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Artificial Intelligence and Machine Learning In Finance: A Literature Review

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Abstract

Machine Learning (ML) has grown significantly in recent years as a result of new computer technologies, but Artificial Intelligence (AI) still requires significant innovation from data scientists and engineers to advance. Artificial Intelligence (AI) is expected to become a dominant technology in the 2020s. As a result, in this work, We want to infer the intellectual growth of AI and ML in finance research by pursuing and examining the services provided by these concepts using a scoping review and an embedded review. We goose-step the five stages of the scoping review technique and Donthu. Bibliometric review method for a technical literature review. This article examines developments in AI and ML applications in the financial sector of industrialized and developing nations between 1989 and 2022. The major goal is to highlight the specifics of various research kinds that clarify the application of AI and ML in finance sector. Our research's conclusions are distilled into seven categories: Portfolio management and robot advisory are the first two, risk management and financial distress are the third, financial fraud detection and anti-money laundering are the fourth, sentiment analysis and investor behavior are the fifth, algorithmic stock market prediction and high-frequency trading are the sixth, data protection and cyber-security are the seventh, and big data analytics, blockchain, and fintech are the eighth. We also show how AI and ML research improves the financial sector now in each of these fields, as well as how these fields can offer opportunities and solutions to a wide range of financial institutions and businesses. A review of dozens of documents organized into the seven categories of AI and ML application serves as our conclusion.

Keywords: Finance, Scoping review, Artificial Intelligence, Machine Learning

Introduction

The ability to learn from experience and adapt to one's surroundings is referred to as human intelligence (Schlinger, 2003). According to Russell and Norvig (2010), thinking, decision-making, learning, problem-solving, and communication are all components. While the question of human intelligence is still hotly contested, nonhuman or artificial intelligence has long piqued the interest of brilliant minds, including philosophers, mathematicians, writers, and scientists. The pursuit of understanding what constitutes human intelligence and efforts to duplicate and enhance it have been sparked by intelligent machines. Despite sporadic depictions of nonhuman intelligence over the millennia, academics believe 1956 to be the year when artificial intelligence became a legitimate field of study.

Those illustrious founders of billion-dollar firms, including Elon Musk, CEO of Tesla Inc. and SpaceX Inc., Jeff Bezos, Executive Chairman of Amazon Inc., and Mark Zuckerberg, CEO of Meta Inc., shared a unique secret to ensuring their financial viability. All of those well-known figures have confidence in machine learning (ML) techniques and artificial intelligence (AI) systems.

Order to make computers think and behave like people by performing activities like learning and problem-solving, artificial intelligence is the emulation of the human mind (Zhang & Lu, 2021). Machine learning creates systems that get better with time and data, and it has been applied to enhance a number of industries, including autonomous systems, natural language processing, computer vision, and the medical sector (Jordan & Mitchell, 2015). To improve performance, researchers are still studying AI and ML. For moral reasons and to build user confidence in AI systems, it is essential to reduce prejudice and injustice in data (Toreini et al., 2020). Professionals and AI developers may find it easier to trust and comprehend judgments produced by AI systems with the aid of explainable AI (XAI) (Zhang & Lu, 2021; Ghassemi et al., 2021; Alikhademi et al., 2021). According to Gunning et al. (2019), XAI is essentially machine learning and AI technologies that offer human-understandable reasoning for their decisions. The use of AI in banking, healthcare, and education offers up unlimited potential chances with the fourth wave of the fourth Industrial Revolution, which is centered on digital transformation, and has become increasingly a breakthrough in many facets of life.

Statement of the Problem

Since AI is a holistic idea, there are two primary issues in trying to understand it, including how to describe it and how much of human intelligence might be replicable by AI (Stahl, 2021). In general, the definition of AI in the majority of literature studies is that it is the study of how computers and their systems learn to perform complex tasks that would typically need human intelligence. Decision-making, speech recognition, visual perception, and language translation are just a few of these tasks. The science of teaching computers to carry out tasks that require intelligence when carried out by people is another way that AI is widely characterized (Tatsat et al., 2020).

Despite the increasing adoption of artificial intelligence (AI) and machine learning (ML) in the finance industry, there are several challenges and opportunities that need to be addressed. The financial sector's interest in AI and ML has grown significantly due to the potential benefits they offer, such as enhanced customer experience, improved efficiency, and better risk management. However, there are still areas that require further investigation and development to fully realize the potential of AI and ML in finance. Some of the key challenges and questions include:

1. **Ethical Concerns:** The use of AI and ML in finance raises ethical questions, particularly in areas like data privacy, bias in decision-making algorithms, and the potential for automation to replace human jobs.
2. **Limited Understanding:** Despite the growing interest, there might be a lack of comprehensive understanding among financial professionals and decision-makers about the full range of applications and capabilities of AI and ML in the finance industry.
3. **Adoption Barriers:** While some financial institutions have embraced AI and ML, others may face challenges in adopting and integrating these technologies due to factors like cost, resource constraints, and regulatory compliance.
4. **Performance and Reliability:** Ensuring the accuracy, reliability, and transparency of AI and ML algorithms is crucial, especially when they are making critical financial decisions.
5. **Customer Acceptance:** The successful implementation of AI and ML in finance depends on customers' willingness to trust and accept these technologies for their financial needs.

Thus, it is obvious to assert that AI is an effective and efficient instrument for resolving issues that cost time and money in order to attain faster growth and success in the modern era. The transition to AI use necessitates careful research, perspective analysis of potential results, and positive thoughts on mankind.

Research Questions

1. What are the primary applications of AI and ML in the finance industry including asset and wealth management, relationship management, regulation, chatbots, algorithmic trading, robo-advisory, credit scoring, risk management, and cybersecurity?
2. What are the ethical concerns related to the use of AI and ML in finance, such as data privacy, bias, and the potential impact on the job market?

3. How effective is the implementation of AI and ML technologies in Nigerian financial sector considering ethical implications and customer needs?

Research Objectives

1. To identify and explore the various applications of AI and ML in the finance industry, including asset and wealth management, relationship management, regulation, chatbots, algorithmic trading, robo-advisory, credit scoring, risk management, and cybersecurity.
2. To assess the ethical concerns related to the use of AI and ML in finance, such as data privacy, bias, and the potential impact on the job market.
3. To provide recommendations for the Nigerian financial sector on effectively implementing AI and ML technologies while considering ethical implications and customer needs.

Scope of the Study

The scope of the study encompasses the applications of AI and ML in the finance industry, focusing on various aspects such as asset and wealth management, relationship management, regulation, chatbots, algorithmic trading, robo-advisory, credit scoring, risk management, and cybersecurity.

