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Artificial Intelligence & Machine Learning in Finance: A literature review

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Abstract:

In the 2020s, Artificial Intelligence (AI) has been increasingly becoming a dominant technology, and thanks to new computer technologies, Machine Learning (ML) has also experienced remarkable growth in recent years; however, Artificial Intelligence (AI) needs notable data scientist and engineers' innovation to evolve. Hence, in this paper, we aim to infer the intellectual development of AI and ML in finance research, adopting a scoping review combined with an embedded review to pursue and scrutinize the services of these concepts. For a technical literature review, we goose-step the five stages of the scoping review methodology along with Donthu et al.'s (2021) bibliometric review method. This article highlights the trends in AI and ML applications (from 1989 to 2022) in the financial field of both developed and emerging countries. The main purpose is to emphasize the minutiae of several types of research that elucidate the employment of AI and ML in finance. The findings of our study are summarized and developed into seven fields: (1) Portfolio Management and Robo-Advisory, (2) Risk Management and Financial Distress (3), Financial Fraud Detection and Anti-money laundering, (4) Sentiment Analysis and Investor Behaviour, (5) Algorithmic Stock Market Prediction and High-frequency Trading, (6) Data Protection and Cybersecurity, (7) Big Data Analytics, Blockchain, FinTech. Further, we demonstrate in each field, how research in AI and ML enhances the current financial sector, as well as their contribution in terms of possibilities and solutions for myriad financial institutions and organizations. We conclude with a global map review of 110 documents per the seven fields of AI and ML application.

Keywords: Artificial Intelligence, Machine Learning, Finance, Scoping review, Casablanca Exchange Market.
JEL Classification: C80
Paper type: Theoretical Research

1. Introduction

Elon Musk - CEO of Tesla Inc. and SpaceX Inc., Jeff Bezos - Executive Chairman of Amazon Inc., and Mark Zuckerberg – Chief Executive of Meta Inc., among others, those eminent founders of billion dollars companies had one special key in common to ensure their financial sustainability. All those renowned names put their trust and faith in artificial intelligence (AI) systems and machine learning (ML) algorithms.

With the fourth wave of the 4th Industrial Revolution, based on digital transformation, the application of AI in finance, healthcare, and education opens endless potential opportunities and became increasingly a breakthrough in many areas of life.

As a holistic concept, AI creates two main problems in understanding it, namely making it difficult to define; the relationship between what is human intelligence and which part of it might be replicable by AI (Stahl, 2021). Generally, in most literature reviews, AI is defined as the field of study by which a computer, and its systems, develop the ability to carry out complicated operations that normally involve human intelligence. These tasks include but are not limited to, decision-making, speech recognition, visual perception, and translation between languages. Also, AI is commonly defined as the science of training computers to perform tasks that need intelligence when performed by humans (Tatsat et al., 2020).

Hence, it is undeniable, in the modern era, to purport AI as an effective and efficient tool for solving problems that bear time and money to achieve faster growth and success. The shift to the use of AI requires conscientious study and perspective analysis of possible outcomes and beneficial reflections on humanity.

The discovery of this magic system was not possible, until de late 1950s. Mc Frockman (2019) stated that the AI term was explored by a host of philosophers, scientists, and mathematicians who have tried it, but it wasn't until World War II that Alan Turing, a British general practitioner, suggested to people how to use available information to reach decisions and find solutions. Turing concluded that a machine that confers with humans could be called an "intelligent" object.

In 1956, John McCarthy (2006), America's best computer scientist, organized a conference in which the term "artificial intelligence" was invented. McCarthy with his collaborators (McCarthy et al., 2006), in their proposal project at Dartmouth summer research project, claimed that all aspects of learning could be replicated by machines or any other intelligence-related trait (e.g., the use of language, the formation of abstractions and concepts, solving problems). He also created the programming language LISP in 1958, which was considered a compelling section of AI and ML. Although, United States-wide researchers, namely Herbert Simon and Allen Newell, have been interested in understanding the concept of AI, thereby exploring this topic that is about to accelerate world evolution (McFrockman, 2019).

In a more cognitive context, Li and Du (2007) explained, in one of the most cited publications in this field, that AI is "*a variety of intelligent behaviours and various kinds of mental labor, known as mental activities, … [to] include perception, memory, emotion, judgment, reasoning, proving, identification, understanding, communication, designing, thinking and learning, etc.*" (Stahl, 2021, pp. 8-124).

In the 2020s, AI has been increasingly becoming a dominant technology (Hilpisch, 2020). Regardless of the automation work, AI in any field should be considered as a technology that stimulates human capabilities instead of replacing them, creating a combination of human intelligence and machine intelligence (McFrockman, 2019). AI is that torch that enlightens human judgment, till it becomes a decision-making support process rather than decision parti pris.

Stahl (2021) distinguished three interrelated but distinct aspects of the term AI, extracted from the ethical issue types of AI. The first aspect of AI highlighted ML as the primary illustration of a limited understanding of AI and a crucial method that accurately imitates extremely particular cognitive processes. The second aspect is artificial general intelligence, which refers to the endeavour to imitate human skills. Finally, Stahl (2021) argued that the term AI is frequently used to describe convergent socio-technical systems. Each one of these AI aspects has its properties and characteristics that give AI a new definition and make its rise to different types of ethical concerns.

The deployment of AI techniques in finance or any other field is expected to progressively provide competitive advantages to firms' financial health, by improving their efficiency through cost reduction and increasing productivity, as well as ameliorating the quality of services and products offered to customers. With the advent of technology, engineers and data scientists have free access to all the

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historical data that has been collected and stored thanks to the evolution of technology that provides access to more data. As a result, machines enabled with AI are now a part of different tasks, such as prediction, recognition, diagnosis, and so more (Park, 2020).

With ML, as an AI application, comes the importance of focusing on creating systems and models that can access Big Data sets available today, and the system automatically modifies, learns, and enhance predictability and performance through its settings to boost and enhance the experience and ensure the effectiveness of predictive analyses (Abedin et al., 2021). Besides, all ML are elements of AI, but not all AI are considered ML, which make ML a sub-branch of the AI domain. ML refers to the segment of computer science whose purpose is to build and operate existing algorithms to establish generalized models that give accurate patterns and predictions. Using historical data, ML algorithms are based on statistical and mathematical models to help machines mimic human behaviour (Park, 2020).

Thanks to new computer technologies, ML has experienced remarkable growth in recent years; however, AI needs notable data scientists and engineers' innovation to evolve, given that many ML algorithms have been in use for some time, many of their applications remained obscure. Therefore, AI and ML are not new disciplines, but the tools provided by data science have brought them to a new stage of success, which allows humans to solve complex tasks without being smart, hence liability, accountability, and risks all come with human sentimental decisions.

Stepping back in time, several giant corporations were interested in the evolution of AI and starts making considerable efforts. The Japanese government has seized the opportunity and has announced plans to provide 5th-generation computers to promote ML. Thereafter, in 1997, IBM's Deep Blue computer became the first computer to defeat all computers at storing and interpreting information and has allowed businesses to maintain a lot of data. And over the past 15 years, global forces like Google, Amazon, Baidu and others have harnessed AI and ML to develop their profit-making (McFrockman, 2019).

