AI and Machine Learning as Drivers of Change in the Financial Industry

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Abstract

This paper examines the financial sector's implications of Artificial Intelligence (AI) and Machine Learning (ML). It also, highlights the advantages of implementing fraud protection measures, reducing costs, and improving productivity. However, it also raises concerns about the inability of traditional financial institutions, such as banks, insurance companies, and reinsurance businesses, to compete with Fintech companies. Artificial Intelligence (AI) has the capacity to instantaneously analyse vast quantities of data, thereby enabling investors to monitor investment progress and evaluate risk. Personal information may be collected for the purpose of assessing insurance policies and determining rates. The digitalization trend that was evident prior to the COVID-19 pandemic has been accelerated and fortified, particularly in the context of the utilisation of artificial intelligence. 'Big data' analytics and alternative data sources are extensively employed in contemporary artificial intelligence methods. These data are fed into Machine Learning (ML) models, which autonomously learn and enhance prediction and performance by leveraging experience and data, without requiring human training. The authors examine the potential for a broader digital divide between developed and developing nations, as well as the benefits of these technologies in terms of efficiency and financial profundity. The stability of the financial system and the prosperity of banks are contingent upon the effective management of risk. There is no doubt that the implementation of AI in the banking sector has the potential to substantially enhance productivity and profitability, as well as revolutionise the workplace. This paper highlights the rapid transition of banking services to the online environment ,which has enabled banks to achieve significant digitalization gains during pandemics.

Keywords: Artificial Intelligence, Machine Learning, Finance, Service, Bank.

1. Introduction

The financial sector has entered a new phase of innovation and transformation as a result of the implementation of artificial intelligence (AI) and machine learning (ML) technologies. AI and ML have become essential instruments for financial institutions, investment firms, and regulatory bodies due to the proliferation of data, advancements in computing power, and the evolution of algorithmic techniques. The financial industry has been transformed in a variety of ways as a result of the convergence of finance and technology, such as regulatory compliance, investment analysis, fraud detection, customer service, and risk management. The adoption of AI and ML in finance has a multifaceted impact, encompassing both opportunities and challenges. One the one hand, AI-powered algorithms can analyse vast amounts of data with unprecedented speed and accuracy, allowing financial professionals to make informed decisions, optimise operations, and uncover new revenue streams. However, the proliferation of AI and ML raises concerns about data privacy, algorithmic bias, systemic risk, and job displacement, necessitating a thorough examination of the ethical, regulatory, and societal implications. The purpose of this introduction is to offer a comprehensive examination of the primary drivers, applications, benefits, and challenges that are linked to the integration of AI and ML in the financial sector. By investigating the transformative potential of these technologies and the changing financial services landscape, we can acquire a deeper understanding of the opportunities and challenges that await us in the AI-driven finance era. By developing intricate, high-dimensional models, machines have the potential to conduct comprehensive analyses of new data. The finance sector is being transformed by the subtly influencing of company and consumer behaviour by cutting-edge technologies such as artificial intelligence and machine learning. Artificial intelligence and machine learning have a variety of applications, such as the identification of financial misconduct and the automation of tasks (Mahalakshmi et al. 2021). The pervasive use of digital methods, including AI, was hastened by the COVID-19 epidemic. Currently, the financial sector is rapidly incorporating artificial intelligence into asset management, algorithm trading, and credit underwriting (OECD, 2021). These features are significantly facilitated by big data, which encompasses data acquisition, storage, resource management, a computer framework, analysis, mining, and visualisation. When computers, robots, and other devices are programmed to emulate human intelligence, we refer to this as artificial intelligence. Computer graphics, natural language processing (NLP), and an expert system are among the instruments employed by artificial intelligence. The objective of artificial intelligence is to instruct computers to reason and behave in a manner that is comparable to that of humans. Machine learning is a branch of artificial intelligence that enhances the predictive capabilities of software. The primary objective of this research was to determine the extent to which machine learning and AI have transformed the contemporary era, particularly in the financial sector. This research concentrates on the potential, hazards, and consequences of machine learning in the workplace and business operations. This study demonstrates the ability of an AI learning system to solve problems in a sequential manner, operating wholly autonomously and without human intervention.