The study can explore the challenges and barriers faced by financial institutions in adopting AI and ML, as well as the potential benefits and risks associated with these technologies. It may also investigate the current state of AI and ML adoption in the Nigerian financial sector and suggest recommendations for its further development.

However, it's important to note that the study may not cover all possible applications of AI and ML in finance, as the field is rapidly evolving, and new use cases may emerge over time. Additionally, the study may focus on the specific context of the Nigerian financial sector, and the findings might not be directly generalizable to other regions or industries.

Significance of the Study

The significance of the study lies in understanding the applications of Artificial Intelligence (AI) and Machine Learning (ML) in the finance industry. AI and ML technologies have the potential to transform the financial sector in numerous ways, leading to increased efficiency, better decision-making, improved customer experiences, and enhanced risk management. The study aims to shed light on the various areas in finance where AI and ML are being utilized, and how these technologies are impacting the industry.

Some key points of significance are:

1. **Technological Transformation:** AI and ML have the power to revolutionize the financial services industry, making it more competitive and capable of providing innovative solutions to customers.
2. **Improved Customer Experience:** AI-driven chatbots and robo-advisors can enhance customer interactions by providing personalized and efficient services, leading to higher customer satisfaction and retention.
3. **Enhanced Decision-making:** AI algorithms can process large volumes of data and identify patterns, enabling financial institutions to make better-informed decisions and develop more accurate risk assessments.
4. **Financial Inclusion:** The adoption of AI and ML in finance can potentially expand access to financial services, especially in developing economies like Nigeria, by enabling more efficient and cost-effective solutions.
5. **Business Opportunities**: The study can uncover new business opportunities for financial institutions by highlighting areas where AI and ML can be effectively implemented.

Literature Review

This magic system could not be discovered till the late 1950s. According to Mc Frockman (2019), a number of philosophers, scientists, and mathematicians have experimented with the term "artificial intelligence," but it wasn't until World War II that Alan Turing, a British general practitioner, suggested to people, how to use the information at hand to reach decisions and find solutions. Turing came to the conclusion that an item might be considered "intelligent" if it communicates with humans.

The phrase "artificial intelligence" was first used in a symposium that was arranged in 1956 by John McCarthy (2006), the top computer scientist in America. In their proposal project for the Dartmouth summer research project, McCarthy and his colleagues (McCarthy et al., 2006, Haenlein and Kaplan, 2019) asserted that all aspects of learning (such as the use of language, the creation of abstractions and concepts, and problem-solving) could be replicated by machines or any other intelligence-related trait. In 1958, he also developed the programming language LISP, which was regarded as an exciting development in AI and ML. Although two American scholars, Herbert Simon and Allen Newell, have been interested in investigating this problem that is related to understanding the notion of

AI, is about to accelerate world evolution (McFrockman, 2019). In a more cognitive context, Li and Du (2007) defined AI as "a variety of intelligent behaviors 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." in one of the most widely cited articles in this field. (Stahl, 2021, p. 8–124). AI has progressively risen to the status of a defining technology in the 2020s (Hilpisch, 2020). Regardless of the automation job, AI in any industry should be viewed as a technology that augments rather than replaces human talents, resulting in a blend of human intelligence and machine intelligence (McFrockman, 2019). Up until it turns into a decision-making support process rather than a decision-making process itself, AI is that flame that illuminates human judgment.

As a result of the different varieties of AI that raise ethical questions, Stahl (2021) differentiated three connected but distinct components of the word AI. The first aspect of AI emphasized machine learning (ML) as the key example of a constrained concept of AI and a fundamental technique that accurately mimics extremely specific cognitive processes. The second component is artificial general intelligence, or the attempt to replicate human abilities. Last but not least, Stahl (2021) stated that convergent socio-technical systems are usually referred to as AI. Each of these parts of AI has unique qualities and traits that give it a unique definition and give rise to various ethical concerns.

The use of AI techniques in finance or any other industry is anticipated to gradually give businesses a competitive edge by increasing their productivity, lowering costs, and improving efficiency while also raising the standard of services and goods provided to customers. Thanks to the development of technology that makes it possible to access more data, engineers and data scientists now have unrestricted access to all previously gathered and stored historical data. Because of this, AI-enabled robots are currently used for a variety of functions, including prediction, recognition, diagnosis, and more (Park, 2020).

In order to maximize the user experience and guarantee the efficacy of predictive analyses, it is crucial to concentrate on developing systems and models that can access the Big Data sets that are currently available. The system will automatically modify, learn, and improve predictability and performance through its settings. Additionally, while all AI includes features of ML, not all AI is thought of as ML, making ML a sub-branch of the AI domain. The field of computer science known as machine learning (ML) aims to create and use current algorithms to create generalized models that provide precise patterns and predictions. ML algorithms are built on statistical and mathematical models that use past data to assist machines imitate human behavior (Park, 2020).

ML has grown significantly in recent years as a result of new computer technology; yet, AI requires notable data scientists and engineers' ingenuity to advance, considering that many ML algorithms have been in use for a while but many of their applications are still mostly unexplored. Since AI and ML are not new fields, but have advanced due to the tools offered by data science, humans can now handle complicated problems without the aid of intelligence. As a result, liability, accountability, and hazards are all associated with human sentimental decisions.

Going back in time, some large corporations began to make significant efforts because they were interested in the development of AI. The Japanese government took advantage of the chance and declared plans to offer 5th-generation machines to support ML. After that, in 1997, IBM's Deep Blue computer became the first to outperform all computers at information storage and interpretation, enabling organizations to maintain a large amount of data. Additionally, over the past 15 years, major corporations like Google, Amazon, Baidu, and others have developed their profit-making through the use of AI and ML (McFrockman, 2019). The history of artificial intelligence in banking is complex and drawn out, much like the field of AI itself. Prior until now, many researches from the 1950s and 1960s did not place a lot of emphasis on the application of AI in banking. Following McCulloch and Pitts' 1943 recognition of machine learning (ML) and artificial neural networks (ANN), Bayesian statistics and neural networks (NN) were developed in the 1960s (Buchanan, 2019), and they were widely used as an integral part of extensive research cases in audits and stock market forecasting (e.g., Green; 1963; Tracy; 1969; Sorensen; 1969), then fuzzy analog.