The history of AI in finance is long-winded and convoluted, much like the developing science of AI itself. Aforetime, the application of AI in finance was not a major focus of many 1950s and 1960s studies. Thus, thenceforth, a lot of theories focused on creating and building up AI applications for the financial field, from ML and Artificial Neural Networks (ANN) acknowledgment in 1943 by McCulloch and Pitts, to Bayesian statistics and Neural Network (NN) created in the 1960s (Buchanan, 2019) and widely employed as an integral subject of extensive research cases in audits and stock market forecasting (e.g., Green; 1963, Tracy; 1969, Sorensen; 1969), followed by fuzzy analogues in financial mathematics development in 1987 (Buckley, 1987), to the Expert Systems for Personal Financial Planning technique (Brown, Nielson and Phillips, 1990).

Besides all those new theories and methods, AI saw a huge renaissance in the 1980s. For instance, Lotfi A. Zadeh (1975), the developer of fuzzy logic, highlighted in his paper how the execution of fuzzy instructions by a computer can be of great interest and utility in a wide range of issues including pattern recognition, control, AI, linguistics, information retrieval, and decision processes in several psychological, economic, and social disciplines. Also, an expert system prototype for program trading called PROTRADER was developed by Chen and Liang in 1989 and presented as a learning mechanism based on the adjustment of certain crucial key parameters in response to market conditions. Further in 1900, 'The Theory of Speculation' - Louis Bachelier's thesis, was then published as one of the first articles to examine the use of mathematics as a tool to evaluate stocks. With his impressive work considered to have pioneered the use of mathematics in finance, the development of statistical modelling heralded the entry of basic AI into the whole financial sector (Davis & Etheridge, 2006).

Indeed, the fields of applied economics and finance have a long history of statistical and mathematical analysis. In recent years, big data has reignited interest in ML. Many more or less advanced econometric models are still used by economists and financiers to assess risks, generate projections, and manage money (Leung et al., 2014). AI, unlike previous technologies, can make more complicated projects, ranging from product suggestions, and stock price predictions to medical diagnoses.

Given all these facilities, the financial business is well adapted to the benefits of data mining since it collects a significant number of data, i.e., Big Data, from its consumers (Cecchini et al., 2010). Therefore, it comes our key question: **What are the main uses of AI and ML in the 'Finance' field?**

The remainder of this paper is organized as follows: Section 2 presents the methodology, next, Section 3 presents and discusses the applications of AI and ML in finance. Section 4 concludes with the research's pros and cons and scope for future potential studies.

2. Methodology

By definition, a literature study is "a systematic and thorough search of all types of published literature in order to identify as many items as possible that are relevant to a particular topic", according to Sarah Gash, (Ridley, 2012).
To pursue and scrutinize the application of the concepts 'AI and ML in the financial field', we seek to answer the later scoping review question, in which we adopt the scoping review methodology. It is seen to be an important tool for examining the planning and carrying out of this research. The reader is given the information compiled from all pertinent articles, thereby, information is presented in a way that is consistent with the scoping study's goals. Text, tables, and graphics can all be used for this type of review. (Sargeant & O'Connor, 2020)
The process for preeminent scoping reviews consists of following those five big stages: (a) Defining the research problem, (b) locating relevant papers, (c) selecting the study, (d) plotting the data, and (e) compiling, summarizing, and presenting the results. (Arksey & O'Malley, 2005)
We adjoin an embedded review, to delineate and illustrate how the study on AI and ML contributes to fascinating the current financial field, which is a vital component of research that offers context for the subject under study. This kind of review creates a clear connection between the sources and the research question, and it has implications for the layout of upcoming project studies (Efron & Ravid, 2018).
For a technical literature review, we goose-step to Donthu et al.'s (2021) bibliometric review method, which is divided into four guidelines: (a) identify the objectives and scope of the study; (b) select the techniques for analysis; (c) gather the data for analysis, and (d) perform the analysis and report the results.
As a means to thrive our article, we aim to infer the intellectual development of AI and ML in finance research. Following the preparation of the database, the search was done using both the TITLE and KEYWORD criteria (e.g., Artificial Intelligence, Machine learning, Finance, Financial Market, Deep Learning, Big Data, Data Mining, Algorithms). We confined the results of studies and reviews in English journals in the financial sector to gather the most cited papers globally, as well as the most attractive authors, in both developed and emerging countries (e.g., Morocco), associated with the topic for nourishing the literature structure, yielding 110 documents, as indicated in **Appendix A**.
In the next section, the findings of our scoping review are presented with highlights of the extensive employment of AI and ML technologies that are widely prevalent in today's modern global society, along with a great focus on their usefulness in the financial field.

3. Application of Artificial Intelligence and Machine Learning in Finance

3.1. Portfolio Management and Robo-Advisory

As it has for decades, technology will continue to play an important role in many asset management responsibilities. The application of AI and ML in portfolio management has the potential to improve operational workflow efficiency and accuracy, improve performance, increase profits, and enhance customers (Blackrock, 2019). Antoncic (2020) demonstrated the competitive advantage that corporations can gain over their peers thanks to big data analytics services in their business strategies.
Tatsat, Puri, and Lookabaugh (2020) agreed that asset and wealth management organizations are looking into AI technologies to help them make better investment decisions and better use their vast amount of historical data. One example is the employment of robo-advisors, which are algorithms that adapt a financial portfolio to the user's goals and risk tolerance as well as automated financial advice and support. Bhatia, Chandani and Chhateja (2020) run a qualitative study on the Indian market to provide an exclusive understanding of Robo-ability advisories to alleviate behavioural biases from the expert's perception of India's financial institutions.
In the context of estimating stock risk premiums, Gu, Kelly and Xiu (2020) conducted a comparison of ML algorithms for finance. They found that ML techniques are more useful for anticipating bigger and more liquid stock returns and portfolios and proved that the most powerful indicators are the ones associated with price patterns, such as return reversal and momentum. Stock liquidity, volatility, and valuation ratios are the next most powerful indicators. Nahil and Lyhyaoui (2019) also acquainted ML method, by bringing the Kernel Principal Component Analysis (KPCA) into the Support Vector

Machine (SVM) to construct a stocks portfolio characterized by feature information that is low-dimensional and effective, selecting only the well-performing firms in the Moroccan stock market - i.e., Casablanca Stock Exchange.

As for portfolio optimization and option pricing perspectives, Garcia and Gençai (2000) used a feedforward neural network model to estimate a generalized option pricing formula with a functional shape akin to the standard Black–Scholes formula. Chen and Ge (2021) demonstrated the value of the learning-based approach by using a neural network model to fix the portfolio selection optimization problem.

3.2. Risk Management and Financial Distress

Dunis et al. (2016) defined financial risk management (FRM) as the process of managing a firm's economic value by reducing risk exposure via the application of financial instruments, particularly market risk and credit risk. Forecasting default risk by ML algorithms is altering the way we think about risk management by revolutionizing all elements of risk knowledge and control (Tatsat et al., 2020). Hence, finance-based scheduling maximizes project gains and creates schedules that guarantee the contractor's debt is kept within the credit limit at any point throughout the building process (e.g., Ali and Elazouni; 2009, Elazouni and Metwally; 2007, Elazouni and Metwally; 2005).

