“Navigating the technical analysis in stock markets: Insights from bibliometric and topic modeling approaches”

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NAVIGATING THE TECHNICAL ANALYSIS IN STOCK MARKETS: INSIGHTS FROM BIBLIOMETRIC AND TOPIC MODELING APPROACHES

Abstract

In stock markets, technical analysis plays a vital role by offering valuable insights into price trends, patterns, and anticipated market movements, aiding investors in making well-informed decisions. This study employs bibliometric and topic modelling approaches on 589 English-language journal articles indexed in Scopus in the last two decades (from 2003 to 2023), exclusively focusing on technical analysis in stock markets. The keyword co-occurrence analysis identifies five topic clusters. The application of structural topic modelling also unravels five prominent thematic clusters, namely pattern-based forecasting, rule-based trading, algorithmic trading, techno-fundamental trading, and machine learning & sentiment analysis. The topic of pattern-based forecasting involves researching the application of various patterns or models to predict stock prices. Rule-based trading concentrates on utilizing technical analysis tools to generate buy and sell signals, aiming for profitability. The algorithmic trading cluster explores the use of algorithms to systematically execute buy and sell actions, especially in high-frequency trading scenarios. Techno-fundamental trading investigates the integration of both fundamental and technical analysis in trading and investment decisions. Lastly, machine learning & sentiment analysis focus on applying advanced machine learning techniques and sentiment analysis for predicting stock prices, highlighting the use of sophisticated methods in this domain. The three predominant topics in the dataset are "rule-based trading," "machine learning & sentiment analysis," and "algorithmic trading" constituting 26.79%, 23.52%, and 21.11% of the dataset, respectively. These findings underscore the prominence and significance of these themes within the context of the research domain.

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INTRODUCTION

As per the well-established Efficient Market Hypothesis (EMH), stock markets are efficient and making profits in the stock market, by timing the entry and exit, is not feasible (Fama, 1970). In contrast, the proponents of behavioral finance contend that stock markets exhibit irrational behavior, suggesting that participants can exploit inefficiencies to generate wealth (Shiller, 2015). Making money in the stock market by forecasting the anticipated price movement is challenging because stock prices are noisy, complex, chaotic, volatile, and non-parametric (Li & Bastos, 2020). Both retail and institutional investors often resort to technical and fundamental analysis to anticipate future stock or index movements.

Fundamental analysis examines stocks to ascertain their intrinsic worth by investigating financial statements, company products, and management caliber. It emphasizes long-term investing choices and

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looks for cheap or overvalued securities depending on fundamental variables. In contrast, technical analysis uses past price and volume data to forecast future price changes. It locates short- to medium-term trading opportunities using charts, patterns, and technical indicators (Cervelló-Royo et al., 2015; Marshall et al., 2006; Murphy, 1999). Technical analysis primarily focuses on patterns and trends in price data, whereas fundamental research focuses on a company's financial health and prospects. Investors frequently select one or a combination of these approaches based on their investing goals, level of risk tolerance, and preferred analytical methods.

In the stock market, technical analysis is crucial because it offers important insights into price trends, patterns, and anticipated market movements. Technical analysis assists investors in making knowledgeable judgments about the purchase and sale of stocks by looking at past price and volume data. Understanding market sentiment, figuring out entry and exit timings, and managing risk all depend on technical analysis (Pring, 2002). The key benefit of technical analysis is to identify trends and patterns of prices and volume, which is not possible using fundamental analysis. Head-and-shoulders, double-top, and triangle chart patterns can indicate potential trend reversals or continuations, assisting traders in making prompt decisions. Relative Strength Index (RSI), Moving averages, and Moving Average Convergence Divergence (MACD) are technical indicators that also provide quantified insights into market momentum and probable overbought or oversold positions (Vasiliou et al., 2006). Through the identification of support and resistance levels, technical analysis also aids in developing risk management techniques. Trading professionals can use these levels to set stop-loss orders and manage potential losses by indicating areas where prices are expected to reversal or halt. Technical analysis is important because it may be used in real-world situations, even though it has weak theoretical underpinnings and relies heavily on historical data. Investors can get a more thorough understanding of the stock market by combining technical analysis with fundamental analysis, which could enhance their ability to make decisions and potentially improve the results of their investments. Technical analysis involves identification or forecasting of future price movements of any stock using a variety of techniques such as price and volume charts, technical indicators, computer algorithms, and econometric techniques (Park & Irwin, 2007). Technical analysis is omnipresent in all financial markets and financial media (Shynkevich, 2012), and majority of the traders and fund managers place some weightage on technical analysis, especially for short time horizons (Menkhoff, 2010).

Considering the widespread utilization of technical analysis, numerous scholars have extensively investigated and scrutinized this field across various methodologies and indicators (Farias Nazário et al., 2017; Park & Irwin, 2007). Consequently, there is a compelling imperative to amalgamate existing research efforts to present a systematic overview of the accumulated knowledge in this domain.