The 1980s saw a major resurgence in AI in addition to all those novel theories and techniques. For example, the inventor of fuzzy logic, Lotfi A. Zadeh, (1975), highlighted in his paper how the execution of fuzzy instructions by a computer can be very interesting and useful in a variety of issues including pattern recognition, control, AI, linguistics, information retrieval, and decision processes in several psychological, economic, and social disciplines. Additionally, Chen and Liang created the expert system prototype PROTRADER for program trading in 1989. It was marketed as a learning tool based on the adjusting of a few critical parameters in response to market conditions. Louis Bachelier's thesis, "The Theory of Speculation," which was published in 1900, was one of the first works to look at the use of mathematics as a tool for stock evaluation. The development of statistical modeling heralded the introduction of basic AI into the whole financial industry because of his outstanding work, which is regarded as having pioneered the use of mathematics in finance (Davis & Etheridge, 2006).

In fact, statistical and mathematical analysis has a long history in the domains of applied economics and finance. Big data has rekindled interest in ML in recent years. Economists and financiers continue to utilize a variety of more or less sophisticated econometric models to evaluate risks, create projections, and manage money (Leung et al., 2014). In contrast to earlier technologies, AI can complete more challenging tasks, such as making recommendations for products, forecasting market prices, and making medical diagnoses.

Given all these resources, the financial industry is well suited to reap the rewards of data mining because it amasses a substantial amount of Big Data from its customers (Cecchini et al., 2010). When it comes to adopting new technologies, the financial services sector has historically been seen as having a high level of involvement, which has sped up the development of "FinTech," including AI (Citi Group, 2018). For instance, the financial services industry in the Asia Pacific is predicted to spend US$4.29 billion on AI in 2024 (Kapoor and Bisht, 2020). As of now, AI is utilized for asset and wealth management, relationship management, regulation, chatbots, algorithmic trading, robo-advisory, credit scoring, risk management, and cybersecurity (Buchanan, 2019; Chan et al., 2019; Deloitte, 2018). As a result, AI has grown to be a significant issue in the marketing of financial services, necessitating a thorough evaluation of the literature (Cubric, 2020). A review of this nature is essential for guiding (future) empirical research, supporting decision-makers and business professionals, and laying the groundwork for theoretical conceptualizations (Snyder, 2019). In the last five years, there have been a considerable increase in academic studies on AI and its uses in marketing for financial services. The anticipated increase in systematic literature reviews has not materialized, yet.

It was found that most banks in Nigeria utilize chatbots that may enhance engagement with customers The most frequently used platform for this was WhatsApp was the most frequently used platform. The chatbots were not able to perform as well when out of their predefined path. The chatbots used English and not any of the local languages. Managers know the promise of AI and are open to establishing AI in business banking but note the issues hindering the adoption of AI (Mogaji & Nguyen, 2022). However, a study by Mogaji and Nguyen (2022), emphasizes that banks must understand the objectives of the business, the resources available, and customer needs. Banks should train managers and ensure regulators are involved in the development and inform consumers about AI possibilities.

The utilization of AI and ML in financial services is transforming industries and societies. Many Financial firms, from financial technology (FinTech) service providers, to fund management firms, to retail and investment banks, are employing Machine Learning expertise (Goodell *et al.*, 2021).

The rest of this essay is structured as follows: The approach is presented in Section 2, and the applications of AI and ML in finance are then shown and discussed in Section 3. The research's benefits and drawbacks are discussed in Section 4, along with its potential for further research and section 5 is a brief recommendation for Nigerian financial sector.

Methodology

According to Sarah Gash (Ridley, 2012), literature research is "a systematic and exhaustive search of all types of published literature in order to identify as many items as possible that are relevant to a particular topic."

The intend to respond to the latter scoping review issue, in which we use the scoping review approach, in order to explore and carefully examine the application of the ideas "AI and ML in the financial field." It is considered to be a crucial instrument for analyzing the conception and execution of this research. The reader is given data collated from all relevant papers, and it is presented in a way that is in line with the objectives of the scoping research. For this kind of review, text, tables, and visuals can all be utilized. In 2020, Sargeant and O'Connor Defining the research problem, locating pertinent articles, choosing the study, charting the data, and gathering, summarizing, and presenting the findings are the five main steps in the process of performing scoping reviews. (2005) Arksey & O'Malley

The study provides an embedded review, which is a crucial element of research that provides context for the topic under investigation, to outline and demonstrate how the study of AI and

ML contributes to intriguing the current financial area. This form of assessment makes it evident how the sources relate to the research issue and has consequences for how future project studies will be organized (Efron & Ravid, 2018). I goose-step to Donthu et al.'s (2021) bibliometric review method for a technical literature review, which is broken down into four principles: Determine the goals and parameters of the study, then choose the appropriate analytical methodologies, choose the data to be analyzed, conduct the analysis, and present the findings.

The study seeks to infer the intellectual advancement of AI and ML in finance research as a means of advancing my article. After the database was set up, a search was conducted using TITLE and KEYWORD criteria (such as "artificial intelligence," "machine learning," "finance," "financial market," "deep learning," "big data," "data mining," and "algorithms," for example). For the purpose of nourishing the literature structure, I narrowed the results of studies and reviews published in English-language journals in the financial sector to the most highly cited papers worldwide as well as the most alluring authors from both developed and emerging nations (such as Nigeria). This resulted in over 100 documents.

The results of my scoping review are described in the next part with highlights of the extensive use of AI and ML technologies that are widely used in today's contemporary global society, with a strong emphasis on their applicability in the financial sector.

Literatures

Portfolio Management and Robot-Advisory

Technology will continue to be crucial to many aspects of asset management, as it has been for many years. The use of AI and ML in portfolio management has the potential to increase operational workflow accuracy and efficiency as well as performance, earnings, and customer satisfaction (Blackrock, 2019). The advantage over competitors that businesses can achieve by incorporating big data analytics services into their business strategy was illustrated by Antoncic (2020). According to Tatsat, Puri, and Lookabaugh (2020), asset and wealth management companies are investigating AI technologies to aid in improving their ability to use their enormous amounts of historical data and make better investment judgments. The use of robo-advisors, which are algorithms that modify a financial portfolio in accordance with the user's objectives and risk tolerance, is one instance as well as automated financial advice and support. In order to provide a unique knowledge of Robo-ability advisories and reduce behavioural biases from the expert's assessment of India's financial institutions, Bhatia, Chandani, and Chhateja (2020) conducted a qualitative study on the Indian market.