1.1 The benefits of AI in the financial sector

Banks can expedite and automate processes that were previously manual and time-consuming, such as market research, through the use of Artificial Intelligence (AI). Artificial intelligence (AI) has the capacity to instantaneously analyse vast quantities of data, thereby enabling investors to monitor investment progress and evaluate risk. Personal information may be collected for the purpose of assessing insurance policies and determining rates. AI has the potential to be advantageous to the cybersecurity sector by enabling it to identify fraudulent financial transactions. Artificial intelligence has the potential to identify suspicious transactions by comparing them to previous ones. If an anomaly is identified, the system can promptly notify the consumer and the financial institution to verify the transaction's authenticity. AI and ML have the potential to improve the entire customer experience for financial consumers. The expansion of online banking (i.e., contactless banking) has the potential to result in increased endpoint vulnerabilities, such as cell phones, PCs, and mobile devices, which reduces the need for in-person encounters. AI has the potential to automate a variety of fundamental banking operations, including payments, deposits, transfers, and customer support inquiries. AI may also process acceptance and rejection decisions for credit card and loan applications in a matter of seconds.

2. Literature Review

A dynamic and swiftly evolving landscape is revealed in the recent literature on AI and machine learning in financial applications. Sophisticated techniques are being employed by researchers to improve a variety of financial operations, including asset management and fraud detection.

In 2024, Swetha R and Ravi URS investigated the potential of machine learning to process extensive datasets for the purposes of asset allocation and investment portfolio management. They emphasised the urgent necessity of evaluating the advantages and disadvantages of AI-based decision support systems, emphasising that, despite their potential to considerably improve efficiency and accuracy, these systems also present potential risks that must be meticulously managed.

Williams and Jackson (2024) employed AI-driven sentiment analysis to interpret market sentiment and its influence on financial market trends. Their research demonstrated that this technique could enhance the precision of market predictions, providing a valuable resource for financial analysts and investors.

Carter and Hughes (2024) implemented hybrid machine learning models in the U.S. real estate market, which integrated neural networks and decision trees. Their results indicated that these hybrid models substantially enhanced the accuracy and reliability of real estate price predictions, thereby establishing a more robust framework for real estate valuation.

O'Connor and Reynolds (2024) conducted a study on the application of AI-powered predictive analytics in high-frequency trading. Their research emphasised the significant enhancements in trade execution and profitability that could be achieved by incorporating AI into trading strategies, thereby presenting a compelling argument for its adoption.

Martins and Almeida (2024) concentrated on the detection of anomalies and deep learning in European banking fraud data. They demonstrated that the integration of these techniques could effectively identify and mitigate fraudulent activities, thereby reducing financial losses and improving security in banking operations.

Kim and Park (2024) investigated the emerging field of quantum machine learning in Asian financial markets. Their research emphasised the superior performance of quantum machine learning in forecasting, notably in highly complex and volatile markets, indicating a promising future for quantum approaches in finance.

Rodriguez and Sanchez (2024) implemented reinforcement learning and genetic algorithms to optimise trading strategies in Latin American stock markets. Their research suggested that this combination has the potential to produce enhanced returns, demonstrating the potential of these advanced techniques to improve trading outcomes.

The influence of AI on financial markets was investigated by Nusrat Azeema and associates in 2023 through AI reference analysis and keyword datasets. They discovered that AI has a substantial impact on both Return on Assets (ROA) and Return on Equity (ROE), which presents financial institutions with both opportunities and challenges (Azeema et al., 2023). Johnson and Chen (2023) employed reinforcement learning and neural networks to analyse European stock market data, emphasising that these sophisticated methodologies resulted in enhanced trading outcomes. In the same vein, Patel and Singh (2023) implemented decision trees and random forests on Indian banking transaction data, thereby demonstrating a high degree of accuracy in the identification of fraudulent transactions.

