areas.

8. Analysis of network visualization of co-occurrence of keywords (Minimum occurrence = 10 times)



The network visualisation map shows keyword co-occurrence in research articles, showing topic relationships. VOSviewer program creates the map, where each node represents a term and linkages between nodes show keyword co-occurrence. Node size indicates keyword frequency, while cluster colour indicates thematic groups. The largest node in the network is "forecasting" near the centre, indicating that it is the most common keyword and the research's main focus. Forecasting's centrality in numerous study fields is shown by its many keyword links.

The map has three main clusters:

1. The Red Cluster (Machine Learning and Financial Markets) comprises keywords such as machine learning, financial markets, investments, sentiment analysis, deep learning, and natural language processing. It shows how machine learning predicts financial markets, stock prices, and investment trends. Text mining and NLP show how market forecasting uses textual data analysis.

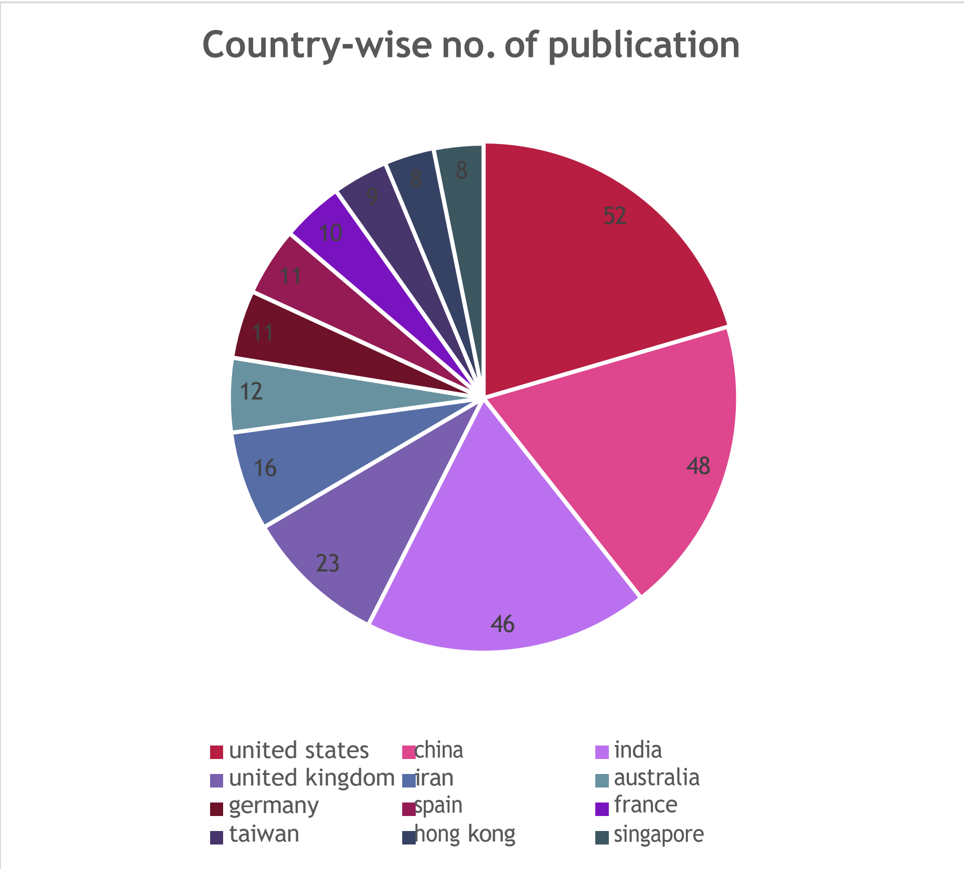
2. Green Cluster (Artificial Intelligence and Decision Support Systems): This cluster explores the role of AI, decision- making, SVMs, and economics in forecasting. It shows the expanding use of AI in financial and corporate decision support systems.

3. Blue Cluster: Financial forecasting utilising neural networks, time series analysis, genetic

algorithms, and technical analysis. It emphasises time-based data and computational methods for stock market and financial trend prediction. The network shows that AI, machine learning, and financial forecasting are often intertwined, making many research fields multidisciplinary.