Gu, Kelly, and Xiu (2020) compared ML algorithms for finance in the context of assessing stock risk premiums. They discovered that ML approaches are more effective at predicting larger and more liquid stock returns and portfolios, and they demonstrated that the strongest indications are those linked to price patterns, such as return reversal and momentum. Next in strength are valuation ratios, volatility, and stock liquidity. Nahil and Lyhyaoui (2019) introduced the ML method by integrating the Kernel Principal Component Analysis (KPCA) into the Support Vector Machine (SVM) to build a stocks portfolio with effective and low-dimensional feature information, choosing only the top-performing companies on the Casablanca Stock Exchange in Morocco.

Regarding portfolio optimization and option pricing perspectives, Garcia and Gençai (2000) estimated a generalized option pricing formula with a functional structure similar to the traditional Black-Scholes formula using a feed forward neural network model. Chen and Ge (2021) used a neural network model to solve the portfolio selection optimization problem, demonstrating the effectiveness of the learning-based approach.

Risk Management and Financial Distress

Financial risk management (FRM), according to Dunis et al. (2016), is the act of controlling a company's economic value by lowering risk exposure through the use of financial instruments, notably market risk and credit risk. By reinventing every aspect of risk knowledge and control, the forecasting of default risk by ML algorithms is changing the way we think about risk management (Tatsat et al., 2020). In order to ensure that the contractor's debt is always kept within the credit limit during the construction process, finance-based scheduling ensures that project gains are maximized (e.g., Ali and Elazouni, 2009; Elazouni and Metwally, 2007; Ali and Elazouni, 2005).

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the credit limit during the construction process, finance-based scheduling ensures that project gains are maximized (e.g., Ali and Elazouni, 2009; Elazouni and Metwally, 2007; Ali and Elazouni, 2005). According to research conducted by Khandani, Kim, and Lo (2010), a nonlinear, nonparametric forecasting model was created using ML techniques. Based on the model's performance, the researchers concluded that the consumer credit-risk analytics data might be very helpful in foretelling systemic dangers like the one they observed, the 2007–2009 Financial Crisis.

The development of statistical methods and data-mining tools, including SVM, ANN, and other models, has made it possible to estimate credit risk with performance accuracy that is both promising and accurate. SVM, according to Trustorff, Konrad, and Leker (2011), is demonstrated to perform significantly better than logistic regression models, particularly in situations with short training samples and large input data volatility. Bekhet and Eletter (2014) used ANN to categorize and forecast the likelihood of default for customers of Jordanian commercial banks using the Logistic Regression Model (LR) and Radial Basis Function Model (RBF). Using a supervised ML system, Acheampong and Elshandidy (2021) investigated whether pertinent soft data that was retrieved from the annual reports of the European bank effects credit risk.

The likelihood that a company will survive or fail during a financial crisis is predicted by ML models for financial failure problems based on a given collection of attributes reflecting a company's financial status. Using the reliable Fruit Fly Optimization Algorithm, Pan (2012) created a financial distress model with excellent classification of Taiwan's enterprises and good prediction capabilities.To predict the default risk of German enterprises, Chen, Härdle, and Moro (2009) suggested the nonlinear model categorized by SVM. Beynon and Peel (2001) investigated the use of rough set theory (RST), in particular the Variable Precision Rough Set Theory Model (VPRS), to forecast the failure of companies chosen from the UK market and the success of other enterprises.

However, recent studies showed that in terms of averting financial crises or foretelling bank failure, fuzzy logic and other AI techniques significantly outperformed earlier traditional analysis methods (e.g., Sanchez, Alfonso, Sanchs-Pedregosa; 2019).

Additionally, the applications of AI and ML in risk management span a wide range of industries. For instance, in the field of agriculture insurance, Ghahari, Newlands, Lyubchich, and Gel

(2019) established a cutting-edge deep learning model to evaluate the climate risks in Canadian agriculture and evaluated its precision, speed, and scalability in prediction delivery.

Financial Fraud Detection and Anti-Money Laundering

The Federal Bureau of Investigation made a distinction between three types of financial fraud in the 2010–2011 Financial Crimes Report: (a) bank fraud, which includes credit card fraud, mortgage fraud, and money laundering; (b) corporate fraud, which includes financial statement fraud and securities and commodities fraud; and (c) insurance fraud, which includes fraud involving health and auto insurance. In order to help institutions and stakeholders make decisions, sophisticated financial statement fraud detection systems have been developed. In managerial statements, recent research has found false financial statement distortion. In addition to Omar, Johari, and Smith (2017), many other researchers have concentrated 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), and Humpherys et al. (2011)).

Zhou and Kapoor (2011) examined data mining techniques for financial and accounting applications, such as identifying credit card fraud, in relation to fraudulent financial statements. Using linguistic credibility analysis in management fraud, Humpherys et al. (2011) found that fraudulent disclosures use more activation language, words, imagery, pleasantness, group references, and less lexical variety than nonfraudulent disclosures. More recently, Hajek and Henriques (2017) defended the study's findings and argued that non-annual report data (analysts' sales and earnings predictions) is crucial for identifying fraudulent companies and that it is possible to develop a method to identify non-fraudulent companies from the content of their financial statements and annual reports.

Using a variety of data mining tools, including SVM, Logistic Regression (LR), Multilayer Feed Forward Neural Networks (MLFF), Probabilistic Neural Networks (PNN), Genetic Programming (GP), and Group Method of Data Handling (GMDH), Ravisankar et al. (2011) identified and tracked organizations that commit financial statement fraud. Additionally, computational intelligence-based methods for using data mining features to identify financial fraud were highlighted by West and Bhattacharya

(2016). The computational fraud detection model (CFDM), which Glancy and Yadav (2011) proposed using text-mining techniques, is recognized as a novel and successful computer model for spotting fraud practices using a quantitative approach.

Scholars and writers were pleased with the findings of ML models in MLD and confirmed the efficacy of these techniques in addressing MLD concerns through a review of money laundering detection (MLD) research (e.g., Garcia-Bedoya et al.; 2020, Singh and Lin; 2020). The auto-regressive (AR) outlier-based MLD (AROMLD) model, for instance, was put to the test by Kannan and Somasundaram (2017) in an effort to reduce the processing time for large non-uniform transactions. A ML model that chooses which financial transactions need to be manually checked for possible money laundering was developed, explained, and proven by Jullum et al. (2020) and used to Norway's most renowned and significant financial services business, i.e. DNB ASA, in order to produce more accurate findings.

Sentiment Analysis and Investor Behaviour

Sentiment analysts analyze enormous amounts of unstructured data, including publications, social media posts, videos, transcriptions, images, audio files, and business papers, to determine market sentiment. In the modern workplace, sentiment analysis, a fantastic example of machine learning in finance, is essential for all companies (Tatsat et al., 2020).