Therefore, financial institutions must always be able to anticipate financial distress in order to evaluate the well-being of both businesses and individuals' finances. Many authors and scholars used various statistical and ML methods to develop financial prediction models and tested their effectiveness in the two main topics of financial distress prevention; Credit scoring (e.g., Plakandaras et al.; 2020, De Moor et al.; 2018, Abdou et al., 2014, Köcenda and Vojtek; 2011, Liu and Schumann; 2005, Huang et al.; 2004, Kim and Han; 2001) and Bankruptcy prediction (e.g., Lahmiri and Bekiros; 2019, Liang et al.; 2015, Hernandez Tinoco and Wilson; 2013, Kwak et al.; 2012). In research driven by Khandani, Kim and Lo (2010), a model for forecasting that is nonlinear and nonparametric was built using ML approaches, and based on the results, they believed that the collected consumer credit-risk analytics data might be very useful in predicting systemic danger as the one they observed - i.e. The 2007–2009 Financial Crisis.

The statistical techniques and data-mining new family tools, in particular SVM, ANN, and some other models, are more developed to assess credit risk with promising performance accuracy. Trustorff, Konrad and Leker (2011) argue that SVM is shown to perform extensively better than logistic regression models, especially under conditions where there are small training samples and high input data variance. Bekhet and Eletter (2014) applied ANN to credit scoring applications using the Logistic regression model (LR) and the radial basis function model (RBF) to classify and predict the probability of default of Jordanian commercial banks consumers. Acheampong and Elshandidy (2021) explored in their research analysis whether relevant soft information, extracted from the annual reports of the European bank, influences credit risk using a supervised ML algorithm.

For financial failure problems, ML models based on a given set of attributes describing a company's financial position, predict the probability that a company can face or fail the financial crisis. Pan (2012) constructed a financial distress model with a very good classification of Taiwan's companies and a good prediction capability using the robust Fruit Fly Optimization Algorithm. Chen, Härdle and Moro (2009) proposed the nonlinear model classified by SVM to forecast the German firms' default risk. Beynon and Peel (2001) examined the employment of rough set theory (RST); particularly the Variable precision rough set theory model (VPRS), to predict the failed and the non-failed companies selected from the UK market.

Although, recent publications demonstrated how fuzzy logic and other AI techniques clearly surpassed the previous traditional analysis methods in preventing financial crises or predicting bank failure (e.g., Sanchez, Alfonso, Sanchís-Pedregosa; 2019).

Furthermore, AI and ML applications in risk management englobe many fields, for example in agriculture insurance, Ghahari, Newlands, Lyubchich, and Gel (2019) chose to establish a modern deep learning model to assess the climate risks in Canada's agriculture and tested its accuracy, speed, and scalability in prediction delivery.

3.3. Financial Fraud Detection and Anti-money laundering

In the 2010–2011 Financial Crimes Report, the Federal Bureau of Investigation distinguished between three types of financial fraud, (a) Bank Fraud; which includes Credit Card fraud, Mortgage fraud and Money laundering, (b) Corporate Fraud; bringing together Financial Statement fraud and Securities and Commodities fraud, (c) Insurance Fraud; englobing Automobile Insurance fraud and HealthCare fraud. Therefore, intelligent financial statement fraud detection technologies have been created to assist institutions and stakeholders in making decisions. Recent studies have discovered fraudulent distortion of financial statements in managerial statements. Omar, Johari and Smith (2017) proved the effectiveness of the ML model in detecting fraudulent enterprises and many other researchers have focused their analysis on structured data using data mining models (e.g., West and Bhattacharya; 2016, Zhou and Kapoor; 2011, Ravisankar et al.; 2011) and text mining models (e.g., Hajek and Henriques; 2017, Goel and Uzuner; 2016, Glancy and Yadav; 2011, Humpherys et al.; 2011).

Regarding fraudulent financial statements, Zhou and Kapoor (2011) discussed data mining approaches for financial and accounting applications, such as detecting credit card fraud. Humpherys et al. (2011) used linguistic credibility analysis in managerial fraud and discovered that, in comparison to non-fraudulent disclosures, fraudulent ones employ more activation language, words, imagery, pleasantness, group allusions, and less lexical variety. More recently, Hajek and Henriques (2017) defended the study's findings and asserted that it is possible to develop a method to identify non-fraudulent companies from their financial statements and annual report content, as well as the importance of non-annual report data (analysts' sales and earnings predictions) to detect fraudulent organizations.

Ravisankar et al. (2011) identified and tracked organizations that commit financial statement fraud using many data mining tools such as SVM, Logistic Regression (LR), Multilayer Feed Forward Neural Networks (MLFF), Probabilistic Neural Networks (PNN), Genetic Programming (GP) and Group Method of Data Handling (GMDH). West and Bhattacharya (2016) also put a spotlight on computational intelligence-based strategies for employing data mining features to detect financial fraud. Glancy and Yadav (2011) employed text-mining techniques to propose the computational fraud detection model (CFDM), which is regarded as a fresh and effective computer model for identifying fraud tactics with a quantitative approach.

Through a review of money laundering detection (MLD) studies (e.g., Garcia-Bedoya et al.; 2020, Singh and Lin; 2020), scholars and authors were satisfied with ML models results in MLD and confirmed the accuracy of these methods in combatting MLD issues. For instance, Kannan and Somasundaram (2017) tested the auto-regressive (AR) outlier-based MLD (AROMLD) model that aims to minimize the amount of time required to handle massive non-uniform transactions. For more proper results, Jullum et al. (2020) created, described, and confirmed a ML model that selects which financial transactions need to be manually examined for potential money laundering, applied to Norway's most well-known and substantial financial services organization – i.g. DNB ASA.

3.4. Sentiment Analysis and Investor Behaviour

To estimate market sentiment, sentiment analysts examine massive amounts of unstructured data such as videos, transcriptions, pictures, audio files, social media postings, publications, and business documents. Sentiment analysis is a great example of ML in finance and is critical for all firms in today's workplace (Tatsat et al., 2020).

In the sales context of commercializing products and increasing brand awareness, predictive analytics with machine algorithms may serve as a private financial counsellor to a customer, advising them on how to enhance their situation, for instance, Chatbots function as virtual employees, using proprietary algorithms that enable businesses to collaborate with their consumers easily and with minimum human interaction (McFrockman, 2019). Kumar and Ravi (2016) presented a thorough examination of the different uses of text mining in finance, including customer relationship management.

The most prevalent use of sentiment analysis in the financial field is the study of financial news, specifically anticipating market behaviour and potential trends (e.g., Mitra et al.; 2016, Lee and Radhakrishna; 2000). In their fruitful book, Mitra, Leela and Mitra (2012) confirmed the employment of ML algorithms to analyse the textual input of news items aiming to calculate quantitative sentiment scores. They also revealed that news analytics naïve outperforms "buy on good news, sell on negative news" methods as demonstrated by both event studies and historical portfolio simulation. The forecasts

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look for incidents that may be absent yet underlying in the financial news. Chan and Franklin (2011) supported the importance of forecasts search for incidents that may be absent yet underlying in the financial news, using a text-based decision support system and natural language processing.