1. LITERATURE REVIEW

Technical analysis utilizes historical prices, trading volume, and various indicators to forecast future price movements of stocks or stock market indices (Marshall et al., 2006). Advocates of technical analysis believe that market participants' emotions and reactions gradually manifest in prices, forming exploitable price patterns. Despite its widespread use among practitioners across different asset classes (Grobys et al., 2020; Huang et al., 2018; Meher et al., 2021; Menkhoff, 2010; Park & Irwin, 2007), it has not gained substantial recognition in academia. For instance, Malkiel (1981) characterizes technical analysis as an "anathema to the academic world," while Lo et al. (2000) label it as "voodoo finance". Technical analysis faces skepticism, as most academics adhere to the prevailing theory in empirical finance, the "Efficient Market Hypothesis" (Fama, 1970). Nevertheless, contemporary approaches to technical analysis are gaining momentum and popularity by amalgamating Eastern technical patterns like candlestick analysis, Western patterns such as head and shoulders, and sophisticated machine learning algorithms (Aguirre et al., 2020; Kumar et al., 2022; Li & Bastos, 2020; Nikou et al., 2019). In addition to that, technical analysis has also entered the mainstream academic research in the

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name of momentum trading hypothesis (Jegadeesh & Titman, 1993) and overreaction hypothesis (De Bondt & Thaler, 1985). Both these hypotheses suggest that stock prices are not efficient and can be exploited to generate profits. Hence, technical analysis is considered very crucial for market participants including investors, traders, and academia (Murphy, 1999; Pring, 2002).

In the realm of technical analysis, candlestick charts are considered the oldest technical analysis tool. Candlestick charts are thought to have been invented in the 18th century and are attributed to Japanese rice traders (Marshall et al., 2006). Steve Nison, who first published candlestick charting methods in his book "Japanese Candlestick Charting Techniques" in 1991, is credited with bringing them to the attention of the West. Mr. Charles H. Dow, the founder of the Wall Street Journal, penned a sequence of articles focusing on price patterns and fluctuations in the stock markets. These articles laid the foundation for the renowned Dow Theory, widely regarded as the bedrock of modern technical analysis (Bishop, 1961; Edwards et al., 2018). The Dow Theory encompasses various patterns, including but not limited to head & shoulders, flags, pennants, double tops, and numerous others (Bishop, 1961). More recently, the researchers have started using statistical and machine learning models to predict stock price movements (Bhandari et al., 2022; Fantin & Hadad, 2022; Fathali et al., 2022; Inani et al., 2022; Kumbure et al., 2022; Nor & Wickremasinghe, 2017).

Overall, it can be affirmed that technical analysis holds paramount importance for practitioners, academia, and financial institutions. The existing body of literature has delved into various facets of technical analysis in the stock market, encompassing diverse elements such as multiple charts, patterns, indicators, and algorithms. Despite its evident utility, a comprehensive and contemporary literature review that synthesizes the collective knowledge on technical analysis has been notably absent. Although some scholars have attempted literature reviews on technical analysis, this study stands apart in its approach. For instance, Park and Irwin (2007) offer a review of technical analysis profitability evidence, revealing that 56 out of 95 modern studies yield positive results. In more recent times, Farias Nazário et al. (2017) present a comprehensive overview of technical analysis literature, categorizing and coding studies published over 55 years, while also suggesting a future research agenda. The research was not able to identify a single study combining the power of bibliometric and topic modelling techniques in the context of technical analysis in the stock markets.

Very recently, bibliometric and topic modelling techniques have been gaining popularity in management research for identifying trending themes in the literature (Aziz et al., 2022; Bai et al., 2021; Boubaker et al., 2023; Goodell et al., 2022; Kumar & Srivastava, 2022; Sharma et al., 2021). The bibliometric analysis can quantitatively evaluate scholarly literature, aiding in assessing research impact, determining journal quality, and evaluating author contributions. Whereas the topic modelling empowers researchers to uncover latent themes or topics within vast collections of textual data using machine learning. Both techniques are popular and recognized for their impartial and mathematical nature compared to the traditional review methods (Goodell et al., 2022). This study attempts to employ a blend of bibliometric and topic modelling techniques for extraction of trending topics and provide a timely synthesis of the literature on technical analysis in stock markets.