For example, Chatbots act as virtual employees, using proprietary algorithms that enable businesses to collaborate with their customers easily and with the least amount of human interaction (McFrockman, 2019). Predictive analytics with machine algorithms may serve as a private financial counsellor to a customer, advising them on how to improve their situation. A complete analysis of the various applications of text mining in finance, including customer relationship management, was presented by Kumar and Ravi in 2016.

The study of financial news, specifically forecasting market behavior and possible trends, is the most common use of sentiment analysis in the financial industry (e.g., Mitra et al.; 2016, Lee and Radhakrishna; 2000). Mitra, Leela, and Mitra (2012) confirmed the use of ML algorithms to analyze the textual input of news items with the goal of calculating quantitative sentiment scores in their successful book. Additionally, event studies and historical portfolio modeling showed that news analytics naive outperforms "buy on good news, sell on negative news" strategies. The forecasts search for events that may not be present but are nonetheless present in the financial news. Chan and Franklin (2011) used a text-based decision support system and natural language processing to assist the significance of forecasts search for incidents that may be absent but underlying in the financial news.

Kim and Kim (2014) examined 32 million Yahoo! Finance messages as part of their study on Yahoo! financial news to determine whether they can predict stock returns, trading volume, and volatility. They found proof that previous stock price performance had a positive impact on investor sentiment, but no proof that the sentiment expressed in online posts by investors may be used to predict volatility or trading volume. By fusing various algorithms in Yahoo! Amazon, Das and Chen (2007) created a sentiment extraction system for stock discussion boards. They looked at investor responses to news, regulatory developments, and company management announcements and found that the suggested model performed better, with a lower false positive rate and higher accuracy.

Future uses of ML will include understanding social media, entertainment apps, and other data sources useful to predicting customer views. Martnez, Román, and Casado (2019) used systems that send orders to the market to open long or short positions to classify any communication about Ibex 35 on social media (Twitter) or news media as good, bad, or neutral in order to gauge the moods of investors based on an AI model. According to a statistical analysis of StockTwits conducted by Oliveira, Cortez, and Areal (2016), the novel lexicons are competitive for assessing investor sentiment when compared to six well-known lexicons. They also created indicators of investor sentiment on Twitter using a lexicon and evaluated these indicators' correlation to survey sentiment indexes.

Additionally, research in AI and ML for finance during this time period examines forecasting and predictive analysis of investor emotion, stock markets, return volatility linked to algorithmic trading, prediction assessment, and self-similar behavior (black nodes); big data analytics; and FinTech. In order to prove that the investor sentiment indicator is consistent with stock market crises, Dahhou and Kharbouch (2021) looked at the Moroccan stock market's financial crisis that occurred between 2000 and 2020. As a result, they showed that the sentiment indicator decreased during those years. Additionally, they used the Granger test to examine the relationship between stock market crises and investor sentiment in Morocco and came to the conclusion that investor sentiment is what triggers and drives stock market crises. Additionally, Bourezk, Raji, Acha, and Barka (2020) used sentiment analysis and machine learning (ML) techniques to establish a connection between the way the general public views a stock and how it changes over time on the Casablanca stock exchange.

Algorithmic Stock Market Prediction and High-Frequency Trading

Algorithmic trading, which has its roots in the 1970s, is the practice of using computers to carry out trades on their own. According to Tatsat et al. (2020), it is based on the use of automated, pre-programmed trading instructions to generate extremely quick, objective trading decisions. Consequently, the application of ML for algorithmic trading has generated a great deal of academic attention due to AI's superiority over conventional econometric models (see, for example, Lo et al.; 2000; Hans and Kasper; 1998; Donaldson and Kamstra; 1997; Hsieh; 1989). The instability of the financial markets makes it difficult and challenging to build a forecasting model. 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.

One area where individual investors might make significant gains through online trading is the stock market. So that investors may make wise decisions about where and when to invest, reliable stock market forecasts are necessary. In this instance, ANN is a widely used soft computing strategy. Given that many conventional econometric techniques fail to capture the swings in exchange rates, it was found by Hans and Kasper in 1998 that ANNs perform well and are frequently more appropriate and effective than linear models. A generalized autoregressive conditional heteroskedasticity (GARCH) model may account for a significant portion of the nonlinearities for all five of the main foreign exchange rates, according to Hsieh's (1989) evaluation study. Investment companies are now consulting data scientists rather than market experts to forecast the long-term performance of stocks. For example, Gosh et al., Elmsili and Outtaj, Touzani and Douzi, Fischer and Krauss, Jiang et al., Nahil and Lyhyaoui, Novak and Veluscek, Arroyo et al., 2011, Gavrishchaka et al., and 2006 all developed complex machine learning (ML) algorithms capable of detecting future market patterns based on historical data trends.

On top of that, individual traders can utilize AI to decide whether to buy, hold, or sell a stock. In this regard, Krauss et al. (2017) and Fischer and Krauss (2018) were implemented as trading strategies by Ghosh, Neufeld, and Sahoo (2022) to assess the effectiveness of random forests (RF) and LSTM networks as training methodologies for predicting out-of-sample directional movements of component stocks. Support Vector Regression (SVR) was maintained by Henrique, Sobreiro, and Kimura (2018) to estimate stock prices in three distinct markets with high and low capitalizations. The findings suggest that the SVR has predictive significance, especially when using a method that updates the model often. Additionally, there is proof that forecast accuracy is improved during times of low volatility. Nahil and Lyhyaoui (2017) proposed an experiment to enhance SVM's performance in the Moroccan stock market by taking into account the growth of the global stock market, which is reflected in three significant stocks on the Casablanca stock exchange market: MASI, MADEX, and Banks Sector Index.

In 2016, Kumar and Ravi made clear the value of text-mining algorithms in the financial industry. However, the work of Feuerriegel and Gordon (2018) to evaluate long-term predictions of stock indices with enormous predictor matrices is extremely creative. They tested text-based models specifically with ML and high-dimensional news, and they found that they are statistically significant in reducing forecast errors from historically lag forecasts.

According to several studies (e.g., Manogna and Mishra, 2021; Verma, 2021; Dbouk and Jamali, 2018; Malliaris and Malliaris, 2013), ML approaches may offer even more doors for gaining distinct insights into the dynamics of numerous market domains, particularly the energy industry. Additionally, the most recent analysis focused on modeling connections between the appearance of events like corporate takeovers, future price movements, and product debuts in media articles (for example, Liu et al.; 2021, Braun et al.; 2020, Manela and Moreira; 2017, Hagenau et al.; 2012).

