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Executive Summary Artificial intelligence (AI) in finance

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Artificial intelligence (AI) systems are machine-based systems that can make predictions, suggestions, or decisions for a given set of human-defined objectives. They vary in autonomy. Massive volumes of data analytics and alternative data sources, sometimes known as "big data," are being used more and more in AI techniques. These types of data feed machine learning (ML) models, which employ them to automatically learn from experience and data and enhance predictability and performance without the need for human programming.

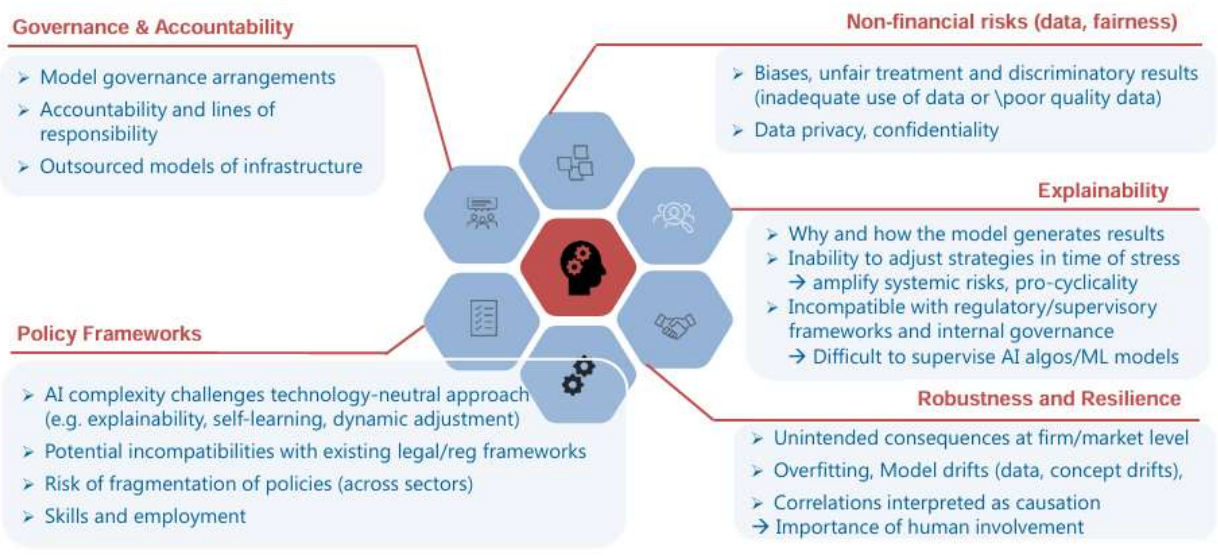
The COVID-19 pandemic has exacerbated and expedited the pre-pandemic trend toward digitalization, particularly in the area of artificial intelligence (AI). According to IDC's 2020[1] prediction, global spending on AI is expected to double between 2020 and 2024, from USD50 billion in 2020 to over USD110 billion. The growing use of AI in finance is made possible by the wealth of data that is available as well as increasingly accessible and reasonably priced processing power in sectors including asset management, algorithmic trading, credit underwriting, and blockchain-based financial services.

It is anticipated that the use of AI in finance will give financial institutions a greater competitive edge through two main channels: (a) increasing the firms' productivity and efficiency through cost reduction, which will increase profitability (e.g., enhanced decision-making processes, automated execution, gains from improvements in risk management and regulatory compliance, back-office and other process optimization); and (b) improving the quality of financial services and products offered to customers, which will result in higher profits (e.g. new product offering, high customisation of products and services). Financial consumers may profit from this competitive edge in two ways: either by lower prices or by better products with more alternatives, personalization, and diversity.