Within the studies of Yahoo! financial news, Kim and Kim (2014) analysed 32 million Yahoo! Finance messages to see if they can forecast stock returns, trading volume, and volatility. They discovered evidence that historical stock price performance had a favourable effect on investor sentiment, but no evidence that investor sentiment from Internet posts has predictive potential for volatility or trading volume. Das and Chen (2007) developed a sentiment extraction algorithm for stock message boards by combining numerous algorithms in Yahoo! Amazon. They reported that the suggested model performed better, with a decreased false positive rate and higher accuracy and examined investor reactions to the news, regulatory developments, and corporate management announcements.

Understanding social media, entertainment applications and other data sources relevant to anticipating client attitudes will be a large part of ML's future uses. To assess investors' moods based on an AI model, Martínez, Román and Casado (2019) employed semantic analysis algorithms that classify any communication about Ibex 35 on social media (Twitter) or news media as good, bad, or neutral, using systems that send orders to the market to open long or short positions. Oliveira, Cortez and Areal (2016) expressed, according to statistical analysis performed on StockTwits, that the new lexicons are competitive for evaluating investor sentiment when compared to six popular lexicons. They also used a lexicon to readily generate indicators of investor sentiment on Twitter and compared their correlation to survey sentiment indices.

Furthermore, during this period, research in AI and ML in finance looks at forecasting and predictive analysis of investor sentiment, stock markets, return volatility linked to algorithmic trading, forecast assessment, and self-similar behaviour (black nodes); big data analytics and FinTech. Dahhou and Kharbouch (2021) examined the stock market financial crisis that afflicted the Moroccan stock market between 2000 and 2020, and as a result, they demonstrated that the sentiment indicator declined during the years of crises, claiming that the investor sentiment indicator is consistent with stock market crises. They also ran the Granger test to investigate the connection between stock market crises and Moroccan investor mood and concluded that investor sentiment causes and drives stock market crises. Besides, Bourezk, Raji, Acha, and Barka (2020) leveraged sentiment analysis and ML techniques to identify the link between the general public's perception of a stock and its evolution movement in the Casablanca stock market.

3.5. Algorithmic Stock Market Prediction and High-frequency Trading

The employment of algorithms to perform transactions autonomously is known as algorithmic trading, which dates back to the 1970s. It is based on using automated pre-programmed trading instructions to produce highly rapid, objective trading judgments (Tatsat et al., 2020). Thereupon, the superiority of AI over traditional econometric models has sparked tremendous academic interest in the use of ML for algorithmic trading (e.g., Lo et al.; 2000, Hans and Kasper; 1998, Donaldson and Kamstra; 1997, Hsieh; 1989). Building a forecasting model is difficult and challenging due to the volatility of the financial markets. In recent years, ANN are useful tools for dealing with a dynamic financial market in terms of prediction (e.g., Berradi and Lazaar; 2019, Dbouk and Jamali; 2018, Labiad et al.; 2018, Moghaddam et al.; 2016, Malliaris and Malliaris; 2013, Nag and Mitra; 2002, Fernandez-Rodrıguez et al.; 2000, Hans and Kasper; 1998, Donaldson and Kamstra; 1997), information processing (e.g., Dash and Dash; 2016) and decision making.

The stock market is one of the routes where individual investors may generate substantial gains thanks to internet trading. As a result, trustworthy stock market predictions are required so that investors may make smart decisions about where and when to invest. In this case, ANN is a frequently utilized soft computing approach. Recognizing the inability of various traditional econometric methods to measure the fluctuations in currency exchange rates (e.g., Chaboud et al.; 2014, Hans and Kasper; 1998) concluded that ANNs function well and are frequently suitable and preferable to linear models. Hsieh (1989) revealed in his examination study that a generalized autoregressive conditional heteroskedasticity (GARCH) model can explain a large part of the nonlinearities for all five major foreign exchange rates. To predict the long-term future of equities, investment firms now turn to data scientists rather than market gurus. Data scientists create complex ML algorithms capable of detecting future market patterns, based on historical data trends and well trained to recognize triggers for market irregularities (e.g., Gosh et al.; 2021, Elmsili and Outtaj; 2021, Touzani and Douzi; 2021, Fischer and Krauss; 2018, Jiang et al.; 2018, Nahil and Lyhyaoui; 2018, Novak and Veluscek; 2016, Arroyo et al.; 2011, Gavrishchaka et al.; 2006).

Aside from that, individual traders may use AI to make decisions related to purchasing, holding, or selling a stock. In this context, Ghosh, Neufeld and Sahoo (2022) applied Krauss et al. (2017) and Fischer and Krauss (2018) as trading strategies to evaluate the performance of random forests (RF) and LSTM networks as training approaches for forecasting out-of-sample directional movements of component stocks. Henrique, Sobreiro and Kimura (2018) maintained Support Vector Regression (SVR) to forecast stock prices in three separate markets with high and small capitalizations. The results indicate that the SVR has predictive value, particularly when utilizing an approach of updating the model regularly. There is also evidence of enhanced forecast precision during periods of decreased volatility. In the Moroccan stock market, Nahil and Lyhyaoui (2017) suggested an experiment to improve SVM's performance by including the worldwide market's evolution, which is represented in three important stocks on the Casablanca stock exchange market: MASI, MADEX, and Banks Sector Index.

Kumar and Ravi (2016) revealed the importance of text-mining algorithms in finance. Nevertheless, to evaluate long-term predictions of stock indexes with large predictor matrices is such an innovative work done by Feuerriegel and Gordon (2018). They conducted tests with ML and high-dimensional news in particular and approved that text-based models are statistically significant in minimizing forecast errors from historically lagged forecasts.

ML techniques may open even more doors for acquiring unique insights into many market fields movements, especially in the energy market (e.g., Manogna and Mishra; 2021, Verma; 2021, Dbouk and Jamali; 2018, Malliaris and Malliaris; 2013). Besides, the latest review has concentrated on modelling correlations between the emergence of events such as business takeovers, future price movements and product launches in media articles (e.g., Liu et al.; 2021, Braun et al.; 2020, Manela and Moreira; 2017, Hagenau et al.; 2012).

The newest challenge for algorithmic trading is to comprehend how short-term market movements diverge from long-term valuations by sentiment analysis prediction, which can increase returns miraculously (e.g., Elbousty H., Krit S.; 2021, Matsubara et al., 2018, Schumaker et al., 2010). Schumaker, Robert and Chen (2010) used SVM to estimate the stock price after releasing financial news items for 20 minutes. During five weeks, the suggested technique was tested on 9211 financial news stories and 10,259,042 stock prices containing S&P 500 stocks. Furthermore, they discovered that the Proper Noun scheme outperforms the others. For analysing news articles' daily stock price movements and forecasting them, Matsubara, Takashi, Akita, and Uehara (2018) proposed a successful deep neural generative model that identifies relevant phrases closely associated with future stock price movements.

Algorithmic and high-frequency trading in financial markets and financial regulation were also among the top hot topics for AI and ML applications in finance (e.g., Borch; 2017, Coombs; 2016, O'Hara; 2015). Borch (2017) discussed in his paper how and why the Flash Crash is used as a point of comparison when talking about high-frequency trading and algorithmic financial markets and added a close examination of the frequent impact connection with the Flash Crash and its various ways.