Understanding how short-term market movements vary from long-term valuations through sentiment analysis prediction, which can enhance returns amazingly (e.g., Elbousty H., Krit S.; 2021, Matsubara et al., 2018, Schumaker et al., 2010), is the newest challenge for algorithmic trading. Using SVM, Schumaker, Robert, and Chen (2010) calculated the stock price 20 minutes following the release of financial news. The suggested method was tested over the course of five weeks on 10,259,042 stock prices that included S&P 500 equities and 9211 financial news pieces. They also found that the Proper Noun scheme performs better than the others. Matsubara, Takashi, Akita, and Uehara (2018) suggested a successful deep neural generative model that recognizes pertinent phrases strongly connected with potential future stock price movements for the analysis and forecasting of news items' daily stock price movements. The top hot subjects for AI and ML applications in finance included financial regulation and algorithmic and high-frequency trading in financial markets (e.g., Borch; 2017, Coombs; 2016, O'Hara; 2015). When discussing high-frequency trading and algorithmic financial markets, Borch (2017) highlighted how and why the Flash Crash is used as a point of reference. He also provided a close investigation of the frequent impact link with the Flash Crash and its many ways.

Although there has been a lot of research on the difficulty of forecasting stock market price changes and the development of trading strategies based on those recommendations, it is essential to confirm the applicability of such studies in new and emerging markets, particularly the cryptocurrency market. The behavior of the well-known decentralized digital currency, Bitcoin, has been the subject of a lot of research (e.g., Gerritsen et al., 2020; Atsalakis et al., 2019; Valencia et al., 2019; Huang et al., 2019; Adcock and Gradojevic, 2019). The researchers Valencia, GómezEspinosa and Valdés-Aguirre (2019) recommended utilizing traditional ML algorithms on publicly accessible social media data (Twitter) in order to estimate cryptocurrency market movements for Bitcoin, Ethereum, Ripple, and Litecoin. The results showed that neural networks (NN) outperformed more traditional models like SVM and RF, proving that it is possible to predict cryptocurrency markets by combining machine learning with sentiment analysis.

Automation successfully overcomes the protracted decision-making process with high-frequency trading. By accounting for order size, fuzzy logic reduces trading uncertainty and costs in choppy markets by requiring more conservative and consistent decision-making than buy or sell suggestions. There has been a paucity of research and studies on the use of fuzzy logic in finance, and they are typically conducted in conjunction with other methodologies like ANN or reinforcement learning. Gradojevic and Gencay (2013) found that, for EUR-USD exchange rates, fuzzy technical indicators perform better than moving average-based technical indicators and filter rules, especially on turbulent days. The PATSOS model, developed by Atsalakis et al. (2019), is a computational intelligence technique that uses a hybrid Neuro-Fuzzy controller to predict future trends in the daily price of Bitcoin. The model outperformed two other computational intelligence models that were created using a more straightforward neuro-fuzzy approach and ANN.

Data Protection and Cyber Security

With the advent of deep learning systems, data engineering and pre-processing expenses are going down. Many banks and financial institutions have recently started using AI in their applications to deliver an exceptional level of customer experience, which has led to the dismissal of staff because operations like account creation, money transfers between accounts, and bill payment are all handled through mobile banking apps. These AI chatbots, which are supported by natural language processing, are quickly and effectively providing banking and organizational clients with information by noting frequent inquiries and responding in a short amount of time without having to leave their current location.

According to research by Königstorfer and Thalmann (2020), commercial banks may employ AI to reduce loan losses, enhance payment security, automate compliance-related duties, and enhance consumer targeting.

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According to research by Königstorfer and Thalmann (2020), commercial banks may employ AI to reduce loan losses, enhance payment security, automate compliance-related duties, and enhance consumer targeting. However, issues with data privacy are closely linked to data security worries, and cybersecurity is a perennial challenge in information and communication technology (ICT). According to Stahl (2021) new types of security issues may be present in AI systems.

Malware identification is yet another challenging problem in the cybersecurity industry. Surya (2019) showed how ML may help in both slowing down human actions to achieve network security and helping to detect different hacker assaults that are challenging to spot before they occur. Therefore, host-based intrusion prevention, vulnerability assessment, personal firewalls, anti-malware, and anti-spyware are all necessary in businesses. Despite the advanced security measures in place, system vulnerabilities become a crucial weapon for malware developers. The two main categories of malware detection techniques are anomaly-based detection and signature-based detection. Cybersecurity applications for the financial sector were divided into five categories by Kumar and Ravi (2016): phishing detection, spam detection, malware detection, intrusion detection, and fraud detection. Based on the anomaly-based methodology, they also looked at the malware in their investigation. Zhan et al. (2011) employed anomaly detection in the email system to assess whether an email is legitimate or spam. They proposed weak estimators like the Stochastic Learning-Based Weak Estimator (SLWE) and the Maximum Likelihood Estimator (MLE) for forecasting the distributions of events that deviate from the norm.

Big Data Analytics, Blockchain, Fintech

Because of advancements in computer technology, big data is now easily accessible in a number of business sectors (e.g., Zheng et al., 2018, Minhaj Khan and Salah, 2018, Christidis and Devetsikiotis, 2016, Kshetri, 2016, Zyskind et al., 2015). A model for understanding the relationships between data, information, and knowledge was addressed to study changes in strategy, organizational and cost structures, digitization, business analytics, outsourcing, offshore, and cloud computing in the research lead by Bhimani and Willcocks (2014). After then, they focused on the opportunities and difficulties presented by big data in relation to management accounting and the finance function.

ML may be used to improve business decisions in order to capitalize on the immense potential of Big Data. Hanafy and Ming (2021), for instance, studied how auto insurance companies use machine learning in their operations and how ML models may be used, in addition to large data, in the prediction of claim occurrence.