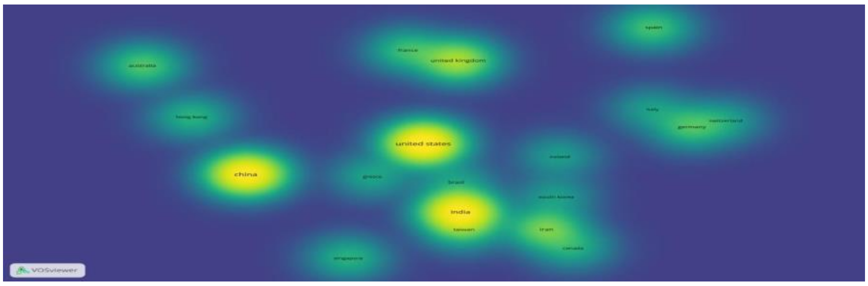
The strong association between sentiment research, stock price forecast, and financial markets indicates the growing importance of social media and text data in financial decision-making. The network map shows that predicting dominates the literature, with strong linkages to machine learning, neural networks, and AI. Keyword clustering shows that modern forecasting methodologies, especially in banking and commerce, increasingly use powerful AI and data mining tools.

9. Analysis of Top 12 country-wise publication



The pie chart represents the number of publications by country. The United States has the highest number of publications (52), followed closely by China (48) and India (46). The United Kingdom accounts for 23 publications, while Iran has 16. Australia has 12 publications, Germany and Spain each have 11, and France has 10. Taiwan has 9 publications, while Hong Kong and Singapore each have 8. The chart visually demonstrates the distribution of publications among these countries.

10. Analysis of country-wise publication (Minimum no. of publication = 5)



The density visualization map represents the **distribution of publications by country in the domain of forecasting, machine learning, and financial markets**. The map is generated using **VOSviewer software**, where each country is represented based on the number of publications and research contributions in the selected field. The intensity of the color indicates the volume of publications, with **yellow representing the highest concentration** of publications, followed by **green and blue** for moderate and low contributions, respectively.

This map shows that the US, China, and India are the leading research contributors, with the brightest yellow spots signifying the most publications. This shows that these countries lead financial market research in machine learning, financial forecasting, and AI. Academic research and financial forecasting technology are led by the US. Due to the growing use of machine learning in FinTech and stock market predictions, the Chinese research community publishes a lot. India is another major contributor, showing its growing interest in AI, data mining, and financial market analysis. India's global technical influence is expanding due to its research output. With moderate contributions from green regions, the UK, Germany, France, and Australia also produce significant research. These nations have developed machine learning models for financial forecasting and sentiment analysis.

4. CONCLUSION

This study strengthens the discourse on the incorporation of AI in financial activities, promoting further investigation and implementation of deep learning models in stock market prediction. Advancements in AI present significant opportunity to improve decision-making, mitigate risks, and reveal new insights inside the dynamic financial markets. It clearly indicates that considerable focus is directed towards this research domain, resulting in increasingly specialised and extensive literature. Artificial intelligence has emerged as a formidable instrument for addressing decision-making challenges in real-world scenarios. In finance, predicting the stock market is a crucial and intricate endeavour due to its three primary characteristics as nonlinearity, interaction patterns, and chaos. The findings of the study shows that the highest level of number of publications is noted between 2021 and 2022 approximately equal to 40. Subsequent to 2022, it indicates a considerable decrease in publications, significantly declining by 2025. The analysis related to the journal based on number of publications revealed that Knowledge-Based Systems has the most publications, surpassing 35, followed by Decision Support Systems with around 20 publications. The outcome related to journal based on the number of citations indicates that The International Journal of Forecasting has over 3500 citations, making it the most prominent journal in the dataset and the second most cited journal in management science and decision-making systems is Omega. The results related to most cited authors indicates that Zhang G., Eddy Patuwo B., and Y. Hu M. had the most citations, 3359. Secondly, most cited author is Tay F.E.H. and Cao L. with 955 citations, followed by Schumaker R.P. and Chen H. with 606 citations. The analysis related to maximum used keywords indicates that the keyword "forecasting" appears 120 times, indicating its importance in study. Many research focus on forecasting techniques and their applications in banking, commerce, and investing. Forecasting models are used in corporate operations and market analysis. "Financial markets" appears 60 times, indicating that financial market predictions are important. High keyword frequency indicates rising interest in predicting stock prices, exchange rates, and other financial indicators using advanced methods. The terms "artificial intelligence", "machine learning", and "neural networks" appear 40 to 50 times, indicating the growing use of AI in predictive modelling. The findings related to country having maximum number of publications indicates that The United States has the highest number of publications (52), followed closely by China (48) &India (46).

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