2. METHODS

The study has obtained metadata from Elsevier's Scopus database, which is recognized as one of the most extensive academic databases for multidisciplinary research (Ahmed et al., 2022; Corbet et al., 2019). To curate the necessary articles pertaining to the subject of technical analysis in the stock market, it utilized a specific combination of keywords based on prior scholarly work (Almeida & Vieira, 2023; Li & Bastos, 2020). Consequently, it employed the following search string:

"TITLE-ABS-KEY (("Technical Analysis" OR "Technical Indicator*" OR "Technical Trading") AND ("Stock Market" OR "Equity Market" OR "Share Market")) AND PUBYEAR > 2002 AND PUBYEAR < 2024 AND (LIMIT-TO (SUBJAREA, "COMP") OR LIMIT-TO (SUBJAREA, "ECON") OR LIMIT-TO (SUBJAREA, "BUSI")) AND (LIMIT-TO (DOCTYPE, "ar")) AND (LIMIT-TO (SRCTYPE, "j")) AND (LIMIT-TO (LANGUAGE, "English"))"

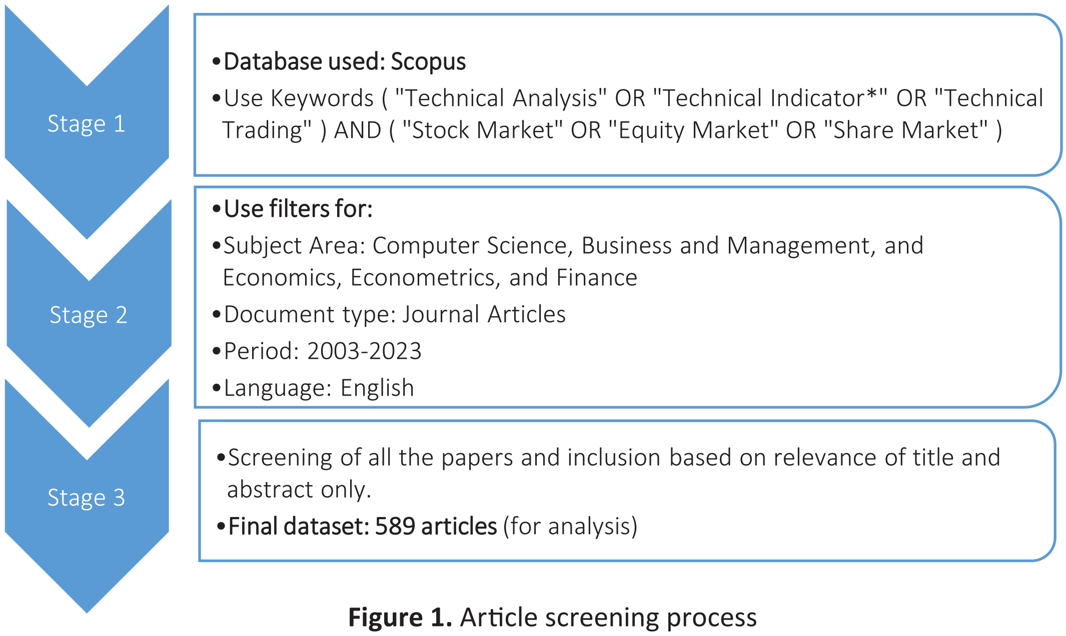

Figure 1. Article screening process

The study conducted a search for the specified keywords within the titles, abstracts, or article keywords to identify relevant literature for analysis. This search query enabled us to pinpoint the literature that would undergo examination. The analyzed studies consist of journal articles published in English over the past two decades (from 2003 to 2023), with a specific focus in the fields of Computer Science, Business and Management, and Economics, Econometrics, and Finance. Following this, a thorough review was conducted to exclude any incomplete or irrelevant research records. This rigorous procedure resulted in a dataset of 589 articles, forming the core foundation for subsequent bibliometric and topic modelling analysis. Figure 1 visually outlines the meticulous selection process, offering a clear illustration of the systematic identification and curation of these articles.

This study employs the Bibliometrics package in the R Studio environment, integrating the user-friendly graphical interface known as Biblioshiny (Aria & Cuccurullo, 2017). This software tool enables to effectively analyze and visually represent bibliometric data. The utilization of bibliometric analysis has gained significant recognition as a quantitative approach for assessing research influence, identifying emerging subjects, supporting decision making, and enabling benchmarking. This methodology presents an impartial approach to data collection, measuring productivity, and mapping knowledge domains (Boubaker et al., 2023). The study harnesses the VOSviewer tool to construct visual graphs, aligning with recommended practices in the scholarly literature (Baker et al., 2021; van Eck & Waltman, 2010). The widespread use of VOSviewer is endorsed for visualizing bibliometric networks, facilitating the identification of intricate patterns within extensive datasets. By capitalizing on the capabilities of the Bibliometrics package and the VOSviewer tool, the study aims to gain comprehensive insights into the intricate research landscape of the chosen subject matter.

Structural Topic Modelling (STM) represents an advanced and innovative approach applied in the realm of text analysis and natural language processing. It empowers researchers to uncover latent themes and subjects within vast collections of textual data. STM proves particularly valuable when dealing with unstructured text data, such as academic papers, social media posts, news articles, and various other written sources. STM incorporates document-level covariates into traditional topic modelling, aiming to identify topic prevalence in literature review papers. This paper utilizes STM to identify prominent topics and their proportion in the literature. STM can discern the primary themes by examining the most frequently associated words for each topic. Furthermore, STM provides metrics for both exclusivity and prevalence for each topic, offering insights into how unique and widespread a particular subject is within the dataset. The underlying concept of this method revolves around the notion that any given document can encompass a multitude of distinct

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subjects, each indicated by the frequency of specific phrases. The program assesses the likelihood of various themes being present in each document, based on the specified number of topics. Typically, the program assigns the topic that most accurately encapsulates the essence of the document. The optimal number of topics is determined by comparing coherence scores across different topic quantities.