In 2023, Gomez and Torres combined blockchain analytics with machine learning to improve the security and fraud detection capabilities of cryptocurrency transactions. Silva and Mendes

(2023) employed gradient boosting machines to anticipate fraudulent insurance claims, thereby offering insurers enhanced risk assessment instruments.

Brown and Davis (2023) conducted a comparison of neural networks and support vector machines for the purpose of predicting U.S. mortgage loan defaults, with neural networks demonstrating superior predictive capabilities. Nguyen and Le (2023) implemented k-means clustering and logistic regression to enhance loan approval processes in Southeast Asian microfinance data.

The diverse applications and substantial advantages of AI and machine learning in finance are further exemplified by prior research, including those conducted by Niu JiXiang in 2022, who employed SHAP with XGBoost for loan prediction, and Li and Ma in 2022, who employed reinforcement learning for cryptocurrency trading (JiXiang, 2022; Li & Ma, 2022). These studies collectively underscore the transformative impact of AI and machine learning on financial markets, providing potent tools for prediction, risk management, and decision-making in an increasingly complex and data-driven financial landscape.

Research gap

There are still several research gaps in the field of AI and machine learning in finance despite notable progress, and there remains a plethora of directions still to be explored and perfected.

Ethical, Legal and Regulatory constraints:

Most of the studies on AI in finance deal with the technical aspects of the AI approach and how it can be implemented in practice, but not the regulations and the ethical issue with respect to AI in finance in general. While Swetha and Ravi URS (2024) cautioned the trade-offs in benefits and costs, guidelines on how to control these risks tend to be less investigated. Further research should grasp the specific ethical frameworks and regulation regimes for AI implementation in the sphere of financial decision-making.

Integration of AI Techniques:

Although individual AI techniques (reinforcement learning, neural network, and machine learning) presented have been well explored and studied (Johnson & Chen, 2023; Patel &

Singh, 2023; Gomez & Torres, 2023), the integration of these techniques to form hybrid models have still not received enough attention. Hybrid machine learning models have been shown by Carter and Hughes (2024), but further research is needed to understand how different AI techniques can be combined and optimized.

For instance, combining different AI methods may also increase the accuracy of financial models.

Quantum Machine Learning:

Kim, and Park (2024) touted the importance of quantum machine learning in financial forecasting. But this area is too young, with few real world use case and application. Empirical research and pilot projects are required to assess the possibilities of quantum machine learning in finance in more detail.

This comes back to scalability, and research in this area must focus on real-world applications and scalability, i.e. what are the practical advantages of quantum approaches compared to traditional AI methods.

AI in Emerging Markets:

This has been predominantly set in developed markets such as the U.S. or the European markets (Williams & Jackson, 2024; Martins & Almeida, 2024). There are not nearly enough conclusive works on the use of AI in emerging markets. While the studies of Nguyen and Le (2023) gave some brief light on the understanding on microfinance in Southeast Asia, studies on how AI can effectively impact and be used for microfinance in various economic contexts are scant. Future work should examine the specific challenges and potential opportunities of implementing AI/automated decision aids in the context of emerging markets, such as infrastructure constraints or different regulatory settings.

Impact on Financial Inclusion

Literature regarding financial inclusion and AI has discussed relatively few opportunities for AI to support financial inclusion in the specific context of enabling access to financial services via providing improvements in AI. While studies by Silva and Mendes (2023) and Nguyen and Le (2023) explored AI applications in credit scoring and have shown some positive outcomes in risk assessment and loan management processes, even if AI could work well within the lender it may not work well at the societal level.

An interesting line of future work would be to explore the potential of AI to increase access to financial services creating opportunity for underserved populations.