Although much research cover both the challenge of predicting stock market price movements and the creation of effective trading techniques based on those recommendations, which made it critical to validate the relevance of such studies in new and emerging markets, particularly the Cryptocurrency market. Much research has been conducted solely to investigate the behaviour of the famous decentralized digital currency, i.e., Bitcoin (e.g., Gerritsen et al.; 2020, Atsalakis et al.; 2019, Valencia et al.; 2019, Huang et al.; 2019, Adcock and Gradojevic; 2019). Intending to forecast cryptocurrency market movements for Bitcoin, Ethereum, Ripple, and Litecoin, the researchers' Valencia, Gómez-Espinosa and Valdés-Aguirre (2019) suggested using conventional ML algorithms on publicly available social media data (Twitter). The results indicated that combining ML and sentiment analysis is conceivable to anticipate cryptocurrency markets, with the outperformance of Neural Networks (NN) on the conventional models such as SVM and RF.

With high-frequency trading, automation conquers the long decision process in different. By adjusting for order size, fuzzy logic minimizes trading uncertainty in turbulent markets and trading expenses by requiring decision-making that is more consistent and conservative than buy or sell suggestions. Research and studies on the application of fuzzy logic in finance have been limited, and they are

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generally studied in conjunction with other approaches such as ANN or reinforcement learning. The findings of Gradojevic and Gencay (2013), by high-frequency experiments, revealed that fuzzy technical indicators outperform regular moving average technical indicators and filter rules for EUR-USD exchange rates, particularly on volatile days. Atsalakis et al. (2019) proposed the PATSOS model, a method of computational intelligence that makes use of a hybrid Neuro-Fuzzy controller to forecast the future trends in the daily price of Bitcoin and its results surpassed two other computational intelligence models developed using a simpler neuro-fuzzy approach and ANN.

3.6. Data protection and Cyber Security

Introduction of deep learning systems, the costs of data engineering and data pre-processing are decreasing. Recently, a huge number of banks and financial institutions have begun to use AI in their applications to provide an exceptional level of customer experience, hence dismissing personnel since operations such as creating accounts, transferring money between accounts, and paying bills are all handled through mobile banking apps. These AI chatbots, powered by natural language processing, are serving banking and organizational clients swiftly and efficiently by noting regular questions and providing data in minutes without leaving their current location. Königstorfer and Thalmann's (2020) findings pointed out that commercial banks may use AI to decrease loan losses, improve payment security, automate compliance-related tasks, and improve consumer targeting. However, data protection problems are inextricably connected to data security concerns, and not only in AI, but cybersecurity is also a long-standing issue in information and communication technology. AI systems may be vulnerable to new kinds of security flaws (Stahl, 2021).

In the cybersecurity world, malware identification is another difficult issue. Surya (2019) discussed how ML may assist in detecting various hacker assaults that are difficult to identify before they occur, as well as slowing down human actions to accomplish network security. Thus, anti-malware, anti-spyware, personal firewalls, vulnerability assessment, and host-based intrusion prevention are all required in organizations. System vulnerabilities become a significant weapon for malware developers, despite the high-level security procedures in place. Anomaly-based detection and signature-based detection are the two types of malware detection approaches. Kumar and Ravi (2016) classified financial services cyber security applications into five categories: Phishing detection, Spam detection, Malware detection, Intrusion detection, and Fraud detection. They also examined the malware in their study based on the anomaly-based approach. To determine if an email is normal or spam, Zhan et al. (2011) used anomaly detection in the email system. They introduced weak estimators for predicting the distributions of events that depart from the typical pattern, such as the Stochastic Learning-Based Weak Estimator (SLWE) and the Maximum Likelihood Estimator (MLE).

3.7. Big Data Analytics, Blockchain, FinTech

Big data is now readily available in a variety of business areas due to advances in computing technology (e.g., Zheng et al.; 2018, Minhaj Khan and Salah; 2018, Christidis and Devetsikiotis; 2016, Kshetri; 2016, Zyskind et al.; 2015). In research driven by Bhimani and Willcocks (2014), a model for understanding data, information, and knowledge relationships was addressed to investigate changes in strategy, organizational and cost structures, digitization, business analytics, outsourcing, offshore, and cloud computing. Afterward, they emphasized the possibilities and challenges of Big Data in the connection between the finance function and management accounting.

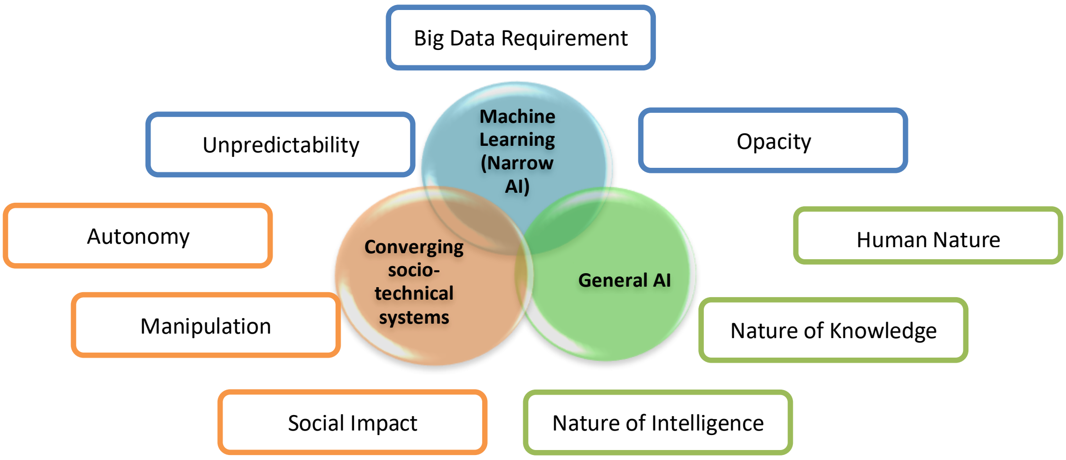
In order to tap into the enormous potential of Big Data, ML may be used to make better business decisions. For example, in the insurance industry, Hanafy and Ming (2021) observed how car insurance companies employ ML in their operations and how ML models may be applied, besides big data, in claim occurrence prediction.

Moreover, in the previous decade, several technological revolutions occurred, including sectors where the use of AI and big data is crucial, such as cloud computing, data mining, augmented/virtual reality, and Fintech (e.g., Noor et al.; 2019, Gabor and Brooks; 2017) and, most importantly, Blockchain and Internet of Things (IoT) (e.g., Minhaj Khan and Salah; 2018, Zheng et al.; 2018, Christidis and Devetsikiotis; 2016, Zyskind et al.; 2015).

4. Conclusion

By all odds, financial services are the future fruits of AI and ML. Indeed, AI is altering how organizations function and make investments as humanity relies more and more on digital operations and shifts to online platforms in the wake of a changing environment.
A few multinational corporations that oversee big data and the AI revolution, may or may not respect people's rights when using their information for commercial or political objectives. Thus, AI systems must assure citizens safety and security, and be a force safeguard for society's good (Stahl, 2021). Wherefore, the following figure presents the major key aspects of the various applications of the term "AI".