The study performs STM by utilizing the R packages "stm" and "tm." The dataset contained multiple columns and focused only on the abstract column for STM analysis. In the data cleaning phase, it extracted the abstracts, converted them to lowercase, and eliminated numbers, punctuation, and symbols. Additionally, common English stop words devoid of specific meanings were removed to improve topic identification. To address variations in word tense and number, it applied stemming techniques to extract the root forms of words.

3. RESULTS

Table 1 presents the summary of the final dataset used in the study. It depicts various aspects of the bibliometric analysis conducted for the period 2003 to 2023. The analysis was based on a dataset of 589 documents from 292 different journals. The annual growth rate of the publications is calculated at 18.13%, indicating a significant increase in the number of documents over the years. On average, each document received approximately 19.76 citations, highlighting the impact and relevance of the research. The analysis involved 1367 authors, and among the documents, 71 were authored by a single individual. On average, each document had around 2.83 co-authors, illustrating the collaborative nature of the research. Approximately 17.49% of the co-authorships were international, indicating global collaboration among researchers. These findings highlight growth, collaboration, and impact within the field, as indicated by high citations and international partnerships.

Table 1. Descriptive summary

Source: RStudio Biblioshiny interface in the "Bibliometrix" package.

Description	Results
Timespan	2003-2023
Number of Journals	292
Documents	589
Annual Growth Rate %	18.13
Average citations per doc	19.76
Authors	1367
Single-authored docs	71
Co-Authors per Doc	2.83
International co-authorships %	17.49

Figure 2 represents the yearly distribution of articles from 2003 to 2023. The number of articles has shown variations, with an upward trend in recent years. Notable increases occurred between 2011 and 2022, with the highest count of 69 articles in 2022. This progression indicates growing research activity and interest in the subject over time.

Source: RStudio Biblioshiny interface in the "Bibliometrix" package.

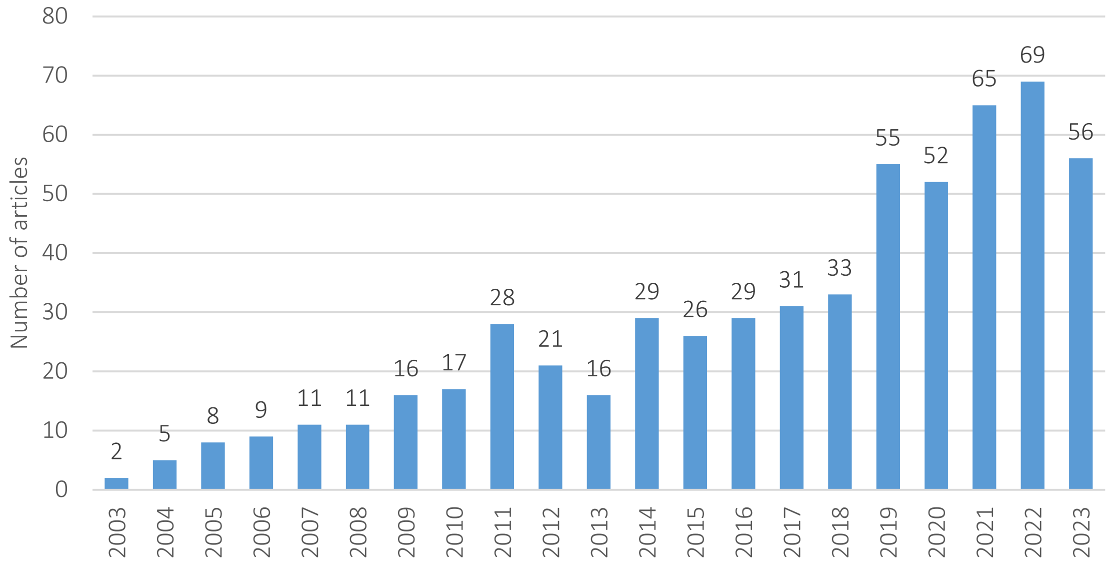
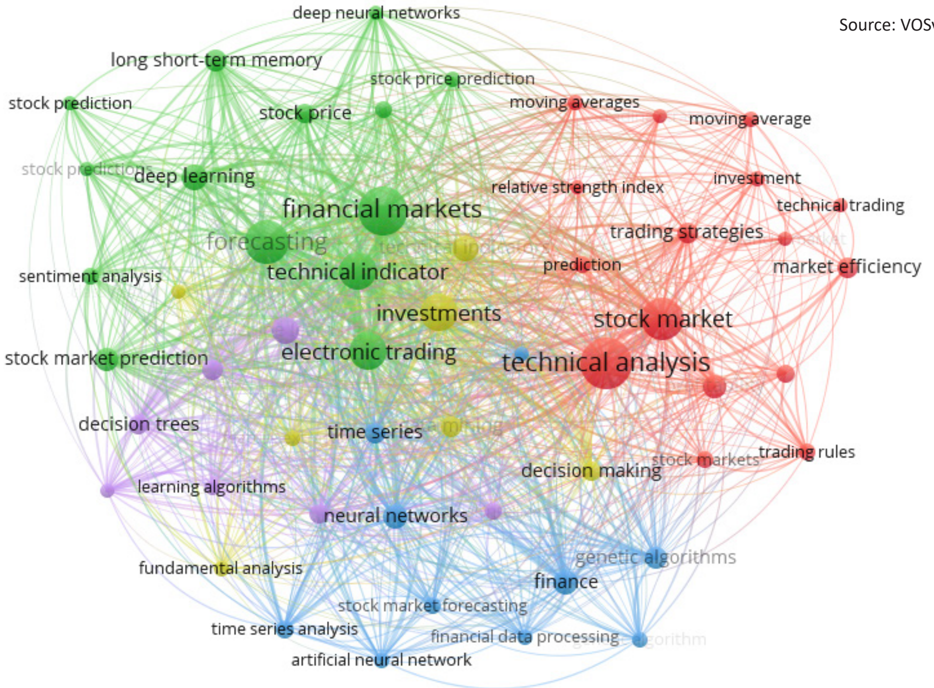