Long-term implications and sustainability

The vast majority of academic papers. concentrate on(A study of., Artificial intelligence in finance) short-term results, and almost all investigate immediate advantages. The lifecycle and sustainability of AI-based financial models are not well understood. An example would be implications from ratcheting automated AI trading on market stabilisation

3. AI Systems, ML And The Use Of Big Data

According to the OECD's AI Experts Group (AIGO), an AI system is a machine-based system that is capable of forecasting, suggesting, or making decisions that affect actual or virtual environments in response to a specific set of human-defined objectives (OECD, 2019). It gathers data from humans and/or machines to construct an understanding of the world, then abstracts that understanding into models (either automatically, as with ML, or manually), and finally employs inference from those models to offer recommendations for the next steps. (OECD, 2019) AI systems are designed to operate with progressively greater autonomy. Figure 1 illustrates the following: Artificial intelligence systems A system of artificial intelligence is considered to have reached the end of its lifespan after the initial stages of (i) planning and design, (ii) data collection and processing, (iii) model construction and interpretation, and (iv) deployment, operation, and monitoring (OECD, 2019). An AI study taxonomy categorises AI studies based on their scope: applications (e.g., natural language processing), training methods (e.g., neural networks), optimisation (e.g., one-shot learning), and studies that consider ethical and legal considerations (e.g., transparency) (Samuel, 1959). Machine learning (ML) is a subset of artificial intelligence that explains the ability of software to "self-improve" by learning from relevant data sets without being explicitly taught by human programmers. Its applications range from the detection of fraud and AML to the prediction of borrower default and image recognition. The various types of machine learning include supervised learning ('classical' ML, consisting of advanced regressions and categorization of data used to improve predictions) and unsupervised learning (processing input data to understand the distribution of data to develop, for example, automated customer segments), in addition to deep and reinforcement learning (based on neural networks and applicable to unstructured data like images or voice) (US Treasury, 2018).

4. Artificial Intelligence In Finance: Opportunities And Risks

The policy considerations that result from the application of AI and ML to the financial industry. One It provides policymakers in the financial sector with a comprehensive understanding of the history and current state of AI/ML systems, as well as their deployment and use cases, as well as the new challenges they are encountering. AI and ML systems have made significant progress in the past decade. Currently, artificial intelligence (AI) systems are capable of performing activities that are clearly defined and typically necessitate human intelligence. However, the development of a computer that has the capacity to comprehend or acquire any intellectual work that a person performs is not readily achievable. The learning process of the majority of AI systems is facilitated by ML, which is rooted in scientific disciplines such as arithmetic, statistics, and decision theory. Much of the recent advancements, including self-driving vehicles, digital assistants, and face recognition, are the result of advancements in ML, particularly in deep learning algorithms. Fintech enterprises have been the primary catalyst for the rapid increase in the use of artificial intelligence and machine learning (AI/ML) technologies in the financial sector. The financial industry's recent adoption of technology advancements, such as cloud computing and big data, and the expansion of the digital economy have made the successful implementation of AI/ML systems feasible (WEF, 2020). According to a recent survey, the vast majority of financial institutions (77%) anticipate that AI will be either extremely essential or very important to their operations in the next two years. McKinsey (2020a) anticipates that the finance sector could be worth $1 trillion as a result of artificial intelligence. Artificial intelligence (AI) and machine learning (ML) are transforming the finance and insurance sectors. AI/ML systems are transforming the following: client interactions with financial service providers (chat bots), investment decisions (robo-advisors), credit decisions (automated mortgage underwriting), and identity verification (picture recognition). Automation, the implementation of predictive analytics to enhance product offerings, and the provision of improved risk and fraud management with enhanced regulatory compliance are all contributing to substantial cost reductions for financial institutions. Lastly, AI/ML systems offer central banks and other authorities with this responsibility new tools for enhancing systemic risk surveillance and fortifying prudential monitoring. The banking industry has been further motivated to implement AI and ML as a result of the COVID-19 pandemic. According to research conducted by the Bank of England (2020) and McKinsey (2020b), numerous financial institutions and banks anticipate that AI and ML will play a more significant role in the industry following the pandemic. Customer relationship management and risk management are critical growth sectors. During the epidemic, banks are seeking to improve their underwriting process and fraud detection by leveraging their expertise in AI/ML to manage the high volume of loan applications. In the same vein, managers who depended on extensive supervisory activities that occurred outside of the office may wish to explore AI/ML-supported tools and procedures after the epidemic has passed. Recent advancements in artificial intelligence and machine learning may further exacerbate the expanding digital divide between developed and developing nations. The benefits of AI and ML deployment have been primarily observed in developed and some developing countries. These technologies have the potential to enhance access to credit and reduce the overall cost of credit risk assessments, particularly in countries lacking a centralised credit registry (Sy, A., R. et al. 2019). Nevertheless, numerous economies are experiencing a decline in their development as a result of inadequate investment, human resources, and access to research. In order to address this disparity, governments must establish a policy agenda that is digitally friendly and is based on four primary policy pillars: investments in infrastructure, policies that foster a supportive business environment, skills, and risk management frameworks (IMF 2020).

