Review Article

Sailing through the COVID-19 Crisis by Using AI for Financial Market Predictions

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The outbreak of COVID-19 has brought the world to an unprecedented position where financial and mental resources are drying up. Livelihoods are being lost, and it is becoming tough to save lives. These are the times to think of unprecedented solutions to the financial challenges being faced. Artificial intelligence (AI) has provided a fresh approach to finance through its implementation in the prediction of financial market prices by promising more generalizable results for stock market forecasting. Immense literature has attempted to apply AI and machine learning for predicting stock market returns and volatilities. The research on the applications of AI in finance lacks a consolidated overview of different research directions, findings, methodological approaches, and contributions. Therefore, there is a need to consolidate the extant literature in this upcoming field to consolidate the findings, identify the research gaps in the existing literature, and set a research agenda for future researchers. This paper addresses this need by synthesizing the extant literature in the form of a systematic review for addressing the use of AI in stock market predictions and interpreting the results in a narrative review. The gap formed through this article is the use of a combination of AI as a subject with the neural network as another area and stock market forecasting as another theme, and it will pave the way for future research studies. The analyses help highlight four important gaps in the existing literature on the subject.

1. Introduction

The world is facing an unprecedented situation with the outbreak of COVID-19 across the globe. Locking down the economies has emerged as a prominent measure to contain the spread of the coronavirus but leads to the loss of livelihoods, nevertheless. Whether or not to impose lockdown is the dilemma of saving lives versus livelihoods [1]. Recent empirical evidence shows that fake news associated with COVID-19 leads to panic, distrust, and confusion, whereas isolation leads to confusion in the thoughts of individuals [2]. Policymakers worldwide are choosing from these two choices of imposing

lockdown or not, depending upon their demographics, economic situation, medical infrastructure, and social dynamics [3, 4]. The psychological effects of the crisis affect people's capacity to make prudent financial and nonfinancial decisions [5–7]. This unprecedented crisis calls for unusual solutions to help sustain people's well-being. Using techniques such as artificial intelligence for predictions is emerging as one key idea in such a situation.

Complex economic relations and models and high-frequency events in ever-evolving markets make propagating linear relations amongst economic and financial variables outdated [8, 9]. For estimating complex nonlinear relations and predicting stock market returns, computer science and econometric analysis go hand in hand. Advancements in computing technologies and econometric methodologies are changing the face of stock market predictions in recent times. Typically, econometric modeling, such as autoregressive (AR), moving average (MA), autoregressive moving average (ARMA), autoregressive integrated moving average (ARIMA), generalized autoregressive conditional heteroskedasticity (GARCH) model, buying and hold (B and H) strategy, random walk (RW), stochastic volatility (SV) model, has been employed for predicting stock returns [10], which is now being complemented by artificial intelligence and machine learning systems including artificial neural networks (ANNs), multilayer perceptron (MLP), fuzzy inference systems (FIS), adaptive neuro-fuzzy inference systems (ANFIS), and support vector modeling [11, 12].

Artificial neural networks (ANNs) can be considered as neural networks replicated in vitro. A neural network is a meshwork of billions of neurons (cells which are the basic unit of the nervous system) that are involved in processing information. ANNs are analogous to these neural structures as input is required with an optimum amount of threshold to process the inputs and provide a relevant output [13]. Within the neural framework, each neuron carries a weighted combination of many input signals, which is further converted to the activation threshold, and ultimately, an output is generated. Likewise, it is the nature of ANNs where many input signals are combined as a weighted input signal and are transformed as output after the mathematical calculation of all the input signals. The structure of MLP is a three-layered network with an input layer, hidden layer, and output layer [14], which utilizes a backpropagation algorithm for learning. Various algorithms, such as fuzzy logic (FL), probabilistic reasoning (PR), neural networks (NNs), and genetic algorithms (GAs), can be used in symbiotic association in soft computing to solve complex problems of the real world [15].

Artificial intelligence has provided a new and fresh approach to finance through its implementation in the prediction of financial market prices by promising more generalizable results for stock market forecasting. Immense literature has attempted to apply artificial intelligence and machine learning for predicting stock market returns and volatilities [13, 16–45]. Nevertheless, the research on the applications of artificial intelligence in finance lacks a consolidated overview of different research directions, findings, methodological approaches, and contributions. Therefore, there is a need to consolidate the extant literature in this upcoming field to consolidate the findings, identify the research gaps in the existing literature, and set a research agenda for future researchers. This paper addresses this need by synthesizing the extant literature in the form of a systematic review for addressing the use of AI in stock market predictions and interpreting the results in a narrative review.

This paper provides a new outlook on the conceptual synthesis of the extant literature. The researchers can further utilize the existing studies for developing more complex models using machine learning (ML) techniques for forecasting returns, modeling risk, and portfolio construction. The complexity of the nonlinear data can better be served with ML techniques. Multiple-layer perceptron (MLP), support vector machine (SVM), and long short-term memory (LSTM) model are the methods used for quantitative finance. A combination of these methods for deep belief networks and extreme learning machines can predict stocks more accurately [46]. The authors have resolved the conceptual way of explaining the need for more research work in deep learning for advancement in prediction modeling in financial markets. Chatrabgoun et al. [47] explain the use of the Bayesian network with pair-copula construction (BN-PCC) for tackling the issue of heavy tail data in financial applications [48].

Big data in recent times is providing more nonlinear datasets, which can be computed through the use of the ML technique. Furthermore, decision-making involves controlling the variables, which leads to uncertainty for allowing more accurate forecasts in financial markets. Thus, this study serves well by providing an account of variables associated with market prediction and the methodology used to study them, such as hybrid models [49]. However, this becomes pertinent that the models used in the previous studies shall be reinvigorated for their application on nonlinear datasets presented by big data. Techniques such as MLP, SVM, and LSTM can be rekindled with sentiment and emotional analysis for deep learning and prediction accuracy. This paper contributes to the literature in a more unified way by conceptualizing the extant literature and its major findings and methodology implemented for paving the way to future researchers to develop advanced prediction models and frameworks for understanding the variables related to uncertainty in the markets for accuracy in financial market forecasting.

The rest of the paper is organized as follows. In Section 2, the research questions briefly discussed in the introductory section are formulated, and the methodology is introduced. Section 3 presents the findings, where the authors introduce the paradigms associated with artificial intelligence and its use in the predictions of stock behavior under the sections named as descriptive findings. Section 4 involves thematic discussions, whereas Section 5 drives some insights concerning future research and practice.

2. Materials and Methods

2.1. Research Questions. Liberalization of the financial markets, along with the developments in strong communications and trading facilities [50], has led to a variety of investment alternatives. While the financial markets of the

developed nations are highly integrated, the conventional capital markets theory has also evolved, and the financial analysis techniques have upgraded considerably [51].