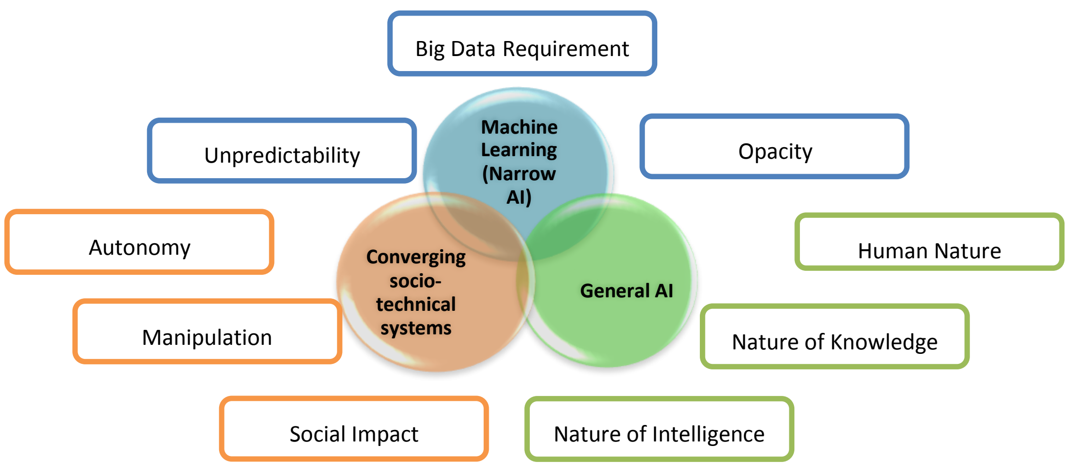
The previous ten years also saw a number of technological revolutions, particularly in fields where the use of AI and big data is essential, such as cloud computing, data mining, augmented/virtual reality, Fintech, and, most significantly, Blockchain and the Internet of Things (IoT) (e.g., Minhaj Khan and Salah; 2018, Zheng et al.; 2018, Christidis and Devetsikiotis; 2016, Zyskind et al.

Discussions

Financial services are most likely to reap the benefits of AI and ML in the future. Indeed, as mankind increasingly relies on digital operations and moves to online platforms in response to a changing environment, AI is transforming how firms operate and make investments.

When using people's information for commercial or political purposes, a small number of multinational firms, which are in charge of big data and the AI revolution, may or may not respect their rights. AI systems must therefore guarantee citizens' safety and security and act as a force for societal benefit (Stahl, 2021). Therefore, the key components of the numerous applications of the word "AI" are shown in the following figure.

Figure 1: Artificial Intelligence's different features



Source: Stahl (2021)

To make a definitive conclusion on this approach, ethics must also be ingrained in AI viewpoints by providing new opportunities for human employment. Indeed, the use of AI systems to replace humans with smart technology in laborious, repetitive, or dangerous occupations is expected to become a major factor in what is now called to as the "post-industrial society" (Stahl, 2021).

Due to persistent risks to its ability to remain inventive and competitive, the financial sector is moving toward cloud-based technology and AI-enabled services to offer the best solutions for consumers. This literature assisted us in determining the evolution of AI and ML in finance research, as well as in selecting the best research technique, a scoping review methodology, to investigate and evaluate the benefits of these concepts.

The proposed paradigm takes into account a substantial body of findings from other academics as well as the authors' own research interests. The scoping study's ability to provide a comprehensive and transparent procedure for mapping research areas is one of its main advantages. As contrast to a thorough systematic review, reviewers can quickly identify the subject of interest based on the quantity, kind, and qualities of exploratory data (Arksey & O'Malley, 2005). The PRISMA Extension for Scoping Reviews (PRISMA-ScR) (Tricco et al., 2018) also offers standards for the appropriate reporting of scoping studies.

The following articles were chosen for our study's review out of a list of the top publications on AI and machine learning in the banking sector, which included over 100 documents. The papers that have received the most citations, have the highest bibliometric scores, were published most recently, and are a part of the main line of inquiry for literature research.

If we didn't understand the restrictions placed on scoping investigations, we would be lying to ourselves. For instance, because to the vast volume of data presented, they do not evaluate the quality of the evidence in primary research reports. Choosing a large number of studies rather than delving deeply into a smaller number of studies can complicate decisions about how much width is more important than depth. Scoping studies deal with a larger range of study designs and methodology than systematic reviews since they eventually provide a descriptive and narrative summary of previous and ongoing research (Arksey & O'Malley, 2005).

However, this scoping research offers a more thorough summary of the results and a review road map for our topic matter. As a result, it provides an effective method for summarizing and disseminating the study, which we divided into seven fields: Portfolio management and robot advisory are the first two, risk management and financial distress are the third, financial fraud detection and anti-money laundering are the fourth, sentiment analysis and investor behavior are the fifth, algorithmic stock market prediction and high frequency trading are the sixth, data protection and cyber-security are the seventh, and big data analytics, blockchain, and fintech are the eighth. It is intended for data scientists, financial analysts, and any other reader—individual or institution—who is interested in this topic but lacks the time or resources to conduct such research on their own. The focus is on the specific research details that clarify the use of AI and ML in the finance industry.

In this article, I made the fundamental claim that AI improves our ability to spot patterns, foresee events, create rules, automate processes, and communicate. Banks and insurance firms, in particular, are actually experiencing substantial growth and opportunities. Therefore, it is not surprising that AI is the financial industry's top goal. As a result, this overview identifies emerging trends in AI and ML applications in finance and illustrates how these fields of study contribute to the current financial landscape by creating new opportunities and providing solutions for a variety of businesses. I finish with a worldwide analysis of over 100 documents divided into the seven application areas for AI and ML.

Future research may compare various ML strategies in each of these financial domains, or in a particular domain or application.

Conclusion

The study delved into the applications of AI and ML in the finance industry, revealing their widespread adoption across various domains, including asset and wealth management, relationship management, regulation, chatbots, algorithmic trading, robo-advisory, credit scoring, risk management, and cyber-security. These technologies have shown promise in enhancing efficiency, accuracy, and customer experience within financial services.

However, the study also identified several ethical concerns related to the use of AI and ML in finance. Data privacy emerged as a critical issue, with the potential for sensitive financial information to be mishandled or misused. Bias in algorithms raised concerns about unfair and discriminatory outcomes, impacting customer experiences and financial inclusion. Moreover, the potential impact on the job market was a key consideration, as the automation of certain tasks could lead to workforce displacement and the need for upskilling.

Financial institutions faced various barriers and challenges in adopting AI and ML technologies. Regulatory compliance, lack of expertise, and concerns about data security were prominent obstacles. Overcoming these challenges required innovative solutions and strategic planning.

The application of Artificial Intelligence (AI) and Machine Learning (ML) in the finance industry has gained significant momentum in recent years. It has the potential to revolutionize various aspects of finance, including portfolio management, risk management, fraud detection, sentiment analysis, algorithmic trading, and data security.