4.1 The Application of Artificial Intelligence to Bank Risk Management

There has been a lot of talk about how artificial intelligence (AI) may be refined and implemented into conventional financial services and operations since the advent of FinTech (Zhang and Kedmey, 2018). There is a lack of study on the current and prospective impact that AI has and might have on bank risk management, despite the fact that wealth management and investment banking benefit from the usage of AI. This is an issue that warrants deeper scrutiny and inquiry. Successful risk management requires accurately identifying, measuring, and monitoring the many threats to which financial institutions are exposed. Credit risk, liquidity risk, reputation risk, and operational risk are all important types of financial risk. This section will analyze current research and critically evaluate how AI may be employed in the discovery, measurement and monitoring process for each of these hazards.

4.1.1 Credit Risk

The primary responsibility of a bank is to provide loans to its consumers. The bank is uncertain about the likelihood of receiving its funds back from the consumer, which presents an inherent risk. Credit risk is the potential for a financial institution to incur financial losses as a result of a client's failure to fulfil a contractual obligation or redeem a loan that the institution has provided. Another type of credit risk is the deterioration of a counterparty's creditworthiness. It poses one of the most significant threats to institutions and is very difficult to resolve. The Basel rule requires banks to maintain capital reserves in order to safeguard themselves from credit risk (Stulz, 2015). The methods employed by banks to manage credit risk are contingent upon the complexity and nature of the credit operations they conduct. To accurately model credit risk, it is necessary to assess the likelihood of default (PD), the Exposure at Default (EAD), and the Loss Given Default (LGD). It is imperative for a bank to identify and monitor each of these three credit risk factors in order to optimise its performance. The assessment of credit risk involves the examination of two critical characteristics: anticipated loss and unexpected loss. The bank's reserves are adequate to cover the anticipated loss that was incorporated into the initial assessment. Consequently, the following formula is employed to determine it, and it does not accurately represent the bank's actual risk. The formula for determining the probable loss is as follows: PD x EAD x LGD (Saunders Cornett, 2014). When we discuss unexpected loss, we are referring to the unpredictability of actual loss rates in comparison to predicted loss. This indicates that the bank may experience a greater financial loss than they had initially anticipated.

4.1.2 Operational Risk

The term "operational risk" refers to the potential for financial loss that may arise from the failure of internal control, operations, and accounting systems, as well as the failure of procedures and processes, and the failure of personal supervisory roles (due to human error or fraudulent behaviour). A multitude of potential complications may arise in this scenario, and the bank may incur substantial losses if they do. Methods for accomplishing this should be consistent with the operational risk criteria that were initially established as part of the Basel II framework (Guill, 2016), but have since been modified. The Basel Committee for Banking Supervision (BCBS) has established standardised measurement approaches (SMAs) for operational risk. This singular method approach combines the business indicator (BI), a representation of operational risk exposure, and the internal loss multiplier, a risk-sensitive component of operational loss data that is unique to the bank (BIS, 2016). The components are as follows: • interest, dividends, and leases; • services component; and • finances component. The average of each of these parameters is calculated over a three-year period (BIS, 2016). Before the SMA was implemented, operational risk was challenging to estimate due to the absence of a reliable numerical proxy for quantifying it. A more quantitative foundation for evaluating operational risk may be established as a consequence of the SMA's emphasis on data analytics as part of the modelling process.

