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Artificial intelligence in the modern banking and financial industry (Applications, Risks, Policies and Regulations)

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Abstract
This article aims to highlight the importance of adopting artificial intelligence in the modern banking and financial industry. After a concise and simplified explanation of the operating modes of artificial intelligence (AI) applications in finance, this research paper highlights the role of artificial intelligence applications in increasing the competitive advantages of financial companies. Then, this research paper attempts to lay out and address the potential risks related to: the financial institutions that use these technologies, consumers or customers and investors, and the pro-cyclicality and systemic risk in the markets. This requires the interaction and intervention of policy makers and regulators. By assessing the effects of deploying these new technologies and determining the benefits and risks related to their use, the paper ends up with proposals and recommendations for policy makers and regulators in the form of responses and directions aimed at supporting innovation in the field of AI in finance, while guaranteeing the protection of consumers and financial investors.

Keywords:
Artificial intelligence;
Finance and financial services;
Risks;
Policies and Regulations.

JEL Classification Codes: O380 ; G00 ; G280.

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1. INTRODUCTION

There is a large and increasingly widespread use of artificial intelligence (AI) techniques in the field of finance, including several areas such as investment portfolio and asset management, credit underwriting, smart contracts, and blockchain-based finance, which are enabled by the large quantity of available data (Big Data) and the computing power that is within reach today.

When Machine Learning (ML) models are fed big data, they improve predictability and performance in an automatic manner through experience and data, without any human interaction or pre-programing to do so. The use of artificial intelligence in finance is predicted to increase the competitive advantages of financial companies, by improving their efficiency through the reduction of costs and the enhancement of productivity, as well as the improvement of products and services quality. Furthermore, these competitive advantages can be beneficial to consumers as they provide customized and quality products. AI enables the extraction of information lurking in data to unlock insights to be harnessed in investment strategies and possibly enhance financial inclusion by allowing creditworthiness analysis of customers with limited credit history (Such as thin file small and medium-sized companies, i.e. limited data). Moreover, the use of applications of artificial intelligence in the field of finance may engender or sharpen financial and non-financial risks, and bring about potential risks and considerations related to the protection of financial consumers and investors (i.e. the risks of biased, unfair or discriminatory consumer results, or concerns relating to data usage and management). Therefore, this research paper attempts to answer the following question: Why is the deployment of artificial intelligence in the field of finance closely related to policy makers and regulatory frameworks?

The lack and difficulty to explain AI model's operations could lead to potential systemic and pro-cyclical risks in the markets, and could lead to a potential misalignment with existing internal regulatory and governance supervising bodies, which could challenge the technology-neutral approach adopted in policy making and regulatory frameworks. Although many of these potential risks are not unique to this domain, the use of these technologies can amplify these vulnerabilities due to their complexity, dynamic adaptability and their level of autonomy. This paper attempts to help policy makers and regulators assess the implications of using these new technologies and identify risks and benefits associated with their use. It proposes policy responses and pro-active regulatory directions aimed at supporting AI innovation in finance and at the same time ensuring that its use is compatible with guaranteeing financial stability, market integrity and fair competition, while at the same time ensuring the protection of financial consumers and investors. The risks arising from the deployment of AI technologies must be identified and mitigated in order to support and enhance the use of responsible AI. Requirements related to today's regulatory and supervisory framework may need to be revised and modified at times, as appropriate and needed, to address and deal with some of the observed incompatibilities of existing policies and regulatory frameworks with AI applications.

Accordingly, using a descriptive analytical approach, the research paper, in its first part, deals with the applications of artificial intelligence, for the sake of simplification and concise explanation, in both asset management and investment portfolios, credit brokerage and creditworthiness rating, in addition to the integration of artificial intelligence in blockchain-based financial products. The second part deals with the potential risks associated with these applications in the field of finance and the modern banking industry. Then the research paper concludes with a final part that suggests recommendations for policy makers and regulators in order to support and enhance the use of responsible AI in finance.