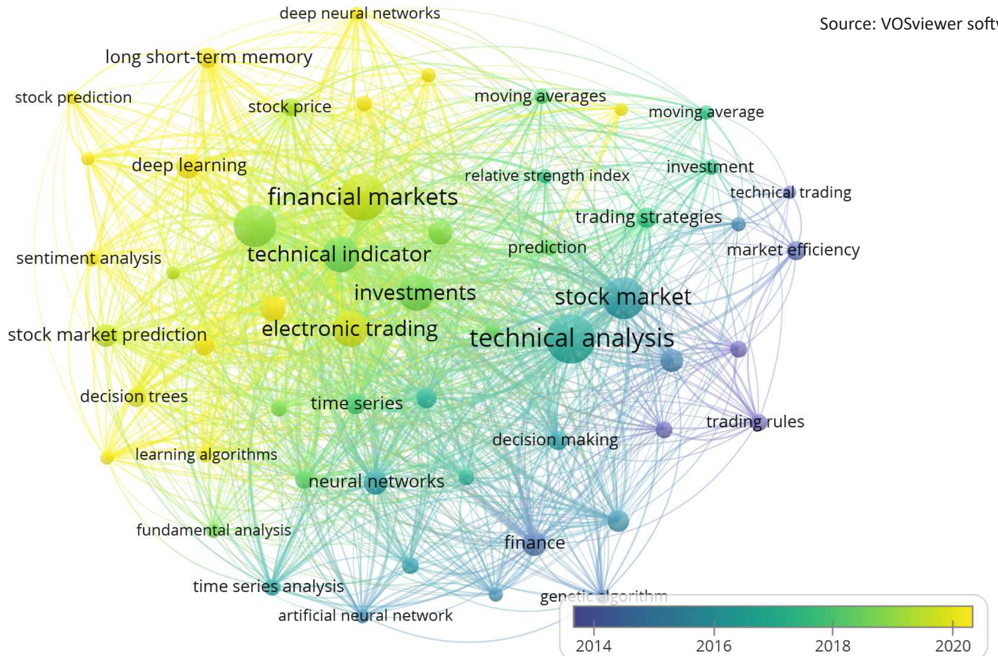
Figure 2. Year-wise growth of literature



Source: VOSviewer software.

Figure 3. Keyword co-occurrences

Figure 3 presents the visualization of keyword co-occurrence, facilitating the identification of various topics. The links between nodes indicate co-occurrence, with larger nodes representing higher frequency. The proximity of nodes indicates stronger co-occurrence. Out of a total of 2727 keywords extracted from the sample articles, the diagram reveals five distinct clusters of related subjects from 57 keywords, each appearing at least 15 times. Certain generic and irrelevant terms such as “commerce”, “optimization”, and “costs” were intentionally excluded from the analysis.



Source: VOSviewer software.

Figure 4. Temporal evolution using overlay visualization

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Source: RStudio "stm" package.