With the important changes taking place over the last two decades in international finance, most of the financial markets are highly embraced now. The authors in [52] use the daily historical price of the North American stock index DJI and Nasdaq (USA), IPC (Mexico), and TSE (Canada) to foresee the stock indices' sign variations by implementing the logic models and fuzzy logic models which provided favorable returns when used as a trading strategy. Additionally, O'Connor and Madden [53] assess the magnitude of the impact of using external indicators such as commodity prices and currency exchange rates in predicting movements in the Dow Jones Industrial Average index, basing the trading decisions on a neural network that provide reliable results. Other papers on the developed financial markets include [20, 45, 54–58]. Qiu et al. [59] apply the artificial neural network involving a hybrid approach based on the genetic algorithm (GA) and simulated annealing (SA) to improve the prediction accuracy of the ANN of the Japanese Nikkei 225 index and proved it to perform better.

Cao et al. [19] use artificial neural networks to anticipate stock prices for the companies listed on the Shanghai stock exchange and opine neural networks as a useful method to predict prices in emerging markets, such as China. Additionally, Chen and Li [60] compare the five models, namely, the linear AR model, the LSTAR and ESTAR smooth transition autoregressive model, and the two ANN models that are MLP and JCN, and find that neural network technique made more accurate predictions. Additionally, other papers with the Chinese stock market as the sample include [55, 57, 61, 62]. Considering the Asian markets, particularly the Nikkei 225 closing index and Shanghai B-share closing index, Dai et al. [22] develop a time series forecast model by integrating nonlinear, independent component analysis and neural networks and prove a better option for the Asian stock markets.

RQ1: –to consolidate the findings of the existing literature related to the impact of artificial intelligence on stock market predictions

In order to generate optimum investment returns in the real-world stock exchange, many studies have employed decision support systems (DSS) techniques, soft computing models, and hybrid structures. However, Pham et al. [58] propose a hybrid Kansei-SOM model, a recent method using Kansei assessment combined with DSS techniques using collective decision-making for investment in the stock market and show that the proposed method performs better than the other prevailing methods. Another paper by Lin et al. [63] proposes a new technique called empirical mode decomposition combined with the k-nearest neighbors (EMD-KNN) method in forecasting the stock index, and the results demonstrate it to be more successful than the other methods. Additionally, the authors in [64] develop a new model combining the EMD with stochastic time strength neural network (STNN) and conclude it as a better model in forecasting stock market fluctuations.

Many researchers and financial analysts focus on nonlinear ties in the movement of the financial market, which calls for a new form of financial analysis, i.e., the nonlinear analysis of integrated financial markets. The study by Poddig and Rehkugler [51] employs artificial neural networks (ANNs) and other econometric models to establish the United States, Japan, and Germany's global reserve, bond, and currency business model. A paper by Cao et al. [19] compares the predictive potential of linear models and multivariate models of the neural networks and suggests neural network as an enhanced and effective method for forecasting stock market movements.

Reviewing the stock market's microstructure from a new perspective, Liang [65] uses the neural network technique to learn the complex linking of stock market information sources and determine that experiments illustrate this association statistically. Alternatively, Li et al. [66] study another theme in the concerned field that is the trading volume and the asset price risk using the sentiment analysis and machine learning approaches, including the ANN and support vector machine (SVM). Another topic of interest is captured by Liang [67] with a focus on studying the relationship between stock news on the Internet and stock price movements using neural network.

RQ2: –to understand the potential of different methodological AI approaches to capture the increased complexity and the complex nature of economic and political relations influencing stock price movements and their volatility

The intense research in neural networks produced new techniques for many potential applications, including the ability to forecast future movements of stocks, indices, and currencies, and additionally, Rehkugler and Poddig [68] conclude that, on comparing its results with those of a traditional model based on the multivariate regression analysis, the neural networks produced relevant results. Many papers sustained the implementation of the ANNs for a long time, even after their inception [69–71].

With the aim to outperform the other individual models, approaches involving the integration or the hybridization of different models in a composite model consisting of numerous linear prediction models, nonlinear models, or variations of both are implemented [46]. Kim et al. [72] investigate the efficiency of a hybrid approach with the time-delay neural networks (TDNNs) and the genetic algorithms (GAs) in identifying time-based stock market predictive tasks and find that evaluating the integrated solution is better than the traditional TDNN and the recurrent neural networks (RNNs). Additionally, to predict the settlement price of stock index futures, Li [30] develops a hybrid model involving the decomposition of empirical mode and function of the radial base that results into higher prediction accuracy. Forecasting future trends are one of the key considerations when using a prediction model. Hence, researchers continue to provide upgradations in the time series models. Since the artificial neural networks need a large amount of data, Khashei et al. [73] propose a modern hybrid neural artificial networks and fuzzy regression model for time series forecasting and conclude it to yield better results.

Bohn et al. [74] discuss the new system named MoneyBee that predicts the stock market values, especially from the German stock market, and conclude this information technology product as an innovation due to its cooperation between multiple high-level program groups.

The estimation of stock market movements is one of the key fields, with several approaches used, including the conventional computational techniques to artificial neural networks. However, the traditional approach to statistical economics has difficulties scaling because of noise and nonlinearity in time series [75]. Considering this feature of the traditional approach, Zhang et al. [75] propose the simple wave signal decomposition-based prediction model and the introduction of the α-counting instantaneous frequency of the simple wave and find it a better model.

Clearly, the literature states that whenever a new hybrid model is implemented, or a new approach is adopted to predict the stock market movements, the results produced are positive and favorable from the investment point of view. Hence, this indicates that every new technique and methodology implemented will lead to consistent improvements in the relevant models in artificial intelligence and, in particular, neural networks.

RQ3: to highlight the future research directions that may create value with AI in the context of stock market predictions

Recent research studies have paved the way for the inclusion of neural networks with AI for forecasting stock markets. Rather et al. [46] suggested the use of AI models for optimal portfolio selection through intelligent modeling. Further, risk modeling and return forecasting can be modelled by using the subfield of AI, which is machine learning (ML) [48]. This may enhance the probability to achieve better optimization models in the prediction of stocks in the longer run.

RQ4: to understand the capacity of AI in predicting the financial market behavior during pandemic times as COVID-19

The present review is an attempt in providing a constructive path for forecasting stock markets, and the use of AI models in predicting the financial market behavior during pandemic times seems promising. The correlation that may arise due to sentiment-related volatility in stock markets [76] may be analysed through the machine learning models.