Figure 1: Artificial Intelligence's different features



Source: Stahl (2021)

To draw a clear-cut deduction regarding this model, ethics must also be imprinted in AI perspectives by creating new alternative employment for humans. Indeed, job loss is anticipated to become a key factor in what is now referred to as the "post-industrial society" owing to AI systems that are used for replacing humans with smart technology in arduous, repetitive, or unsafe tasks (Stahl, 2021).
The financial field is transitioning to cloud-based technologies and AI-enabled services to provide the ideal solutions for consumers as a result of ongoing threats to persist competitively innovative.
This literature helped us to infer the development of AI and ML in finance research, as well as assist in narrowing down our core topic and choosing the appropriate research strategy, a scoping review methodology to pursue and scrutinize the services of these concepts.
The given framework incorporates a significant stream of other researchers' statements as well as personal interests in the subject matter. One of the scoping study's primary strengths is that it can offer an exhaustive and transparent process for mapping research areas. Reviewers can highlight the topic of interest in terms of the number, nature, and characteristics of exploratory data in a relatively brief amount of time, as opposed to a detailed systematic review (Arksey & O'Malley, 2005). Also, guidelines for proper reporting of scoping studies are provided by the PRISMA Extension for Scoping Reviews (PRISMA-ScR) (Tricco & al., 2018)
Our study reviewed 110 documents, choosing the following papers from a survey of the most essential publications concerning AI and ML research in the finance field: The most cited articles, those with the highest bibliometric, those that have been published most recently, and those that are part of the primary path of the literature studies.
We would be deceitful if we weren't aware of the limitations of scoping studies. For instance, they don't assess the quality of evidence in primary research reports because of the enormous amount of data provided. Choosing a vast number of studies rather than engaging in a deep study of a smaller number of research, can entangle choices related to what extent the width is more essential than depth. Scoping studies, as compared to systematic reviews, deal with a wider variety of study designs and methodologies since they eventually offer a descriptive and narrative recap of past and current research (Arksey & O'Malley, 2005).

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Nevertheless, this scoping study provides a more extensive description of the findings and a review map for our subject theme. As a result, it offers an efficient means of the research's summarizing and disseminating, which we developed into seven fields: (1) Portfolio Management and Robo-Advisory, (2) Risk Management and Financial Distress (3), Financial Fraud Detection and Anti-money laundering, (4) Sentiment Analysis and Investor Behaviour, (5) Algorithmic Stock Market Prediction and High-frequency Trading, (6) Data Protection and Cybersecurity, (7) Big Data Analytics, Blockchain, FinTech. The purpose is to emphasize the minutiae of research that elucidate the employment of AI and ML in the finance, designed for data scientists, financial analysts, and any other reader—individual or institution—who is interested in this topic but do not acquire the occasion or resources to conduct such work by themselves.
Fundamentally, in our paper, we asserted that AI helps us recognize patterns, forecast outcomes, develop rules, automate procedures, and communicate more effectively. In reality, financial services -namely banks and insurance companies - are all experiencing significant growth and opportunity. Therefore, it comes as no surprise that AI is at the head of the financial field priority. Hence, our review highlights trends in AI and ML applications in the finance and demonstrates how AI and ML research adds to the present financial area, as well as how they contribute in terms of those possibilities and solutions for myriad organizations. We conclude with a global review of 110 documents per the seven fields of AI and ML application.
A future study might focus on comparing different ML approaches in each of these financial fields, or a specific domain or application.
Grossus modus, our findings are referenced and mapped in the following section, supporting academics with essential information whenever they investigate the expansion of AI and ML applications in finance, with a spotlight on the focal point of their wide emergence range of benefits.

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Appendix

Appendix A: Dataset of listed documents per financial field of AI and ML application

Table 1: Portfolio Management and Robo-Advisory

Literature Authors	Year	Title	Source
Antoncic Madelyn	**2020**	A paradigm shift in the board room: Incorporating sustainability into corporate governance and strategic decision-making using big data and artificial intelligence.	Journal of Risk Management in Financial Institutions, 13(4), pp. 290-294.
Bhatia, A., Chandani, A., Chhateja, J.	**2020**	Robo advisory and its potential in addressing the behavioral biases of investors — A qualitative study in Indian context.	https://doi.org/10.1016/j.jbef.2020.100281
Chen, S., Ge, L.	**2021**	A learning-based strategy for portfolio selection.	https://doi.org/10.1016/j.iref.2020.07.010
Garcia, R., and R. Gencay.	**2000**	Pricing and hedging derivative securities with neural networks and a homogeneity hint.	https://doi.org/10.1016/S0304-4076(99)00018-4
Gu, S., B. Kelly, and D. Xiu.	**2020**	Empirical Asset Pricing via Machine Learning.	http://dx.doi.org/10.1093/rfs/hhaa009
Nahil A., Lyhyaoui A.	**2019**	Portfolio Construction Using KPCA and SVM: Application to Casablanca Stock Exchange	https://doi.org/10.1007/978-3-030-11928-7_80

Source: *Authors*

Table 2: Risk Management and Financial Distress

Literature Authors	Year	Title	Source
Abdou, A.H., Alam, S.T., Mulkeen, J.	**2014**	Would credit scoring work for Islamic finance? A neural network approach.	https://doi.org/10.1108/IMEFM-03-2013-0038
Acheampong, A., Elshandidy, T.	**2021**	Does soft information determine credit risk? Text- based evidence from European banks.	https://doi.org/10.1016/j.intfin.2021.101303
Ali, M.M., Elazouni, A.	**2009**	Finance-based CPM/LOB scheduling of projects with repetitive non-serial activities	http://dx.doi.org/10.1080/01446190903191764
Bekhet H.A., Eletter S.F.K.	**2014**	Credit-risk assessment model for Jordanian commercial banks: Neural scoring approach	https://doi.org/10.1016/j.rdf.2014.03.002
Beynon, M.J., Peel, M.J.	**2001**	Variable precision rough set theory and data discretization: An application to corporate failure prediction	https://doi.org/10.1016/S0305-0483(01)00045-7
Chen, S., Härdle, W.K., Moro, R.A.	**2011**	Modeling default risk with support vector machines.	https://doi.org/10.1080/14697680903410015
De Moor, Luitel, Sercu, Vanpée	**2018**	Subjectivity in sovereign credit ratings.	https://doi.org/10.1016/j.jbankfin.2017.12.014
Elazouni, A.M., Metwally, F.G.	**2005**	Finance-based scheduling: Tool to maximize project profit using improved genetic algorithms	https://doi.org/10.1061/%28ASCE%290733-9364%282005%29131%3A4%28400%29
	2007	Expanding finance-based scheduling to devise overall-optimized project schedules	http://dx.doi.org/10.1061/(ASCE)0733-9364(2007)133:1(86)
Ghahari, Newlands, Lyubchich, Gel.	**2019**	Deep learning at the interface of agricultural insurance risk and spatio-temporal uncertainty in weather extremes.	https://doi.org/10.1080/10920277.2019.1633928
Hernandez Tinoco, M., Wilson, N.	**2013**	Financial distress and bankruptcy prediction among listed companies using accounting, market and macroeconomic variables.	https://doi.org/10.1016/j.irfa.2013.02.013
Huang, Z., Chen, H., Hsu, C.-J., Chen, W.-H., Wu, S.	**2004**	Credit rating analysis with support vector machines and neural networks: A market comparative study.	https://doi.org/10.1016/S0167-9236(03)00086-1
Khandani A.E., Kim A.J., Lo A. W.	**2010**	Consumer credit-risk models via machine-learning algorithms	https://doi.org/10.1016/j.jbankfin.2010.06.001