1. **Portfolio Management and Robo-Advisory**: AI and ML technologies are being used to optimize portfolio management processes, enhance investment decisions, and provide personalized financial advice through robo-advisors. These automated platforms can adjust portfolios according to users' objectives and risk tolerance, providing efficient and cost-effective financial services.
2. **Risk Management and Financial Distress**: ML algorithms are transforming risk management by enabling more accurate and timely identification of market risks and credit risks. These technologies can process vast amounts of historical data to predict financial crises and assess credit risk with high precision.
3. **Financial Fraud Detection and Anti-Money Laundering**: AI and ML are proving invaluable in detecting financial fraud and money laundering activities. By analyzing vast amounts of data, including textual information from news and social media, these algorithms can identify patterns indicative of fraudulent behavior.
4. **Sentiment Analysis and Investor Behavior**: Sentiment analysis using AI and ML helps understand market sentiment by analyzing unstructured data, such as news articles and social media posts. These insights can be valuable for predicting market behavior and guiding investment decisions.
5. **Algorithmic Stock Market Prediction and High-Frequency Trading:** AI-driven algorithms are becoming increasingly prevalent in algorithmic trading, where they can make rapid and data-driven decisions to optimize trading strategies and predict stock market movements.
6. **Data Protection and Cyber Security:** While AI offers numerous benefits in finance, it also raises concerns about data privacy and cyber threats. ML techniques are being applied to enhance cybersecurity measures and detect potential security breaches.
7. **Big Data Analytics, Blockchain, and FinTech**: AI and ML play a critical role in leveraging big data analytics in the finance sector, enabling better decision-making and insights. Additionally, blockchain technology and FinTech applications are being powered by AI,

revolutionizing various financial processes.

Recommendations

Based on the findings of the research, the following recommendations are proposed:

1. **Ethical Framework Development:** Financial institutions should establish comprehensive ethical frameworks to guide the development and deployment of AI and ML systems. This should include mechanisms for ensuring data privacy, transparency, and fairness in algorithms.
2. **Bias Mitigation Strategies:** Implement bias mitigation techniques to minimize the impact of biases in AI and ML algorithms. Regular audits and reviews of the systems should be conducted to identify and rectify any biases that may arise.
3. **Continuous Monitoring and Regulation:** Regulatory bodies should work in collaboration with the financial industry to create robust oversight and monitoring mechanisms for AI and ML technologies. This will ensure compliance with ethical standards and prevent any potential misuse.
4. **Investment in Workforce Development:** Financial institutions should invest in the continuous training and upskilling of their employees to adapt to the evolving technological landscape. This will empower the workforce to work alongside AI and ML systems and contribute effectively to their development and use.
5. **Customer Education and Engagement:** Engage customers through educational initiatives to increase their understanding and trust in AI and ML technologies. Clear communication about how these technologies are used and the benefits they provide can enhance customer acceptance.
6. **Piloting and Collaboration:** Financial institutions should consider piloting AI and ML technologies in specific areas before full-scale implementation. Collaboration with technology providers, regulators, and other stakeholders can facilitate successful integration.
7. **Local Context Consideration:** For the Nigerian financial sector, it is crucial to adapt AI and ML technologies to suit the local context, taking into account unique customer needs, cultural considerations, and ethical implications.
8. **Data Governance and Security:** Strengthen data governance practices and cybersecurity measures to protect sensitive financial information. A robust data security framework will instil confidence in customers and safeguard against potential breaches.

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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. 290294.
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: Author

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 approaches.	https://doi.org/10.1108/IMEF M-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-
	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/s1115 6-010-0190-3

Source: Author

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/JMLC04-2020-0033
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.13 92
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/JMLC07-2019-0055
Kannan, S., Somasundaram, K.	2017	Autoregressive-based outlier algorithm to detect money laundering activities.	https://doi.org/10.1108/JMLC07-2016-0031
Omar, N., Johari, Z.A., Smith, M.	2017	Predicting fraudulent financial reporting using artificial neural network.	https://doi.org/10.1108/JFC11-2015-0061
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/JMLC09-2020-0100
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: Author

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/S13864181(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: Author

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/s106 14-010-9230-2
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/JPIF08-2019-0100
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.12 186
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 nonlinear 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/S09275398(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
FernandezRodrıguez, 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/S01651765(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
Gradojevic, N., and R. Gencay.	2013	Fuzzy logic, trading uncertainty and technical trading.	http://dx.doi.org/10.1016/j.jbankfin.2012.09.012
Hagenau, M., Liebmann, M., Neumann, D.	2012	Automated news reading: Stock price prediction based on financial news using context-capturing features.	http://dx.doi.org/10.1109/HICSS.2012.129
Hans, F. P., Kasper V. G.	1998	Forecasting Exchange Rates Using Neural Networks for Technical Trading Rules.	https://doi.org/10.2202/15583708.1033
Henrique B.M., Sobreiro V.A., Kimura.	2018	Stock price prediction using support vector regression on daily and up to the minute prices	https://doi.org/10.1016/j.jfds.2018.04.003
Hsieh, D. A.	1989	Testing for nonlinear dependence in daily foreign exchange rates.	The Journal of Business 62, no. 3 (1989): 339–68
Huang, J.-Z., W. Huang, and J. Ni.	2019	Predicting Bitcoin returns using high dimensional technical indicators.	https://doi.org/10.1016/j.jfds.2018.10.001
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
Lo, A. W., Mamaysky H., and Wang J.	2000	Foundations of Technical Analysis: Computational Algorithms, Statistical Inference, and Empirical Implementation.	http://dx.doi.org/10.1111/0022-1082.00265
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
Manela, A., Moreira, A.	2017	News implied volatility and disaster concerns.	https://doi.org/10.1016/j.jfineco.2016.01.032
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.14 87
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
Moghaddam, Moghaddam, Esfandyari	2016	Stock market index prediction using artificial neural network	https://doi.org/10.1016/j.jefas.2016.07.002
Nag, A.K., Mitra, A.	2002	Forecasting daily foreign exchange rates using genetically optimized neural networks	https://doi.org/10.1002/for.838
Nahil A., Lyhyaoui A.	2017	Stock price prediction based on SVM: The impact of the stock market indices on the model performance	http://ipco-co.com/PET_Journal/vol21ACECS/18.pdf
	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
Novak, M. G., Veluscek, D.	2016	Prediction of stock price movement based on daily high prices.	https://doi.org/10.1080/14697688.2015.1070960
O'Hara M.	2015	High frequency market microstructure	https://doi.org/10.1016/j.jfineco.2015.01.003
Schumaker, Robert P., and Hsinchun Chen.	2010	A discrete stock price prediction engine based on financial news.	http://dx.doi.org/10.1109/MC.2010.2
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.14 89

Source: Author

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: Author

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
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: Author