2.2. Methods. The research approach is influenced by the works in [77–80]. It is important to note that a systematic review involves reading several excerpts from an article, considering not only the overview of the keywords and the abstract but a thorough examination of each paper, taking their methods, conclusions, and findings into consideration. This is imperative to categorize their content more meaningfully while examining a particular field of study. Therefore, this review takes into consideration the research works that directly or indirectly discuss the applications of neural networks and artificial intelligence in predicting stock market by carrying out the following activities:

(1) Analyzing the articles previously published

(2) Providing a short description of the contribution of these articles

(3) Categorizing and coding the different parameters

(4) Describing their different contributions

(5) Providing the scope for future research to fill the gaps identified herein

The authors jointly delineated two keywords, namely, "neural network" and "stock market forecasting." "Fuzzy logic" and "artificial intelligence" were decided as synonymous with "neural network." In contrast, "stock return," "share market," and "share price" were decided to be used as synonymous with the "stock market" for searching the literature. The worldwide accepted online database, Web of Science (WoS), was used for searching the relevant papers. The search was conducted on the Web of Science database on December 24, 2017, using the following BOOLEAN criteria: TS = ((Neural Network* OR Fuzzy Logic* OR Artificial Intelligence) AND (stock market* or stock return* or stock price* or share market* or share return* or share price*)).

This resulted in an initial list of 1040 papers, as shown in Figure 1.

The list of 1040 papers is discussed for designing an objective criterion to select/reject the papers for review. Manual exclusion and inclusion are done by the authors as follows.

Each paper was examined individually by the authors as A (accept), B (reject), and C (doubtful), which was carried out solely based on the abstract and the keywords. The results are showcased in Figure 1, which exhibits that 1040 papers were extracted from the database in the first stage, out of which 250 papers were accepted for review, 605 were rejected, and 185 were put in the doubtful category.

The second stage carried out the reassessment of these papers, which involved going through the entire paper for better understanding and correct categorization. 128 papers were rejected based on an irrelevant field of study. Eventually, 57 were accepted from the list of doubtful papers.

Finally, a total of 307 papers were selected for the systematic review. Table 1 highlights the categories and subcategories for the systematic literature review.

3. Results

3.1. Descriptive Results

3.1.1. Geographical Distribution. The first category deals with the geographical base studied in the existing literature. Table 2 represents the geographical area distribution.

It is evident from Table 2 that the majority of contributions focus on countries from Asia, which is assigned code B. Asia is representative of 39% of research in artificial neural networks (ANNs) for stock market prediction. Code C, representing the USA, shares 15% of its research work in this context. CW countries share 13% of their knowledge base in this background. At the same time, 33% of geographical distribution does not belong to any particular geographical location. It is important to undertake more research in designing prediction models for stock markets. As stock markets play a major role in a country's economic growth, it is important to have some prediction models which can help
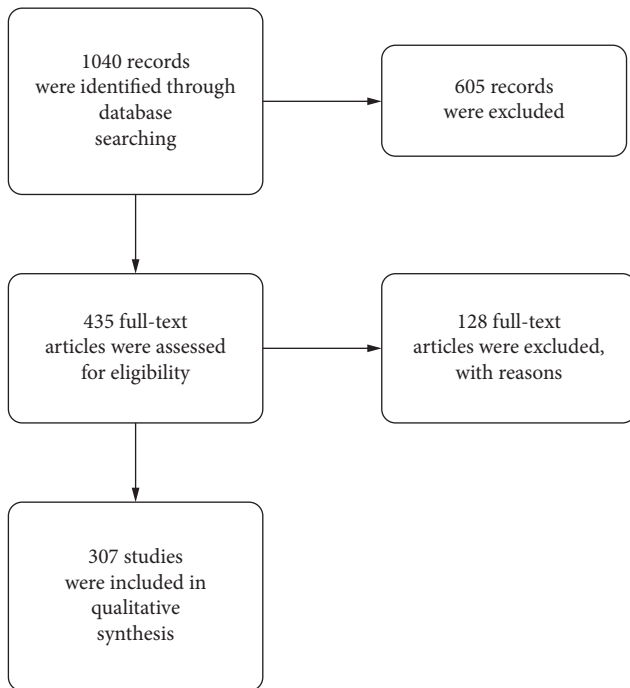
FIGURE 1: Study flow diagram (PRISMA figure).

in the forecasting of price movements in stock markets for the benefit of investors. Figure 2 represents the geographical area distribution.

3.1.2. Context. The second category relates to the coverage and is divided into three categories: A stands for developed countries, B for developing countries, and C for not applicable. Table 2 depicts that 55% of the contribution is made by developed countries and 41% is by developing countries. The majority of studies have taken place in developed countries. This is suggestive of the fact that researchers in developed nations have started analyzing the issue of prediction of stock prices. However, this is a major concern of investors across the globe, and such studies need to be undertaken in developing nations also (Figure 3).

Gap 1: studies focusing on the future of artificial neural networks in stock market prediction models in developing countries must be taken up.

3.1.3. Method. This category of coding indicates the method applied to the available. Table 2 presents the methodology with seven categories.

Category D presents the maximum number of papers. These papers have used more than one method of analysis. Conceptual papers are denoted as code C, which represents the next highest number of studies. Figure 4 presents the methodology from the existing literature.

It can be concluded that conceptual and theoretical work has been done in this context. The gap which emerges is as follows.

Gap 2: there is much wider scope in the field of artificial intelligence to implement other methodological approaches;

for instance, conducting a case study or a survey or an experiment using a hybrid model can further help in the development of more generalized models of stock prediction.

3.1.4. Main Subject. The category of the main subject is classified into five types, as mentioned in Table 2. The maximum number of publications are available in the field of neural network and other computing techniques. The analysis of this category implies that a major part of the literature talks about studies on the combination of artificial intelligence and neural networks [14, 57, 81–83]. Research related to predicting stock indices, such as genetic algorithms and neural networks, and linear and nonlinear models recognizes patterns by estimating coefficients and their statistical significance. However, most agents in the stock market use language that incorporates qualitative aspects such as the price of the asset, but the authors in [52] opine that predictive models of fuzzy logic achieve statistically significant and positive returns when used in trading strategy [84]. Model predictive control (MPC) is regarded as the most widely applied control technique capable of handling constraints and incorporates other economic considerations [85]. In the context of portfolio optimization, where the challenge also lies in finding the optimal trade-off between risk and return over a fixed time horizon, Herzog et al. [86] propose to use the model predictive model (MPC) to optimize the portfolio by the probabilities and parameters of the implied regime including transaction costs, risk aversion, and other restraints. Nystrup et al. [84] employ the model predictive control (MPC) to optimize a portfolio based on forecasts of the mean and variance of financial returns from a hidden Markov model and conclude that MPC yields better returns and relatively lesser risk than investment in other stock markets. On the other hand, Yamada and Primbs [87] employ MPC in the context of the hedge funds incorporating the issues of gross exposure and transaction costs, while Dombrovskii and Obedko [88] adopt MPC to develop feedback portfolio optimization strategies, indicating extensive reliability on this technique in financial applications, especially in cases of portfolio optimization and dynamic hedging. Concerning our main topic, extensive work could be taken up, which will ultimately lead to algorithms and prediction models in this background (Figure 5).