Kim, K.-S., Han, I.	**2001**	The cluster-indexing method for case-based reasoning using self- organizing maps and learning vector quantization for bond rating cases.	https://doi.org/10.1016/S0957-4174(01)00036-7
Köcenda, E., Vojtek, M.	**2011**	Default predictors in retail credit scoring: Evidence from Czech banking data.	https://doi.org/10.2753/REE1540-496X470605
Kwak, W., Shi, Y., Kou, G.	**2012**	Bankruptcy prediction for Korean firms after the 1997 financial crisis: Using a multiple criteria linear programming data mining approach.	https://doi.org/10.1007/s11156-011-0238-z
Lahmiri, S., Bekiros, S.	**2019**	Can machine learning approaches predict corporate bankruptcy? Evidence from a qualitative experimental design.	https://doi.org/10.1080/14697688.2019.1588468
Liang, D., Tsai, C.-F., Wu, H.-T.	**2015**	The effect of feature selection on financial distress prediction	https://doi.org/10.1016/j.knosys.2014.10.010
Liu, Y., Schumann, M.	**2005**	Data mining feature selection for credit scoring models	https://doi.org/10.1057/palgrave.jors.2601976
Pan, W.-T.	**2012**	A new Fruit Fly optimization algorithm: Taking the financial distress model as an example	https://doi.org/10.1016/j.knosys.2011.07.001
Plakandaras, V., et al.	**2020**	Forecasting credit ratings of EU banks.	https://doi.org/10.3390/ijfs8030049
Sanchez, Alfonso, Sanchís-Pedregosa	**2019**	Fuzzy Logic and Its Uses in Finance: A Systematic Review Exploring Its Potential to Deal with Banking Crises	http://dx.doi.org/10.3390/math7111091
Trustorff, J.H., Konrad, P.M., Leker, J.	**2011**	Credit risk prediction using support vector machines.	https://doi.org/10.1007/s11156-010-0190-3

***Source:* Authors**

Table 3: Financial Fraud Detection and Anti-money laundering

Literature Authors	**Year**	**Title**	**Source**
Garcia-Bedoya, Granados, Cardoz Burgos.	**2020**	AI against money laundering networks: The Colombian case.	https://doi.org/10.1108/JMLC-04-2020-0033
Glancy, F.H., Yadav, S.B.	**2011**	A computational model for financial reporting fraud detection	https://doi.org/10.1016/j.dss.2010.08.010
Goel, S., Uzuner, O.	**2016**	Do sentiments matter in fraud detection? Estimating semantic orientation of annual reports.	https://doi.org/10.1002/isaf.1392
Hajek, P., Henriques, R.	**2017**	Mining corporate annual reports for intelligent detection of financial statement fraud - A comparative study of machine learning methods	https://doi.org/10.1016/j.knosys.2017.05.001
Humpherys, S.L., et al.	**2011**	Identification of fraudulent financial statements using linguistic credibility analysis	https://doi.org/10.1016/j.dss.2010.08.009
Jullum, M., et al.	**2020**	Detecting money laundering transactions with machine learning.	https://doi.org/10.1108/JMLC-07-2019-0055
Kannan, S., Somasundaram, K.	**2017**	Autoregressive-based outlier algorithm to detect money laundering activities.	https://doi.org/10.1108/JMLC-07-2016-0031
Omar, N., Johari, Z.A., Smith, M.	**2017**	Predicting fraudulent financial reporting using artificial neural network.	https://doi.org/10.1108/JFC-11-2015-0061
Ravisankar, P., et al.	**2011**	Detection of financial statement fraud and feature selection using data mining techniques	https://doi.org/10.1016/j.dss.2010.11.006
Singh, C., Lin, W.	**2020**	Can artificial intelligence, RegTech and CharityTech provide effective solutions for anti-money laundering and counter-terror financing initiatives in charitable fundraising.	https://doi.org/10.1108/JMLC-09-2020-0100

West, J., Bhattacharya, M.	**2016**	Intelligent financial fraud detection: A comprehensive review	https://doi.org/10.1016/j.cose.2015.09.005
Zhou, W., Kapoor, G.	**2011**	Detecting evolutionary financial statement fraud	https://doi.org/10.1016/j.dss.2010.08.007

***Source:* Authors**

Table 4: Sentiment Analysis and Investor Behaviour

Literature Authors	Year	Title	Source
Bourezk H., Raji A., Acha N., Barka H.	**2020**	Analyzing Moroccan Stock Market using Machine Learning and Sentiment Analysis	http://dx.doi.org/10.1109/IRASET48871.2020.9092304
Chan, S.W.K., Franklin, J.	**2011**	A text-based decision support system for financial sequence prediction	https://doi.org/10.1016/j.dss.2011.07.003
Dahhou N., Kharbouch O.	**2021**	Study of Stock Markets and Investor Behaviour: Case of the Casablanca Stock Exchange	http://doi.org/10.31695/IJASRE.2021.33988
Das, Sanjiv R., Chen	**2007**	Yahoo! for Amazon: Sentiment extraction from small talk on the web	http://dx.doi.org/10.1287/mnsc.1070.0704
Kim, S.-H., Kim, D.,	**2014**	Investor sentiment from internet message postings and the predictability of stock returns	https://doi.org/10.1016/j.jebo.2014.04.015
Kumar, B.S., Ravi, V.	**2016**	A survey of the applications of text mining in financial domain	https://doi.org/10.1016/j.knosys.2016.10.003
Lee, C.M.C., Radhakrishna, B.	**2000**	Inferring investor behavior: Evidence from TORQ data	https://doi.org/10.1016/S1386-4181(00)00002-1
Martínez, R.G., Román, M.P., Casado, P. P.	**2019**	Big data algorithmic trading systems based on investors' mood.	https://doi.org/10.1080/15427560.2018.1506786
Mitra, G., and Xiang Y.	**2016**	The Handbook of Sentiment Analysis in Finance.	New York, NY: Albury Books.
Mitra, L., and Mitra G.	**2012**	The Handbook of News Analytics in Finance.	http://dx.doi.org/10.1002/9781118467411
Oliveira, N., Cortez, P., Areal, N.	**2016**	Stock market sentiment lexicon acquisition using microblogging data and statistical measures	https://doi.org/10.1016/j.dss.2016.02.013

***Source:* Authors**

Table 5: Algorithmic Stock Market Prediction and High-frequency Trading

Literature Authors	Year	Title	Source
Adcock, R., and Gradojevic. N.	**2019**	Non-fundamental, non-parametric Bitcoin forecasting.	https://doi.org/10.1016/j.physa.2019.121727
Arroyo, J., Espínola, R., Maté, C.	**2011**	Different approaches to forecast interval time series: A comparison in finance	http://dx.doi.org/10.1007/s10614-010-9230-2
Atsalakis, G. et al.	**2019**	Bitcoin price forecasting with neuro-fuzzy techniques.	https://doi.org/10.1016/j.ejor.2019.01.040
Berradi. Z., Lazaar M.	**2019**	Integration of Principal Component Analysis and Recurrent Neural Network to Forecast the Stock Price of Casablanca Stock Exchange	https://doi.org/10.1016/j.procs.2019.01.008
Borch Christian	**2017**	High-frequency trading, algorithmic finance and the flash crash: Reflections on eventalization	http://dx.doi.org/10.1080/03085147.2016.1263034
Braun, J., Hausler, J., Schäfers, W.	**2020**	Artificial intelligence, news sentiment, and property market liquidity.	https://doi.org/10.1108/JPIF-08-2019-0100
Chaboud A.P., Chiquoine B., Hjalmarsson E., Vega, C.	**2014**	Rise of the machines: Algorithmic trading in the foreign exchange market	https://doi.org/10.1111/jofi.12186
Coombs Nathan	**2016**	What is an algorithm? Financial regulation in the era of high-frequency trading	http://dx.doi.org/10.1080/03085147.2016.1213977