2. Artificial intelligence applications and their benefits in finance and the modern banking industry

Based on the ability of machine learning models to identify signals and capture important interaction and correlations in big data, as well as improve workflow and risk management, AI techniques are being applied in asset management and market buying activities for asset allocation and stock selection. AI technologies may be reserved for large asset managers or institutional investors with the ability and resources to invest in such technologies. AI models in lending can lower the cost of credit underwriting and promote the extension of credit to “thin filed customers whose files and accounts do not give a clear picture of the borrower,” potentially enhancing financial inclusion. Using AI can create data processing efficiencies to assess the creditworthiness of potential borrowers, optimize underwriting decision-making and enhance lending portfolio management. It could also allow the provision of credit scoring to "non-graded" customers with limited credit history, support real economy financing SMEs (Small and Medium Enterprises) and possibly enhance financial inclusion for populations struggling on the creditworthiness side (underbanked parts of the population). The use of AI technologies in blockchain-based finance can advance latent efficiency gains in systems based on distributed ledger technologies (DLT) and improve the scope and functions of smart contracts. This is done by increasing smart contracts’ autonomy, which allows the underlying code to be modified dynamically in response to market conditions. However, this combination of AI in DLT systems can also introduce, if not magnify, challenges to traditional AI-based financial products, such as the lack of explainability of AI decision-making mechanisms and the difficulty of monitoring these AI based networks and systems. Currently, AI is mostly used to manage smart contract risks, to identify defects in the code. However, it has to be noted that smart contracts have been around long before the introduction of AI applications and are based on simple code. And today, most smart contracts used are not physically related to AI technologies, and many of the proposed benefits of using AI in DLT systems are still at their theoretical stage at this point.

2.1 Asset management (portfolio allocation)

With improving customer experience as its ultimate goal, AI and ML use in asset management can achieve the strengthening of risk management, enhancement of performance while increasing the efficiency and accuracy of operational workflows (Blackrock, 2019 and Deloitte, 2019). Natural Language Generation (NLG), a subtype of artificial intelligence, has the capacity to "humanize" and simplify data analysis for financial advisors to report for their clients (Gould, 2016), the fact that ML models are capable of monitoring thousands of risk factors and test portfolio performance against thousands of market/economic scenarios, gives this technology a capacity to enhance risk management for asset managers and other large institutional investors. Moreover, the use of AI can significantly lower back-office costs for investment managers, and offset extensive manual reconciliations with automated ones, which would contribute to lower costs and increased speed. Depending on the type of AI technology used, feeding ML models with big data would give asset managers all sorts of recommendations relevant to decision-making on portfolio allocation and/or stock selection. Big data has replaced traditional data sets or packages, which is now easily available to all investors and used by asset managers to gain insights into the investment process. When talking about the investment community, information has always been of the essence and data has been the bedrock of many investment strategies. And although structured data has been at the core of these “traditional” strategies, the emergence of massive amounts of raw or unstructured/semi-structured data now promises to provide a new informational advantage for investors who are employing artificial intelligence to implement their strategies. Artificial intelligence allows asset managers to digest enormous amounts of data from numerous sources and derive insights to inform their strategies in extremely short time frames. Investment hedge funds are at the forefront of FinTech (Financial Technology) users, and take advantage of the use of big data, AI and ML algorithms for transaction execution as well as back office functions and tasks (Kaal, 2019). A class of hedge funds "AI pure play" has emerged in recent years which are entirely AI and ML based, like Aidiyia Holdings and Cerebellum Capital (BNY Mellon, 2019). Regarding forecasting performance, there is clear evidence that ML models outperform traditional or classical forecasts of macroeconomic indicators (Kalamara et al., 2020). In fact, this advantage is more pronounced during periods of economic stress when we can say that forecasts are most important. There is also evidence for the outperformance of AI-driven techniques when it comes to identifying meaningful but previously unknown correlates in financial crisis patterns, as ML models prove to be superior to logistic regression in out-of-sample predictions models

(Bluwstein et al., 2020).