3.1.5. Themes. The themes are divided into ten different categories, as depicted in Table 2. It can be drawn that a major part of the studies available is in the field of computer sciences and business economics (Figure 6).

There arises a need for more studies to be taken up under themes of material sciences, soft computing, optimization techniques, automation, and control system. This brings us to the following gap.

Gap 3: the scope of research lies in the trade-off between different optimization algorithms and the adoption of the best algorithm as the solution. This can be achieved by filling the gaps under other themes of science as they can provide

Table 1: Categories and subcategories of the systematic literature review.

Category	Meaning	Codes for alternatives
1	Geographical distribution	Commonwealth countries Asia USA Not applicable
2	Context	Developed countries Developing/emerging countries Not applicable
3	Methodology	Quantitative Qualitative Conceptual Quantitative/qualitative or qualitative/quantitative Survey Case study Not applicable
4	Main subject	Stock return prediction Other financial returns prediction Artificial intelligence Neural networks Other computing techniques
5	Themes	Neuroscience Optimization techniques (science tech.) Business economics Soft computing (engineering) Material science Automation and control system Operational research and management science Physics and mathematics Computer science Other topics
6	Contribution	New perspectives Consistent with previous literature Previous model with different datasets/time periods Comparative study Not applicable
7	Analysis period	Less than 3 years Between 3 and 5 years Between 5 and 10 years More than 10 years Not applicable

Table 2: Codes and categories of selected papers.

| Code	Geographical distribution	Context	Method	Main subject	Themes	Contribution	Analysis period
A	40 (13%)	169 (55%)	3 (1%)	23 (7.49%)	6 (2%)	40 (13.02%)	25 (8.14%)
B	120 (39%)	126 (41%)	9 (3%)	43 (14%)	4 (1%)	34 (11.07%)	14 (4.56%)
C	46 (15%)	12 (4%)	52 (17%)	24 (7.87%)	54 (18%)	35 (11.40%)	124 (40.39%)
D	101 (33%)	NA	126 (41%)	51 (16.61%)	15 (5%)	45 (14.65%)	144 (46.90%)
E	NA	NA	31 (10%)	52 (16.93%)	2 (1%)	43 (14.33%)	NA
F	NA	NA	37 (12%)	NA	4 (1%)	NA	NA
G	NA	NA	49 (16%)	NA	4 (1%)	NA	NA
H	NA	NA	NA	NA	19 (6%)	NA	NA
I	NA	NA	NA	NA	192 (63%)	NA	NA
J	NA	NA	NA	NA	7 (2%)	NA	NA
Multiple	NA	NA	NA	114 (37.13%)	NA	109 (35.50%)	NA

Geographical region
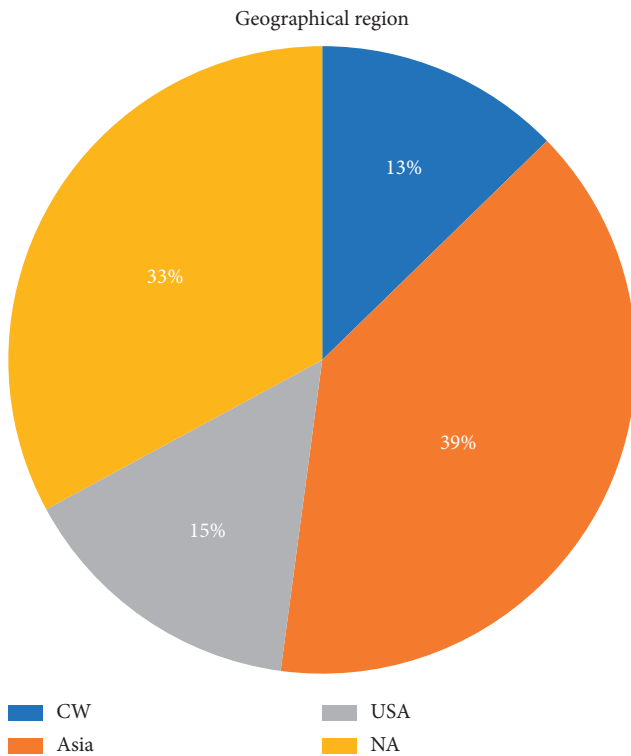
FIGURE 2: Distribution of the geographic region in the existing literature.
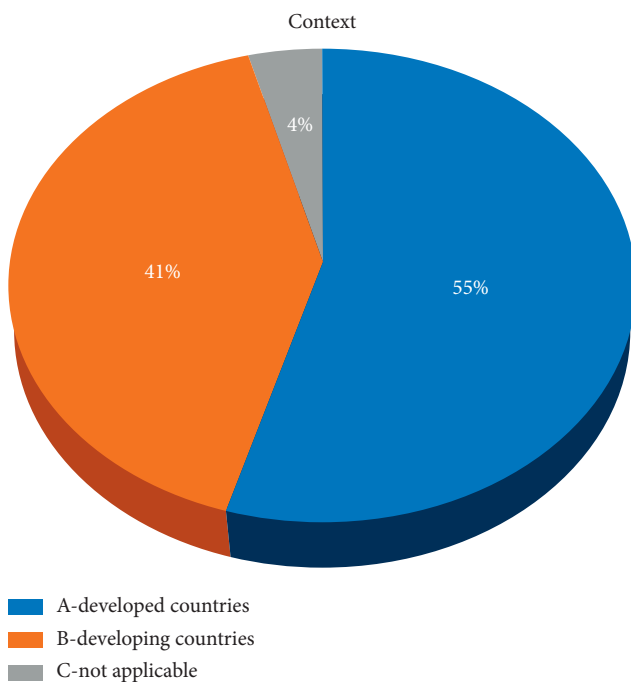
Context

FIGURE 3: Context of existing research papers.

better insights into AI for the development of stock market prediction models.