Dash R., Dash P.K.	**2016**	A hybrid stock trading framework integrating technical analysis with machine learning techniques	https://doi.org/10.1016/j.jfds.2016.03.002
Dbouk, W., Jamali, I.	**2018**	Predicting daily oil prices: Linear and non-linear models.	https://doi.org/10.1016/j.ribaf.2018.01.003
Donaldson, R., and M. Kamstra.	**1997**	An artificial neural network-garch model for international stock return volatility	https://doi.org/10.1016/S0927-5398(96)00011-4
Elbousty H., Krit S.	**2021**	Stock Market Forecasting Model from Multi News Data Source Using a Two-Level Learning Algorithm	http://dx.doi.org/10.17762/turcomat.v12i5.1746
Elmsili B., Outtaj B.	**2021**	Predicting Stock Market Movements Using Machine Learning Techniques	https://doi.org/10.5281/zenodo.4869914
Fernandez-Rodrıguez, F., C. Gonzalez-Martel, and S. Sosvilla-Rivero.	**2000**	On the profitability of technical trading rules based on artificial neural networks: Evidence from the Madrid stock market.	https://doi.org/10.1016/S0165-1765(00)00270-6
Feuerriegel, S., Gordon, J.	**2018**	Long-term stock index forecasting based on text mining of regulatory disclosures	https://doi.org/10.1016/j.dss.2018.06.008
Fischer, T., and C. Krauss.	**2018**	Deep learning with long short-term memory networks for financial market predictions.	https://doi.org/10.1016/j.ejor.2017.11.054
Gavrishchaka, Valeriy, and Banerjee S.	**2006**	Support Vector Machine as an Efficient Framework for Stock Market Volatility Forecasting	http://dx.doi.org/10.1007/s10287-005-0005-5
Gerritsen et al.	**2020**	The profitability of technical trading rules in the Bitcoin market.	http://dx.doi.org/10.1016/j.frl.2019.08.011
Ghosh, P., Neufeld, A., Sahoo, J.K.	**2022**	Forecasting directional movements of stock prices for intraday trading using LSTM and random forests.	https://doi.org/10.1016/j.frl.2021.102280
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Jiang et al.	**2018**	Cross-domain deep learning approach for multiple financial market predictions.	http://dx.doi.org/10.1109/IJCNN.2018.8489360
Kumar, B.S., Ravi, V.	**2016**	A survey of the applications of text mining in financial domain	https://doi.org/10.1016/j.knosys.2016.10.003
Labiad B., Berrado A., Benabbou L.	**2018**	Short Term Prediction Framework for Moroccan Stock Market Using Artificial Neural Networks	https://doi.org/10.1145/3289402.3289520
Liu, K., Zhou, J., Dong, D.	**2021**	Improving stock price prediction using the long short-term memory model combined with online social networks.	https://doi.org/10.1016/j.jbef.2021.100507
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Malliaris, A.G., Malliaris, M.	**2013**	Are oil, gold and the euro inter-related? Time series and neural network analysis.	https://doi.org/10.1007/s11156-011-0265-9
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Manogna, R.L., Mishra, A.K.	**2021**	Forecasting spot prices of agricultural commodities in India: Application of deep-learning models	https://doi.org/10.1002/isaf.1487
Matsubara, Takashi, Akita R., and Uehara	**2018**	Stock price prediction by deep neural generative model of news articles.	http://dx.doi.org/10.1587/transinf.2016IIP0016
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	2018	Short-term stock price forecasting using kernel principal component analysis and support vector machines: the case of Casablanca stock exchange	https://doi.org/10.1016/j.procs.2018.01.111
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Touzani Y., Douzi K.	**2021**	An LSTM and GRU based trading strategy adapted to the Moroccan market	https://doi.org/10.1186/s40537-021-00512-z
Valencia, F., Gómez-Espinosa, A., Valdés-Aguirre	**2019**	Price Movement Prediction of Cryptocurrencies Using Sentiment Analysis and Machine Learning	http://dx.doi.org/10.3390/e21060589
Verma, S.	**2021**	Forecasting volatility of crude oil futures using a GARCH–RNN hybrid approach.	https://doi.org/10.1002/isaf.1489

***Source:* Authors**

Table 6: Data Protection and Cybersecurity

Literature Authors	Year	Title	Source
Königstorfer, F., Thalmann, S.	**2020**	Applications of artificial intelligence in commercial banks–A research agenda for behavioral finance	https://doi.org/10.1016/j.jbef.2020.100352
Kumar, B.S., Ravi, V.	**2016**	A survey of the applications of text mining in financial domain	https://doi.org/10.1016/j.knosys.2016.10.003
Surya Lakshmisri	**2019**	Machine Learning on Network Security	International Engineering Journal For Research & Development. Volume 4 / Issue 1 / E-ISSN NO:-2349-0721.
Zhan, J., Oommen, B. J., Crisostomo, J.	**2011**	Anomaly Detection in Dynamic Systems Using Weak Estimators	http://dx.doi.org/10.1145/1993083.1993086

***Source:* Authors**

Table 7: Big Data Analytics, Blockchain, FinTech

Literature Authors	Year	Title	Source
Bhimani, A., Willcocks, L.	**2014**	Digitization, big data and the transformation of accounting information	https://doi.org/10.1080/00014788.2014.910051
Christidis, K., Devetsikiotis, M.	**2016**	Blockchains and Smart Contracts for the Internet of Things	https://doi.org/10.1109/ACCESS.2016.2566339
Gabor, D., Brooks, S.	**2017**	The digital revolution in financial inclusion: International development in the Fintech era	https://doi.org/10.1080/13563467.2017.1259298
Hanafy, M., Ming, R.	**2021**	Machine learning approaches for auto insurance big data.	https://doi.org/10.3390/risks9020042
Kshetri, N.	**2016**	Big data's role in expanding access to financial services in China	https://doi.org/10.1016/j.ijinfomgt.2015.11.014

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Minhaj Khan, A., Salah, K.	**2018**	IoT security: Review, blockchain solutions, and open challenges	https://doi.org/10.1016/j.future.2017.11.022
Noor, U., Anwar, Z., Amjad, T., Choo, K. R.	**2019**	A machine learning based FinTech cyber threat attribution framework using high-level indicators of compromise	https://doi.org/10.1016/j.future.2019.02.013
Zheng, Xie, Dai, Chen, Wang.	**2018**	Blockchain challenges and opportunities: a survey	https://doi.org/10.1504/IJWGS.2018.10016848
Zyskind, G, Nathan, O., Pentland, A. S.	**2015**	Decentralizing Privacy: Using Blockchain to Protect Personal Data	https://doi.org/10.1109/SPW.2015.27

***Source:* Authors**