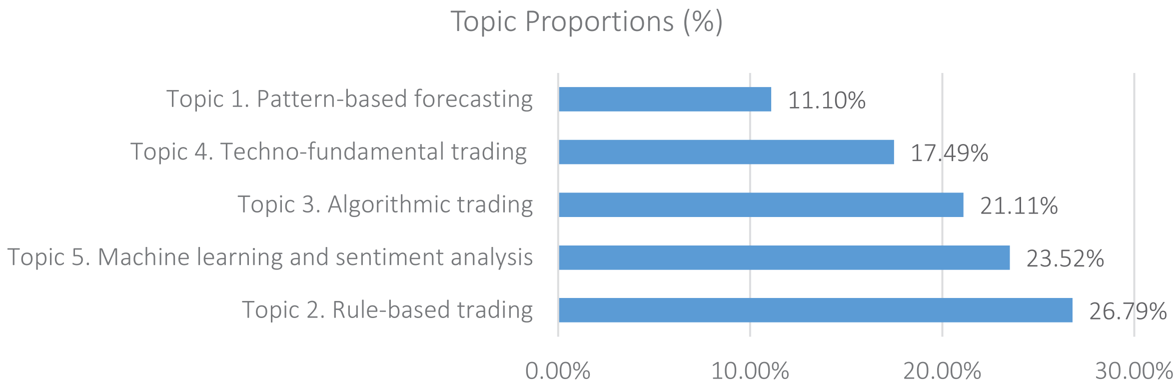

Figure 5. Topics and their proportions

The results of the structural topic modeling indicate that the prevailing body of literature, on the use of technical analysis in stock markets, predominantly centers around five principal themes, as depicted in both Figure 5 and Figure 6. These themes encompass pattern-based forecasting, rule-based trading, algorithmic trading, techno-fundamental trading, and machine learning and sentiment analysis. It is essential to recognize that these five themes signify the primary clusters identified in the analysis, although they do not comprehensively encompass all potential subjects. Thus, it is vital to emphasize that the provided list is not exhaustive but rather preliminary, representing an initial understanding of the major topics uncovered in the analysis. Following a thorough examination and extensive deliberation among all co-authors, the study determined that the optimal number of topics was five, based on empirical evidence and discussions. Each topic is defined using two metrics: the probability of occurrence (Highest Prob) and frequency-exclusiv-

Source: RStudio "stm" package.

Figure 6. Word cloud for each topic generated by STM

ity (FREX) ratings. Initially, the terms most frequently associated with each topic are presented, followed by terms unique to that specific theme, which are not commonly used in other topics. In Figure 5, you will find the latent topics identified, along with their respective proportions. Notably, Topic 2 (Rule-based trading), Topic 5 (Machine learning & sentiment analysis), and Topic 3 (Algorithmic trading) emerge as the most prominent and significant topics, accounting for 26.79%, 23.52%, and 21.11%, respectively. Figure 6 offers a visual summary, presenting word clouds that highlight the most relevant 50 terms within each extracted topic.

4. DISCUSSION

As previously mentioned, the primary objective of technical analysis lies in predicting future stock price movements for profit generation. All these five clusters (in Figure 3) revolve around distinct technical analysis methodologies employed to attain monetary gains. To illustrate, the first cluster (red) encompasses terms like "market efficiency," "technical trading," "trading strategy," and "moving averages." Within this cluster, researchers explore the utilization of technical indicators or strategies (such as RSI, charts, and moving averages) to capitalize on market fluctuations. The subsequent cluster (yellow) integrates concepts such as "fundamental analysis," "data mining," and "classification." This cluster centers on extracting fundamental data and merging it with technical analysis. Meanwhile, the third cluster (purple) delves into employing artificial intelligence and machine learning techniques to forecast stock returns. The fourth (blue) and fifth (green) clusters also delve into utilizing advanced machine learning tools to predict stock and index returns. The blue cluster discusses the implementation of artificial neural networks and genetic algorithms, while the green cluster highlights cutting-edge machine learning techniques like deep neural networks and the incorporation of sentiment analysis in stock price prediction. Figure 4 illustrates the chronological progression of this research field, demonstrating the shift from traditional technical tools (charts, patterns, and indicators) to sophisticated machine learning methods (genetic algorithms, deep learning, and sentiment analysis) in recent years.

The results of structural topic modelling (Figure 5 and Figure 6) show that the topic 1 is centered on pattern-based forecasting which incorporates keywords like pattern, predict, model, and performance. This topic delves into research related to employing various patterns or models to predict stock prices. In such studies, researchers have utilized diverse technical patterns to make predictions about stock prices (Arévalo et al., 2017; Cervelló-Royo et al., 2015). For instance, Liang et al. (2022) applied a stock price forecasting approach utilizing candlestick patterns and sequence similarity. The forecasting process is divided into two stages. Firstly, sequential pattern mining is employed to extract candlestick patterns from multidimensional candlestick data, and the correlation between different patterns and their corresponding future trends is calculated. In the second step, a novel sequence similarity measure is introduced to match diverse candlestick sequences with existing patterns. The effectiveness of this method is verified using real data from 800 stocks in the Chinese stock market, demonstrating stable and superior results compared to complex machine learning models (such as SVM and LSTM). In a very recent study, Cagliero et al. (2023) advocate for the separation of machine learning and pattern recognition processes in a trading system to generate a refined set of double-checked trading recommendations. The proposal involves selectively excluding machine learning-based trading suggestions considered potentially unreliable based on recognized graphical patterns. Various combinations of pattern recognition strategies with diverse machine learning models are explored for this purpose. Similarly, Lin et al. (2021) develop an innovative ensemble machine learning framework designed for predicting daily stock patterns. This framework combines traditional candlestick charting with cutting-edge artificial intelligence methods, shaping an investment strategy grounded in ensemble machine learning techniques. Overall, the focus of this topic is on identifying the trading opportunities in the stock markets based on the price patterns.