3.1.6. Contribution. This classification presents the contribution of the articles understudy, presented in Table 2. The contribution made by category D is the maximum number
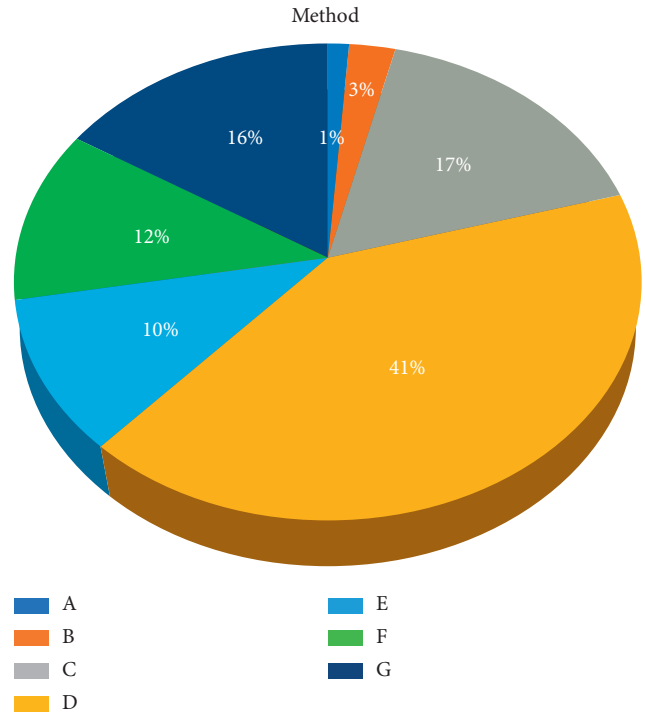
Method

FIGURE 4: Methodology employed in previous papers.

of 45 papers followed by category "E" with 44 and further followed by "A" with 40. Hence, it seems to be an ideal spread of the previous literature with a fine number of papers concentrating on either implementing previously developed models with a new dataset or drawing a comparison between different techniques or an extension of findings from the previous literature (Figure 7).

3.1.7. Analysis Period. The analysis period indicates that, in the last three years, only 25 papers are published. It is also less for a period of 3 to 5 years, accounting for only 14 papers. However, AI as a concept emerged long back in the 1960s and the concept of the neural network is indeed an old established concept in neurology. The merging of these two concepts is still in a quandary. There is a dire need to uptake more work in this field and reap benefits out of AI and neural networks for the prediction of stock markets (Figure 8).

Gap 4: more studies are required to see the consistency throughout the time period since the inception of these three topics, viz., AI, neural networks, and stock market forecasting.

4. Discussion

Using the method suggested in [77–80], an analysis of the relevant literature available on the Web of Sciences (WoS) was conducted to identify the major themes in studying the application of artificial intelligence and related techniques in predicting stock behavior. The methodological details are presented in Section 2 of this paper. The characteristics and parameters studied by the existing literature are segregated and presented in this section.
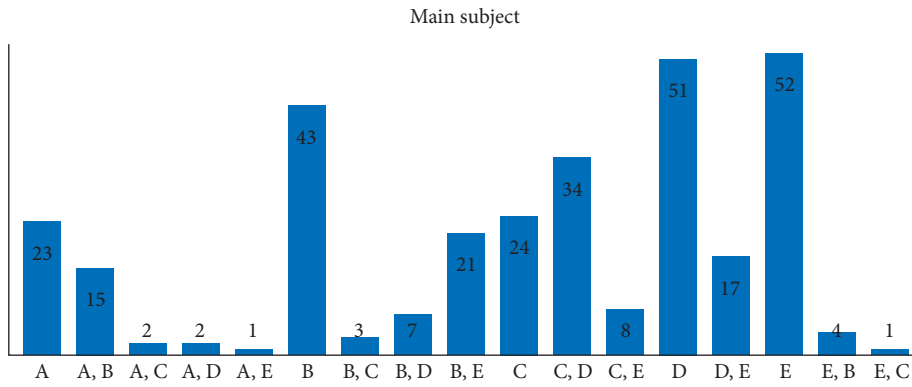
Main subject

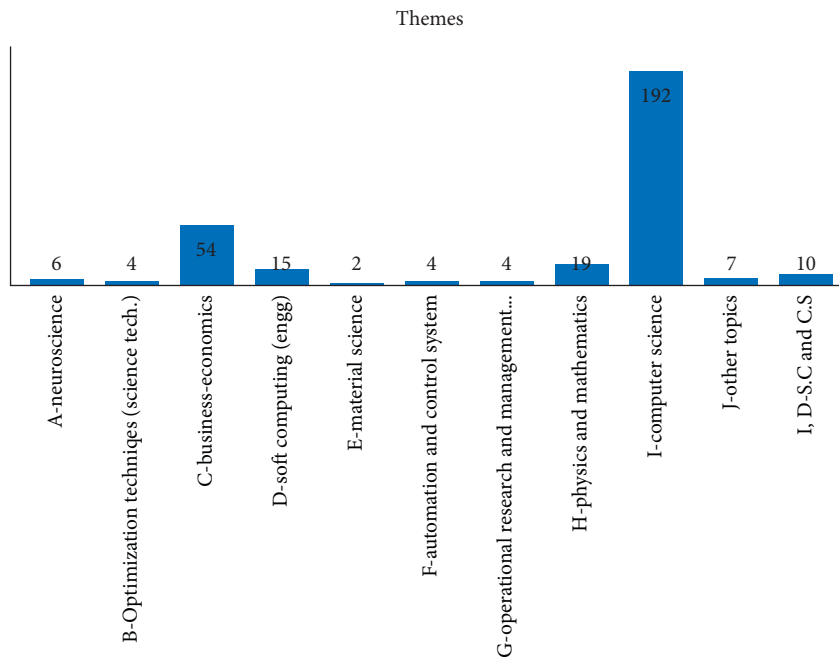FIGURE 5: Distribution of main subject in the existing literature.

Themes

FIGURE 6: Themes of papers.

Contribution

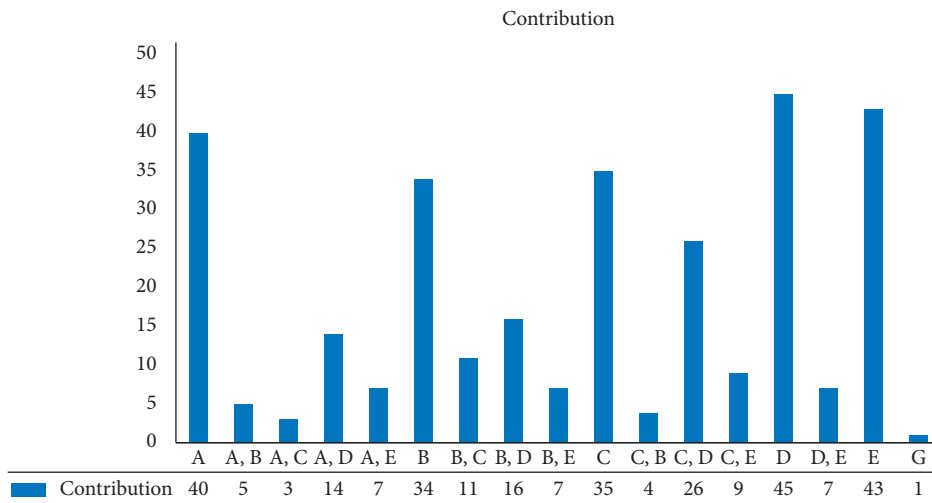|	A	A, B	A, C	A, D	A, E	B	B, C	B, D	B, E	C	C, B	C, D	C, E	D	D, E	E	G
Contribution	40	5	3	14	7	34	11	16	7	35	4	26	9	45	7	43	1