2.2 Credit intermediation and creditworthiness assessment

Banks and FinTech lenders are turning to Models based on artificial intelligence and big data to assess the creditworthiness of potential borrowers and make underwriting decisions, both functions pivotal in finance. In the context of credit assessment and scoring, ML models are used to predict borrower defaults with superior predictive accuracy compared to standard statistical models, especially when working with limited information (Albanesi and Vamossy, 2019). In addition, financial intermediaries use artificial intelligence-based systems to detect fraud, as well as to analyze the degree of interdependence among borrowers, which in turn contributes to an optimized management of their lending portfolio. The availability of big data and advanced analytics models based on artificial intelligence has changed the way credit risk is assessed. AI-powered credit scoring and scoring models combine the use of traditional credit information, when available, with big data that is not intuitively related to creditworthiness (such as social media data, digital fingerprints, and transaction data accessible through open banking initiatives). Adopting AI models for credit assessment can lower the cost of underwriting, while allowing analysis of the creditworthiness of customers with limited credit history “thin files”. Thus, scaling up and extending credit to companies that are viable and have no means to prove their viability through tangible collateral assets or historical performance data, this would enhance access to credit and support the growth of the real economy by easing restrictions on financing Small and medium enterprises. The empirical analysis of the short period, and relatively recent, of these SMEs can reduce the need for collateral by relatively eliminating the prevalent information asymmetry (BIS, 2020). Despite the above, AI-based credit scoring and rating models lack the testing over longer credit cycles or in a market slide, and there is limited empirical support (critical empirical research) regarding the benefits and role of ML-driven technologies in achieving financial inclusion. For example, while some analyses suggest that using ML models to assess credit risk leads to cheaper (inexpensive) access to credit only for a certain group of a certain ethnicity (Fuster et al., 2017), others find that rules for lending decisions which are based on predictive ML help reduce racial bias (Dobbie et al., 2018).

2.3 Integrating AI into blockchain-based financial products

In recent years, applications of distributed ledger technologies (DLT) (like blockchain) have spread across many fields and industries primarily in modern finance and banking. This astonishing rapid growth of blockchain-based applications stems from the benefits of efficiency, speed and transparency offered by these technologies, driven by automation and reduced use of intermediaries (OECD, 2020). This trend of use of DLTs in finance was triggered by efforts to increase efficiencies by reducing the use of intermediaries, including stock exchanges; Payments (CBDC and fiat-backed stablecoins); and tokenisation of assets more broadly, which may lead to a reconfiguration of roles and business models for financial managers. The most remarkable impact from integrating AI technologies into blockchain-based systems may be prominent in smart contract applications, with a practical impact on the governance and risk management of these contracts with many hypothetical (and untested) influences on the roles and operations of DLT-based networks. In theory, using AI could spawn self-organizing DLT chains that would operate on a completely independent basis. Smart contracts (OECD, 2019) are merely applications that are built and run across the blockchain, which consist of self-executing contracts written as code (a token system) on blockchain ledgers, they are executed in an automatic manner upon pre-defined events written in the code. Integrating AI into blockchains can support decentralized applications in DeFi (Decentralized finance) through use cases that increase automation and efficiency in the provision of certain financial services. As a guide, the introduction of AI models can support the provision of customized/personalized recommendations about products and services; assessment of creditworthiness based on users' online data; trading on the basis of financial statements; and investment advisory services (Ziqi Chen et al., 2020). Just like in other blockchain-based financial applications, deploying AI in DeFi may increase the capabilities of the DLT use-case by providing additional functionality, however, it may not fundamentally impact any of the business models associated with DeFi applications. AI and Big Data can be used to invest based on ESG indicators to (a) evaluate company data; (b) evaluate non-company data; and (c) assessment of the consistency and comparability of the ratings to understand the motives behind the ratings. The claimed benefit of AI is that it should be able to contribute to a better informed decision making by reducing cognitive biases and subjectivity that may be related to traditional analysis, reducing ambiguity in ESG data and making use of unstructured data. Looking at empirical evidence for AI-powered alternative ESG ratings suggests that there are significant advantages over traditional approaches, including the use of rigorous real-time analytics, higher levels of standardization and a more open and transparent aggregation process (Hughes, Urban and Wójcik, 2021). However, these methods are unlikely to replace traditional models in the future. Alternatively, it can complement traditional approaches to ESG ratings, and also inform investors about aspects of undisclosed information to rated entities.