The next theme (Topic 2) identified as rule-based trading, features keywords like technical, rule, strategy, and trade. This area of research is focused on utilizing technical analysis tools to generate buy and sell signals, aiming for profitable

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outcomes (da Costa et al., 2015; Vasiliou et al., 2006). This topic is the most important topic as 26.79% of the research papers in the dataset talks about it because the purpose of technical analysis is always to identify the future direction of the market using some trading rules. For example, Chen and Hao (2018) present a comprehensive and effective approach that incorporates principal component analysis (PCA) into the weighted support vector machine (WSVM) for predicting stock trading points (PCA-WSVM). They implement this strategy on stocks from prominent Chinese stock exchange markets, namely the Shanghai and Shenzhen stock exchange markets, demonstrating the effectiveness of PCA-WSVM compared to the buy-and-hold strategy. Another study by Vasiliou et al. (2006) assesses the efficacy of two prominent technical indicators, namely Moving Averages and MACD (Moving Average Convergence Divergence), as tools for trading rules within the context of the Athens Stock Market. The findings of the research, as outlined in the study, present robust evidence in favor of the effectiveness of the examined technical indicators. In nutshell, this topic concentrates on using technical indicators to do rule-based trading in the stock market.

The third theme (Topic 3) is revolving around algorithmic trading, includes terms such as model, algorithm, system, and trade. This theme delves into the use of algorithms to follow systematic approaches for executing trades, particularly in high-frequency trading scenarios (Seddon & Currie, 2017). For instance, Aloud (2020) suggests a straightforward yet effective algorithmic system for stock market trading which leverages a combination of multiple technical indicators, decision trees, and genetic algorithms. The methodology involves the compilation of a set of technical indicators, which are then organized into a decision tree structure based on predefined stock trading rules. The decision tree generates distinct classes corresponding to buy, hold, and sell recommendations, encapsulating the algorithm's trading decisions. A noteworthy contribution of this study lies in the incorporation of genetic algorithms within a two-step classification process. This innovative approach enhances the adaptability and efficiency of the algorithmic trading system, showcasing the integration of genetic algorithms as a key element in the decision-making framework. Similarly, Gómez Martínez et al. (2019) present and elaborate on two algorithmic trading systems specifically designed for IBEX 35 futures, utilizing the paradigm of "big data." These systems are designed to execute market orders for opening either long or short positions, and their decision-making process is grounded in an artificial intelligence model influenced by investors' sentiment. The key innovation lies in the incorporation of investors' mood, gauged through semantic analysis algorithms applied to communications related to IBEX 35 across social media (Twitter) and news media. The algorithms categorize these communications as positive, negative, or neutral. The outcomes reveal that the big data algorithmic trading systems outperform traditional counterparts in key performance metrics such as Sharpe ratio, success rate, and profit factor. In a recent study, Théate and Ernst (2021) introduce a groundbreaking methodology utilizing deep reinforcement learning (DRL) to address the challenge of algorithmic trading. The focus is on determining the optimal trading position dynamically throughout the course of stock market trading activities. This topic is all about using the algorithms to leverage the technical analysis for trading purposes.

The next cluster (Topic 4) pertains to techno-fundamental trading and encompasses keywords such as stock, analysis, fundamental, technical, and investor. This area of study explores the integration of both fundamental and technical analysis in trading and investment decisions. Within this topic, researchers have investigated combinations and comparisons of various fundamental and technical indicators (Nti et al., 2020). For example, de Souza et al. (2018) investigated the synergy between technical analysis and fundamental analysis in BRICS markets. They constructed a portfolio comprising assets from each BRICS member and designed an automated trading system that simulated transactions based on technical analysis techniques. Certain asset groups from each country exhibited performance significantly above the portfolio average, outperforming returns achieved through a buy-and-hold strategy. The study also highlighted the collaborative potential of technical and fundamental analyses in identifying the most dynamic companies in the stock market. In a very important research, Picasso et al. (2019) aspire to integrate technical and fundamental analysis by employing data science and machine learning methodologies. Their study frames the stock market prediction challenge as a classification task for time series data. Input features for this classification include indicators from technical analysis and sentiment extracted from news articles. By incorporating both technical and fundamental aspects, the research represents a significant advancement in merging these analytical approaches. The fusion of traditional technical analysis indicators with sentiment analysis of news articles adds depth to the predictive model, offering a promising foundation for the development of innovative trading strategies that consider both technical and fundamental factors. Similarly, Li et al. (2020) use both stock prices (technical analysis) and news articles (sentiments or fundamentals) in the prediction processes and apply a deep learning model to predict the stock prices in the Hong Kong stock market and get the promising results. This topic combines the power of fundamental and technical analysis.