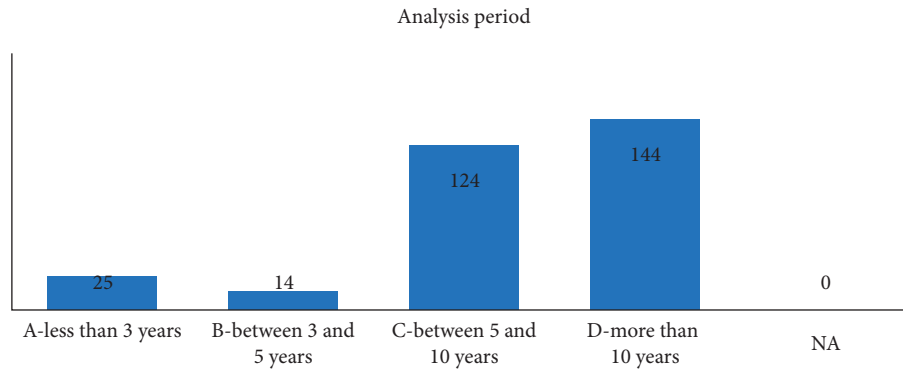FIGURE 7: Histogram showing the contribution to the paper.

Analysis period

FIGURE 8: Analysis period from the existing literature.

4.1. Soft Computing. In the financial world, soft computing is gathering traction. A variety of real and potential soft computing technologies are employed in the financial sector, including commodity and retail market estimates, trade, portfolio management, credit scoring, or projections of financial distress [89]. Soft computing includes a variety of techniques that replicate the ability of the human imagination that applies reasoning approaches that are subjective and not precise. The term "soft computing" was coined by Zadeh in the early nineties [90], concluding fuzzy logic, neural network theory, and probabilistic reasoning as the main components of soft computing. Securities and foreign exchange forecasting is one classical field of soft computation in which forecasts of the conduct of hybrid currencies, currency exchange rates, and stock prices are determined [89]. A significant example of soft computation techniques used in stock market forecasting is given byBoyacioglu and Avci [11], where the authors utilize an adaptive network-based fuzzy inference system, with which they have a prediction accuracy of 98.3% for the Istanbul Stock Exchange. The authors use a combination of macroeconomic variables and indices with a set of if-then rules and layers based on the principles of ANN and fuzzy logic. Current research on predictive models in financial economics and econometrics distinguishes between parametric models and nonparametric models. In the case of option pricing models, the famous Black–Scholes model is an important primer for parametric models estimating option prices.

On the other hand, methods such as extreme learning machines and support vector regressions are mainly nonparametric models, with which financial predictions can be done. Das and Padhy [91] suggest a combination of parametric and nonparametric methods mentioned here in order to increase the predictive power of option pricing models. Here, the hybrid mode superiority is due to return distributions being nonnormal and the need for adaptive learning, which arises from the extreme learning machines method.

4.2. Neural Networks. As a branch of computational science, the neural network encompasses a broad range of techniques of function modeling focused on interconnected processing components, known as neurons, which work together to generate a particular output. Among the important approaches are the multilayer perceptrons, radial basis networks, or self-organizing maps [89]. Jayne et al. [92] investigate the applicability of neural networks by forecasting the values of each share, taking into account the general index value, and state that neural networks learn the complex mapping between ideal attributes and the particular domain parameters. Results from the multilayer perceptron method (MPL) and radial basis function (RBF) tests are good and acceptable considering the type of inversion problem addressed. Corresponding to this, Kim and Lee [93] compare the genetic algorithm (GA) with the linear transformational model (LTM) and fuzzy transformational model (FTM) for the artificial neural networks to function better in predicting the stock market patterns and report reduction in the irrelevant factors for stock market prediction. On the other hand, stock opening price forecasting has also gained momentum in recent years. To improve the accuracy of this forecasting, Qun et al. [94] propose a model incorporating the emotional data along with the actual behavior data and report improvement in the prediction accuracy. Accordingly, Nayak et al. [95] study the neural network of artificial chemical reaction to prepare multilayer perceptrons for stock market index forecasting and conclude significant improvement in the prediction accuracy. It cannot be concluded that neural networks always outperform traditional models in financial markets, as pointed out by Bahrammirzaee [96], who finds out that the opposite can also be true. Nevertheless, the use and performance of NNs are encouraging due to their numeric nature, their distribution-free approach, and the ability of NNs to update data. Nevertheless, due to some limitations in technical aspects of NN, NN itself can sometimes be problematic to use—in that case, hybrid models combining NN approaches with other techniques can be used [96]. One example of such hybridization of NN will be mentioned in Section 4.4.

4.3. Artificial Intelligence. AI is viewed as an alternative to predictive modeling. This computer science, or systems engineering, field was originally introduced in the 1950s to develop machinery intelligence [54]. Since then, a variety of AI methods have developed, including the Bayesian networks, artificial neural networks (ANNs), expert systems, support vector machines, and fuzzy-logic-based techniques.

In comparison with statistical techniques, AI does not make the same data assumptions as regression analysis. It performs well within datasets contaminated by variable noise and is effective in the impartial and semicontrolled analysis of data [54]. However, many real financial applications have uncertain behavior that changes over time, and this problem causes an increased interest in artificial intelligence applicability. Bahrammirzaee [96] reviews three AI techniques, namely, artificial neural networks, expert systems, and hybrid intelligence systems in the financial market and proves the AI techniques are superior to the traditional statistical methods in terms of their accuracy, majorly regarding the nonlinear patterns.