3. Challenges and main risks

The widespread use of artificial intelligence in finance can magnify the risks that already exist due to their ability to learn and dynamically adapt to evolving conditions in a completely independent manner, which will lead to the emergence of new challenges and dominant risks. In terms of data, AI applications can also create an important source of non-financial risks and challenges related to the quality of the data used; electronic security; data privacy and confidentiality and considerations of non-discrimination and fairness. Depending on how they are used, AI methods can either contribute to avoiding discrimination based on human interactions, or intensify biases, unfair treatment and discrimination in financial services. AI bias and discrimination can result from the use of poor quality, defective, or insufficient data in ML models, or unintentionally through inference and authorization (for example, inferring gender by looking at purchasing activity data) (White & Case, 2017). On top of the financial consumer protection considerations, there are potential issues concerning competition that may arise from the use of big data and ML models, with respect to high concentration among market providers in certain markets or increased risks of tacit and silent collusion. The most well-known challenge to machine learning models is the ambiguity surrounding understanding why and how the model generates results, generally described by the term "explainability" associated with a number of important risks. The inability to interpret and explain is not compatible with current laws, regulations and policies, but also with the internal governance, risk management and control frameworks of financial service providers (Gensler and Bailey, 2020). This limits users' ability to understand how their models affect markets or contribute to market shocks, and can amplify systemic risks related to pro-cyclicality. Most importantly, the lack of ability to adjust strategies in times of stress may exacerbate market volatility and bouts of illiquidity during periods of stress and acute stress, exacerbating flash crash events. Practitioners in financial markets who use AI-enabled models should continue efforts to improve the explainability of such models so that they can better understand their behavior in normal market conditions and in times of stress, and manage the risks associated with them. The technology-neutral approach applied by many legal systems (legislations) to regulate financial market products may be challenged by the increasing complexity of some innovative use cases for AI in finance (Federal Reserve, 2011) (EBA, 2020). Potential disagreements and conflicts with current legal and regulatory frameworks may emerge from the use of advanced AI techniques (for example, due to the lack of explainability or adaptability of deep learning models). Furthermore, there may be a potential risk of fragmentation of the regulatory framework in relation to AI at the national, international and sectoral level. In addition to the current regulations that apply to AI models and systems, many published AI principles, guidelines, and best practices have been developed in recent years. Although the industry considers all of these to be valuable in addressing potential risks, opinions differ about the possibility of incorporating them into reality and practice (Bank of England and FCA, 2020). That is why clear governance frameworks that define clear lines of responsibility for AI-based systems throughout their lifecycle, from development to deployment, can enhance the model's existing governance arrangements and frameworks. Clear accountability mechanisms are also becoming increasingly important, as AI models are deployed in critical or high-value decision-making use cases (such as access to credit) (European Commission, 2020). Risks also arise with regards to outsourcing AI to third parties, both in terms of accountability and in terms of competitive dynamics (such as concentration risk and dependency risk). The financial industry's application of AI may also lead to potentially significant job losses across the industry, giving rise to employment challenges. Accordingly, there will be a need to enhance skill sets to develop and manage risks arising from AI. When AI applications become prevalent in finance, AI in finance should be seen as a technology that augments rather than replaces human capabilities. A combination of “man and machine” in which AI contributes to rather than replaces human judgment (helping with decision-making rather than taking charge of decision-making), can allow the benefits of technology to be realized, while maintaining safeguards of accountability and oversight in relation to final decision-making.

The abovementioned risks can be summarized as follows:

a. Non-financial risk (data, equity and fairness)

• Discriminatory outcomes due to biases or unfair treatment (misuse of data or/or poor quality data).

• Data privacy and confidentiality.

b. Explanation “Explainability”

• The how and why models generate results.

• No way to adjust strategies in a time of stress which exposes us to systemic risk amplification, pro-cyclicality.

• Not compliant with regulatory frameworks and defies internal governance

• Difficult to moderate and supervise AI/ models.ML

c. Strength “Robustness” and resilience

• Unintended consequences at the company/market level.

• Model overfits, deviations and drifts (data, concept of drifts).