4.1.3 Liquidity Risk

The liquidity levels of banks are a determining factor in their capacity to fulfil consumer requests for loans and withdrawals from deposits. This is crucial for the institutions' sustainability and the fulfilment of their immediate financial obligations. A financial institution's failure may result from inadequate liquidity (Horcher, 2005). The Basel III framework emphasises liquidity and requires financial institutions to maintain an adequate amount of liquid assets to meet their capital requirements in order to adhere to regulations (Bai et al. 2017). Consequently, it is imperative for a bank to assess, monitor, and analyse its liquidity risk. In response to the Global Financial Crisis (GFC), the Basel III framework was recommended to implement two new quantitative ratios to more accurately measure liquidity risk. The LCR is essentially a stress test, as it ensures that a bank has an adequate amount of highly liquid assets to meet any continuous short-term requirements over a 30-day period. The LCR must be at least 100%. The NSFR was the second quantitative measure that the BCBS developed. The primary objective of the NSFR is to enhance the availability of medium- and long-term liquidity financing to banks, ensuring that they have sufficient stable funding to endure a year of duress. However, research indicates that employing this statistic to rank assets is uncertain (Tavana et al. 2018). Furthermore, the NSFR must be at least 100%.

4.1.4 Reputational Risk

A bank's credibility is directly proportional to the level of confidence customers have in their financial stability, as indicated by research (Fernando et al. 2015). Reputational risk is the likelihood that adverse publicity will negatively impact a company's image and, as a result, its financial performance. Studies have shown that the reputation of a bank becomes more susceptible as its size and revenues increase (Fiordelisi, Soana Schwizer, 2013). Over the past two decades, there has been a heightened emphasis on reputational risk as a result of the high incidence of operating losses caused by internal fraud in a number of institutions and the resulting negative financial consequences. Several studies have employed ordered logit models to evaluate reputational risk. One significant limitation of ordered logit models is that they presuppose that the probability of outcomes is parallel. The models suggest that the probability of a positive or negative reputational outcome is directly proportional to the potency of the variables that influence it. This metric is unsuitable for identifying the fundamental causes of reputational risk, as indicated by the aforementioned research. A bank may derive substantial advantages from the identification, measurement, and monitoring of reputational risk sources if it implements a more adaptable approach, such as one that implements artificial intelligence (AI), which is not predicated on such a rigorous assumption and evaluates a greater number of variables.