Alternatively, Li et al. [97] propose a modern blend prediction model based on AI techniques and integrated forecast concept, which may direct the investor's businesses in the real stock market and prove to be an effective instrument for decision making investments. Additionally, the authors in [59, 98] apply the ANN and genetic algorithm (GA) and find that this hybrid approach improves the stock prediction accuracy significantly and outperforms the traditional backpropagation (BP) learning algorithm. Wu and Duan [83] compare network structures of different neural networks in predicting the price trend of the Chinese stock market and conclude that the dynamic relationship between investors and market volatility can be thoroughly illustrated. Bebarta et al. [99] propose a model that selects optimum nonlinear combinations of Indian stock forecasting. The model proposed by the authors makes use of an evolutionary algorithm to optimize the weight parameters of different functional expansions to improve forecast accuracy.

Management of stock portfolios is a challenging task, and to solve such problems, artificial intelligence models are applied, where Rather et al. [46] conduct a survey highlighting the traditional mathematical models to artificial intelligence-based models available in recent articles. One problem that they identify is that, in many cases, linear and mathematical models for portfolio optimization work fairly well so that there may be no need for AI models. In addition to that, one common limitation of these AI models is the slow convergence and the fact that there is no guarantee for an optimal solution. One example of an unsuccessful attempt to make use of ANN in combination with genetic algorithms is given in [98], where even the improved version of their earlier model has a prediction accuracy of 63%. This also indicates that the complex nature of ANN cannot immediately deliver efficient and concrete predictions even though some scholars found methods to fasten the learning process (see, e.g., [12]).

Nevertheless, the evolutionary computation can deliver evidence from another perspective than optimization, which is known for being a primer in ergodic economic theory, as recently pointed out by Menger-Anderson [100]. Ghandar et al. [101] show that, using evolutionary computing methods, the machine itself can develop evolutionary trading rules with which an excellent performance in ever-evolving market conditions can be reached. On the other hand, Hamed et al. [12] combine ANN and MLP approaches with a method from signal processing called blind source separation technique. The signal processing technique utilized by the authors not only optimizes the learning process of the neural network but also fastens this process. Through this improvement, accurate and efficient results have been obtained for Microsoft stock movements, among others.

4.4. Fuzzy Logic.
After being considered one of the main components of soft computing, fuzzy logic is derived from fuzzy set theory dealing with theoretical reasoning rather than precisely derived rationale. Unlike the traditional logic, it arrives at conclusions based on vague, ambiguous, noisy, or incomplete information [89]. Employing a fuzzy logic-based approach simplifies the design problem and describes the ambiguity and vagueness of pattern functions. It includes uncertainty in the trading decision system that advises the investor on how much and where to invest. Naranjo et al. [102] illustrate this methodology by proposing a fuzzy trading system that reveals improvement in pattern recognition and provides more benefits in a less volatile fashion than most trading structures. However, previous literature finds certain drawbacks in the forecasting models. To refine these, Wei et al. [103] propose a hybrid model employing a fuzzy inference system (FIS) and argue that the model is superior to the previous traditional models due to improvement in the forecasts generated. Since neural networks can be considered as having a black box nature sometimes [104], the problem is that these cannot be used to determine a causality relation between dependent and independent variables. To overcome this problem, instead of rejecting neural networks completely [104], make use of a hybridization technique to generate a fuzzy neural network model. This model combines the reasoning style from fuzzy models and learning styles of neural networks to yield interpretable results and high profits for stock trading decisions. Through this hybrid model, the authors show an improvement of neural network-based decision rules for stock trading. Alternatively, Bekiros et al. [105] propose a volatility-based neuro-fuzzy model to predict FTSE100 and New York Stock Exchange returns. This contribution shows that considering volatility changes in a neuro-fuzzy model can improve the accuracy of stock market forecasts and it outperforms other approaches such as a Markov switching model, a feedforward neural network model, and a buy and hold strategy when transaction costs are also taken into account. The managerial implication of this model is that a neuro-fuzzy model incorporating volatility changes can bring higher returns than the approach for passive fund management.

4.5. Stock Returns.
The economic and social well-being of developing countries with reasonably privatized economies depends heavily on the financial sector in a region, which is seen as an important factor for growth and development. Over the years, researchers are trying to promote financing by offering credit and other financial goods, predict market patterns, model market, and consumer conduct, manage the portfolio, open stock price allocation, predict defaults and bankruptcy, etc. In respect of these, several methods are used that can be classified as parametric (e.g., logistic regression

and discriminatory analysis), nonparametric (e.g., decision trees) mathematical techniques, and soft computing (e.g., artificial intelligence algorithms) techniques [96].

Investors, industrialists, and researchers remained focused on stock estimation and investment in suitable stocks. In the years, several models and techniques of artificial intelligence have been developed to solve such problems. However, Box and Jenkins's ARIMA models have gained popularity in the time series prediction field, while linear prediction models are still used in practice [106]. Complementary to this, Rather et al. [46] survey articles on stock prediction and stock selection for portfolios and opine more precise demand forecasts by AI-based models. Karathanasopoulos [107] introduces a new short-term adaptive model, i.e., partial swarm optimizer combined with linear and nonlinear models to forecast the daily closing returns of FTSE100 exchange-traded funds (ETFs) and find the model to perform well in terms of correct directional change.

On the other hand, Li et al. [108] forecast the REITs and stock indices by Group Method of Data Handling (GMDH) neural network method with Hurst and confirm the model to perform better than the conventional forecasting algorithms, including ARIMA, the single and double exponential smooth, and the neural network backpropagation. Additionally, a paper by Zhong and Enke [109] present a systematic data mining method using artificial neural networks and logistic regression models, to predict the S&P 500 Index ETF (SPY) daily return, and conclude that the risk-adjusted returns of the trading strategies are higher than the comparable benchmark. Bildirici and Ersin [10] focus on an M-GARCH type model that makes use of ANNs to improve forecasting accuracy. The novelty of this model in comparison with similar GARCH models is the increased predictive power of the model involving the regime-switching structure augmented with neural networks. The approach proposed by Chang et al. [110] makes use of the simplest form of business cycle theory, namely, the theory that tells us that there are ups and downs which we call turning points regarding stock prices, but also the economy in general. The novelty of the approach is to decompose historical data into segments, through which the authors identify temporary turning points by using piecewise linear representation. The model therefore gives investors clues about buying, selling, or holding stocks, which is a more preferred approach than forecasting the stock price only.

Additionally, the model predictive control (MPC) technique is developed by Herzog et al. [86] to solve restricted stochastic problems in terms of portfolio optimization, including inherent nonlinearity, constraints, and uncertainty [111]. Dombrovskii and Obedko [88] consider optimum portfolio selection issues subject to investment, trade, and various borrowing and lending rates limitations, use MPC for designing optimization feedback portfolio strategies, and further test the approach on real data of the Russian Stock Exchange, Moscow Interbank Currency Exchange, and New York Stock Exchange. Conversely, to gain insights into the stock market and allocation of capital, Trimborn et al. [112] employ MPC to approximate and solve the optimization of the utility function. To

predict shifts in the term interest rate structure, Zante-deschi et al. [113] propose a dynamic product partition model (PPM) that relates macrovariables to term structures and indicate major economic disruptions, including recessions.