• Interpretation of correlation as causation, this requires human involvement.

d. Governance and Accountability

• Arrangements and settings of the governance model

- Accountability and limits of responsibility
- Outsourced infrastructure models

e. Policy and regulatory frameworks

- The complexity of AI challenges to the neutral approach to technology (eg, explainability and self-learning)
- Potential inconsistencies with existing legal/regulatory frameworks
- Risks of fragmentation of policies and legal frameworks (across sectors)
- Skills and Employment

4. Suggestions and recommendations

Policy makers along with regulators play a key part in ensuring that the deployment of AI in finance is in line with regulatory objectives to enhance financial stability, protect financial consumers, and enhance market integrity and competition. They should strive to support AI innovation in the sector while working to protect financial consumers and investors and promote fair, orderly and transparent markets. Accordingly, the application of regulatory and supervisory requirements to artificial intelligence techniques can be considered within a contextual and proportional framework. The European Union, for example, is studying requirements related to documentation of disclosure of programming methodologies, training, processes used to build, test and validate AI systems, including algorithm documentation. Additionally, human supervision may be required starting from product design phase and throughout its life cycle (European Commission, 2020). Policy makers should consider urging financial sector companies to increase their focus on better data management, with the aim of enhancing consumer protection through AI applications in finance. Policy makers should prioritize imposing disclosure requirements about the use of AI technologies in the provision of financial services that may affect client outcomes. Those responsible for regulatory and legal frameworks should consider how to tackle the perceived conundrum of a potential misalignment of explainability in AI and current laws and regulations. Regulators and policy makers should also consider making explicit model governance frameworks a requirement and put an emphasis on accountability as means to help build trust in AI-driven systems. Providing increased guarantees by financial firms about the robustness and resilience of AI models is essential as policy makers seek to guard against the buildup of systemic risks, which will help AI applications in finance gain trust and confidence. Regulators must consider promoting continuous monitoring and validation of AI models, which are central to their risks, as one of the most effective ways to enhance model resilience, prevent and address model drifts or deviations. Appropriate focus can be placed on human primacy in decision-making when it comes to use cases of higher value and importance, such as lending decisions that significantly affect consumers. Policy makers and regulators should take into account the increasing technical sophistication of AI, and whether resources are needed to keep pace with advances in technology.

There have been attempts and efforts to supervise and regulate AI uses in finance, in May 2019, the OECD released a set of principles for AI focusing on how governments can formulate a people-centred approach to a trustworthy AI, and aiming to promote the use of AI in a way that is innovative, trustworthy, and respectful of human rights. In 2020, the European Commission released a technical book containing policy and regulatory options for an 'Artificial Intelligence Ecosystem of Excellence and Trust'. On April 21, 2021, the European Commission published a proposal for a regulation aimed at addressing the risks of artificial intelligence and establishing harmonized rules on the use of artificial intelligence across its sectors of activity, while also proposing the creation of a European Council on Artificial Intelligence (European Commission, 2021). There have been initiatives at the national level too. In 2018, the French ACPR established a working group comprising professionals from the financial industry (business associations, banks, insurance companies, the financial technology sector and public authorities to discuss the current and potential uses of artificial intelligence in the financial industry, the opportunities and risks associated with them, as well as Challenges Facing Supervisors (ACPR, 2018) The Bank of England and the Financial Conduct Authority launched the Public and Private AI Forum in 2019. The Russian Federation enacted a National Strategy for the Development of AI in 2019, and a concept for the development of the regulatory framework for AI and robotics technologies in 2020.

5. CONCLUSION

The COVID-19 crisis has put the digitization trend on high speed compared to the observed period before the pandemic, including the use of artificial intelligence. Global spending on artificial intelligence is expected to double during the period from 2020 to 2024, growing from $50 billion in 2020 to more than from 110 billion US dollars in 2024 (IDC, 2020). The deployment of artificial intelligence in the modern finance and banking industry, in areas such as blockchain-based financial services, creditworthiness assessment, asset management and credit underwriting, is made possible by the availability of big data and increased and affordable computing power. This research paper attempted to contribute to clarifying and simplifying the operating modes of artificial intelligence applications in some of the most important areas of modern finance and banking industry, while highlighting the role of these applications in increasing the competitive advantages of financial companies, through two main ways: (a) By improving the efficiency of companies through cost reduction and productivity enhancement (which increases the volume of financial investments), and thus increasing profitability; and (b) by improving the quality of financial services and products. However, there are potential risks that have been discussed and detailed in order to find ways and means (policies, regulatory and legal frameworks) to manage and deal with these risks proactively.

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