5. Banks Adoption Of Artificial Intelligence And Machine Learning During The Covid-19 Outbreak

The COVID-19 pandemic was an unforeseen event that had far-reaching consequences worldwide, affecting not only the daily lives of individuals but also the operations of businesses, the products they sell, and the way they satisfy the needs of their consumers. Although the 2008 financial crisis was primarily a financial crisis that impacted the actual economy, the pandemic was primarily a health and geopolitical crisis that tested the response of governments to critical situations and challenged healthcare systems worldwide. It also resulted in a cessation or decline of activity in various industries and prompted modifications to the social and behavioural norms of individuals. Due to the fact that social isolation was one of the primary strategies employed to mitigate the virus's transmission, there has been a significant increase in the use of digital services and financial technology in contemporary society. This was most evident in the emergence of home entertainment, home delivery services, and e-commerce. In the two years following the COVID-19 outbreak, industries have either reduced their activities or suspended their operations. However, the response was not uniform among conventional financial institutions and fintech companies. The financial services sector's digital transformation and financial technology (fintech) played a substantial role in addressing or reducing the challenges presented by this exceptional event (Remolina, 2020). In an effort to combat financial fraud, money laundering, and terrorism financing, as well as to promote the full utilisation of technology, the Financial Action Task Force (FATF) has implemented a series of measures. These measures include the establishment of standards and guidance for trustworthy digital identification mechanisms to facilitate the development of secure global payment systems. Sandy Shen, Senior Director Analyst at Gartner, stated in the early days of the epidemic, "The significance of digital channels, goods, and operations is immediately apparent to enterprises worldwide." This should be a wake-up call to companies that have forsaken digital business and long-term resilience in favour of meeting immediate operational demands. Companies that are capable of redirecting their technological resources and investments towards digital platforms will be better equipped to navigate the current crisis and prepare for the future. Consequently, the COVID-19 pandemic presented previously unnoticed challenges, but it also offered significant opportunities for those who were willing to embrace them and acted as a catalyst for the widespread adoption of new technology. The primary applications of AI and ML in banking include the enhancement of the conversational bank experience in response to the increasing demand for more human-like interactions when managing one's finances, the reinforcement of anti-money laundering systems in response to the increase in online banking that has given rise to new types of fraud, and the development of more precise methods of identifying customers. A revaluation of both corporate strategy and product line is necessary due to the significant changes that are occurring in all sectors, including banking, as a result of both technical development and changes in consumer preferences. Since the COVID-19 outbreak, the velocity of change has increased, necessitating that businesses act promptly to preserve their competitive advantage. McKinsey has identified a novel business model termed "the AI bank of the future" that has the potential to enhance the efficacy, reduce costs, and increase profits of banks by leveraging state-of-the-art technology such as AI and ML. The COVID-19 epidemic served to emphasise and accelerate the necessity for the transformation; however, the primary impetus for the development of new business strategies was the increasing importance of data in recent years. Consequently, in an effort to transform into data-driven enterprises, numerous organisations have prioritised the integration of AI/ML and digital transformation into their operations. As per a 2021 report by Algorithmia, 76% of the target organisations prioritise artificial intelligence and machine learning over other IT initiatives. Nevertheless, 43% of the respondents expressed that they recognised the utility and advantages of AI/ML and concurred that it is more significant than they had initially anticipated. Another indicator of this development is the increase in the percentage of businesses with over 100 data scientists on staff from 2020 to 2021 (29%, a 17 percentage point increase from the previous year). The poll results indicate that one of the most critical applications of artificial intelligence and machine learning is the enhancement of the consumer experience and the automation of business processes. Enhancing the customer experience results in the retention of existing customers and the attraction of new ones, which in turn promotes top-line growth. Additionally, process automations lead to an increase in operational savings.

CONCLUSION

The objective of this paper was to offer a practitioner's viewpoint on the latest developments in financial technology, including AI and ML, and to discuss how financial institutions have prepared for and are continuing to prepare to meet market demands by staying current with technological trends. The study's capacity to advance our understanding of the topic from a technical standpoint is impeded by the fact that researchers in the financial sector who are more likely to study the implications of artificial intelligence and machine learning (Baldwin et al. 2006) or financial technology are not always specialised in technological skills. This article investigates the utilisation of AI, ML, and Big Data in the financial sector and the subsequent consequences. The objective of incorporating AI into the financial sector is to enhance the efficacy of current practices, rather than to entirely replace them. In fact, the financial sector, which encompasses banking, insurance, and the stock market, has undergone significant changes as a result of the progression of science and technology. Banks encounter numerous hazards, and artificial intelligence has the capacity to assist in the resolution of certain management issues. Our research has led us to the conclusion that the banking industry would experience substantial economic benefits as a result of the implementation of AI (Ferrari 2021). A significant transformation transpired during the pandemic, as it was previously believed that conventional institutions would not thrive in an internet environment. We can anticipate that ongoing digitization and innovation will continue even after the epidemic has passed, as we gain a more comprehensive understanding of the necessary steps.

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