4.6. AI and Knowledge Management. Artificial intelligence and knowledge management developed historically from different roots, but they share a common ground due to the subjective, tacit, dispersed nature of knowledge [114]. Sanzogni et al. [114] propose that collective tacit knowledge available in society and transferred to an individual via his or her interactions with the society, tacit relational knowledge based on contingencies concerning human interactions, and tacit somatic understanding lying within the mind of an individual are building the common grounds for these two concepts. The authors point out the fact that AI can be used to support human-driven knowledge processes, which are necessarily subjective. Still, the state-of-the-art research and practices show that AI is leading the way to autonomous intelligent machines which will rather substitute human-driven knowledge processes. The authors note that AI and KM evolved in parallel ways but need to be integrated for further research since AI-based technologies can be a key to the implementation of new knowledge strategies and KM visions for decision-making.

Furthermore, it is also noticed by the authors that AI technologies may be unaware of their actions and the political consequences of these actions, and this challenge can be managed by KM strategies. The latter point seems to be especially relevant for financial markets since disseminating fake or real news has a significant effect on these. In contrast, these build the macroeconomic implications of AI and its complex relationship with KM. Some microeconomic implications can be relevant for individual behavior, especially regarding individuals who directly or indirectly influence stock market prices. A primer in the interaction of these fields had been written by Dong and Zhou [115]. Using ANNs as their point of departure, the authors deliver empirical evidence showing the relation between stock price response and firm size, which differs across different firms. The novelty of this approach is to show that using the whole dividend event data to conclude may lack this differentiation across different types of firms. Hence, managing knowledge on stock price response can be improved by managing knowledge on firm types.

Big data, as an emerging field of application of AI, can be useful for personal knowledge management, as stated by Liu et al. [116]. The authors consider the fields where big data can be useful, such as time management, machine performance monitoring, activity monitoring of mobile devices, healthcare, and web navigation. Concerning financial decision-making, these areas can be improved both for security and for more efficient investment decisions. Nevertheless, this is a challenging issue, since real-world phenomena can be very complex, and often, there can be some omitted variables which may result in false causalities and conclusions [117].

TABLE 3: Research gaps and future agenda.

Gaps	Questions	Related studies
Gap 1–; there is a need to focus on the future of artificial neural networks in stock market prediction models in developing countries	RQ1: to integrate the findings of the previous research in the field of artificial intelligence in stock market prediction models in different parts of the world, with more focus on the developing economies	[10, 19, 22, 26, 60, 118–131]
Gap 2: there is a much wider scope in the field of artificial intelligence to implement other methodological approaches; for instance, conducting a case study or a survey or an experiment using a hybrid model can further help in the development of more generalized models of stock prediction	RQ2: to adopt other methodological approaches involving a case study, an experiment, or a survey	Experiments: [11, 29, 75, 91, 97] Survey: [96, 114] Case study: [91, 132–136]
Gap 3: the scope of research lies in choosing the optimal algorithm as the solution. A combination of other themes may provide better insights and models for stock market prediction.	RQ3: to conduct more research using a combination of other themes for stock market prediction, also because the existing artificial neural networks have not been able to provide effective results [137] and this calls for more advanced techniques such as neuro-fuzzy methods, genetic algorithm, option pricing models, machine learning techniques, and component analysis models	Neuro-fuzzy systems: [104, 105, 138–141] Genetic algorithm and linear representation methods: [28, 93, 142–148] Linear regression models: [21, 116, 122, 149] Option pricing model, machine learning techniques and hybrid combinations with neural networks: [34, 91, 150–153] Component analysis model: [22, 46, 62, 137, 154]
Gap4: more studies are required to maintain consistency throughout the time period since the inception of these three topics, viz., AI, neural networks, and stock market forecasting	RQ4: the majority of the study is concentrated on longer periods. Very few studies have conducted an experiment or a case study on the trading prices spread over the previous 6 months or less	[30, 38, 50, 75, 81, 91, 95, 98, 103, 146, 155–159]

5. Conclusions

The paper discussed the relevance of artificial neural networks (ANNs) in stock market prediction to cope up with the challenge of low financial well-being during the crisis of COVID-19. The existing literature in the field relates that AI and neural networks have a promising future together though the extent to which it can be applied should not be neglected. AI can provide multiple algorithms in solving the problems. The combination of neural networks with AI can provide for the development of human neurons and the functioning of the same in the human body. ANNs can help analyze non-linear problems and more generalization of the solutions provided through this combined approach. Thus, stock prediction tools can be developed through the use of ANNs.

The existing literature on this subject has largely used the conceptual methodology, though a combination of quantitative and qualitative approaches has also been employed in some cases. The theory generalization aspect has not been studied extensively by the literature. It can also be seen that developing countries are not doing so well when confronted with the development of stock prediction models than their counterparts. Witnessing the current era of scientific developments brings us to a state where AI can play a major role in developing models of stock market prediction, and more research studies are needed. The gap formed through this article is the use of a combination of AI as a subject with the neural network as another area and stock market forecasting as another theme, and it will pave the way for future research works. The analyses help highlight four important gaps in the existing literature on the subject.

We focused on the 4 research questions, as outlined in Section 2, and found four important gaps in the existing literature. From these gaps, we formulate the future research agenda to serve as a guideline for future researchers interested in these topics (Table 3).

The limitations of this study can provide a precursor for further studies. The papers have been analysed from the Web of Science only. Other databases can also be referred for addressing new gaps. This study acknowledges the relationship between AI, neural networks, and stock market prediction. Therefore, their use in predicting sentiment-related volatility in stock markets especially during pandemic times of COVID-19 needs attention. Hence, new perspectives can be brought to light through the use of other databases and running more ML models for forecasting

during COVID-19. The exploration of newer ideas will result in more application-based studies.

Disclosure

Conflicts of Interest

The authors declare no conflicts of interest.

Authors' Contributions

G. D. S. and B. E. conceptualized the study; G. D. S. and M. M. were responsible for methodology; G. D. S., B. E., M. M., M. S., and M. J. performed formal analysis; R. S. U. and T. K. investigated the study; S. S. was responsible for resources; G. D. S., B. E., M. J., T. K., M. M., M. S., R. S. U., and S. S. prepared the original draft; M. S., M. J., and B. E. reviewed and edited the manuscript; M. M. visualized the study; R. S. U. supervised the study; G. D. S. was involved in project administration; B. E. was responsible for funding acquisition. All authors have read and agreed to the published version of the manuscript.

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