Lastly, Topic 5 introduces terms like predict, sentiment, deep learning, machine learning, and neural networks. This topic focuses on the application of advanced machine learning techniques and sentiment analysis for predicting stock prices, showcasing the use of sophisticated methods in this domain (Costola et al., 2023; de Oliveira Carosia et al., 2021; Jing et al., 2021). For instance, Sohangir et al. (2018) aim to assess the applicability of Deep Learning models in enhancing the accuracy of sentiment analysis for StockTwits, a financial social network website. Various neural network models were employed to analyze sentiments expressed in StockTwits regarding the stock market. The findings indicate the effective utilization of Deep Learning models for financial sentiment analysis, with the convolutional neural network emerging as the most optimal model for predicting the sentiment of authors within the StockTwits dataset. In a comparable investigation, Jin et al. (2020) introduce a stock market prediction model based on deep learning, incorporating investors' emotional tendencies. This study affirms that considering investors' emotional tendencies is effective in enhancing the accuracy of predicted stock prices. In another investigation, Ren et al. (2019) also incorporates sentiment analysis into a machine learning approach grounded in support vector machines. The study accounts for the day-of-week effect and develops more dependable and practical sentiment indexes. The findings demonstrate that the accuracy of forecasting the movement direction of the SSE 50 Index significantly increases, reaching up to 89.93% with a notable rise of 18.6% following the introduction of sentiment variables. These all studies underscore the importance of sentiment analysis and machine learning in forecasting stock prices.

CONCLUSION

This study conducts an exhaustive and contemporary literature review encompassing 589 journal articles, all indexed in Scopus and written in English over the span of two decades from 2003 to 2023, with a specific focus on technical analysis within stock markets. The outcomes of keyword co-occurrence analysis unveil five distinct potential clusters, each associated with unique methodologies within the realm of technical analysis. The chronological evolution of this research field illustrates a notable transition from conventional technical tools (such as charts, patterns, and indicators) to more advanced machine learning methods (such as genetic algorithms, deep learning, and sentiment analysis), particularly in recent years. The results of structural topic modelling reveal five prominent themes: pattern-based forecasting, rule-based trading, algorithmic trading, techno-fundamental trading, and machine learning & sentiment analysis. Out of these five identified topics, "rule-based trading," "machine learning & sentiment analysis," and "algorithmic trading" topics are the prominent ones, which account for approximately 71% of the literature. These findings underscore the prominence and significance of these topics within the context of the research domain.

This study contributes to the literature in several ways. Firstly, the study employs an unsupervised machine learning text-mining technique called topic modelling to unravel the latent topics in the domain

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of technical analysis in the stock markets. Secondly, it integrates a wider range of latest data spanning the last two decades, encompassing information up to 2023. Thirdly, it uncovers prevailing themes through meticulous keyword co-occurrence analysis as well. Lastly, this study outlines a potential future research agenda that can serve as a guide for fellow researchers interested in the field. The insights provided by the study empower market participants to comprehend prevalent topics in the domain of technical analysis in the stock markets.

The field of technical analysis holds several promising avenues for future research. First, research into how different technical indicators could be combined with fundamental analysis to improve prediction accuracy. A more complete understanding of market dynamics might be provided by combining quantitative indicators with qualitative observations. Second, it is crucial to investigate the possibilities of hybrid models, which combine conventional techniques for technical analysis with cutting-edge machine learning algorithms. Utilizing the advantages of both strategies could result in forecasting tools that are more reliable. Third, it is critical to investigate how market mood affects the results of technical analysis. Deeper insights into market behavior might be obtained by incorporating sentiment analysis, sentiment scores from social media, news, and other sources. Fourth, it is also important to comprehend how technical analysis responds to different market circumstances and how it performs throughout market collapses and rallies. Fifth, given that many sectors display distinctive patterns and dynamics, concentrating on sector-specific study could produce insightful results. Finally, investigating how macroeconomic variables, geopolitical events, and their interactions with technical signals can improve predictive models. It is essential to recognize a limitation of the study, centered around its exclusive focus on English-language papers available in the Scopus database only. The implications and conclusions drawn from the bibliometric analysis might witness changes upon inclusion of data from other sources like Web of Science. Furthermore, it is worth noting that the analysis encompasses articles solely from specific domains (computer science, economics, finance, and business management). The inclusion of articles from other disciplines could potentially alter the insights derived from this study.

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