Why is the deployment of AI in finance relevant to policy makers

Applications of AI in finance have the ability to increase or generate hazards related to money and non-money matters. They can also raise issues with investor and consumer protection. With the potential for pro-cyclicality and systemic risk in the markets, along with the inexplicability and interpretability of AI model processes, the deployment of AI increases risks that could compromise the safety and soundness of a financial institution. The complexity of comprehending the model's output could potentially lead to conflicts with current internal governance and financial supervisory systems, and it might even put the technology-neutral approach to policymaking in jeopardy. Certain dangers related to consumer protection may arise from AI, including worries about data management and usage as well as the possibility of biased, unfair, or discriminatory consumer results. Many of the potential risks related to artificial intelligence (AI) in finance are not specific to AI; however, given the complexity of the techniques used, the dynamic adaptability of AI-based models, and their degree of autonomy for the most sophisticated AI applications, the use of AI could magnify such vulnerabilities.

Figure 1. Relevant issues and risks stemming from the deployment of AI in finance



How is AI affecting parts of the financial markets?

Artificial intelligence (AI) techniques are used in asset management and the buy-side activity of the market for risk management, operational workflow optimization, and asset allocation and stock selection based on ML models' capacity to recognize signals and capture underlying relationships in big data.

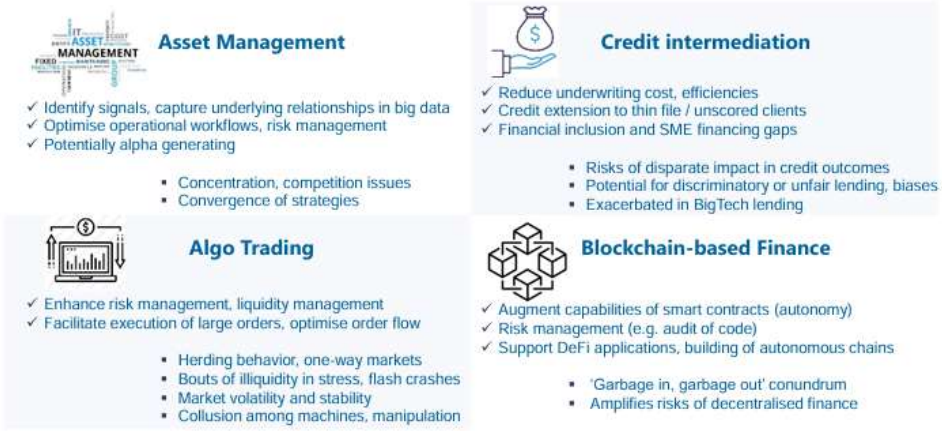
Larger asset managers or institutional investors with the financial means to invest in such technologies may be the only ones able to employ AI techniques.

Artificial intelligence (AI) in trading introduces a new level of complexity to traditional algorithmic trading since the algorithms learn from data inputs and develop dynamically into computer-programmed algorithms (algos) that can recognize and carry out deals without the need for human participation. AI algorithms can improve liquidity management and the execution of big orders in highly digitized markets, such the FX and equity markets, with little influence on the market. This is achieved by dynamically optimizing order size, duration, and size based on market conditions. To improve efficiency and expedite execution, traders can also use AI for order flow management and risk management.

Like with non-AI models and algos, a high number of finance practitioners using the same ML models may lead to herding behavior and one-way markets, which could increase threats to the system's stability and liquidity, especially during stressful periods. While AI algo trading might boost liquidity in regular circumstances, it can also cause convergence, which can result in periods of illiquidity under stressful situations and flash collapses. Market volatility may rise if significant purchases or sells are made at the same time, creating new points of vulnerability. Sharp price movements may result from self-reinforcing feedback loops, which are risked when trading techniques converge. Because cybercriminals may more easily sway agents to operate in the same way, this convergence also raises the risk of cyberattacks. All forms of algorithmic trading carry the aforementioned hazards; however, the introduction of artificial intelligence (AI) increases these risks due to AI's capacity to learn and adapt dynamically and totally autonomously to changing situations. For example, AI models may notice signals and learn the impact of herding, altering their behaviour and learning to front run depending on the earliest of signals. The scale of complexity and difficulty in explaining and reproducing the decision mechanism of AI algos and models makes it challenging to mitigate these risks.

Artificial intelligence (AI) techniques have the potential to worsen illicit trading activities that try to manipulate markets and make it harder for supervisors to spot instances of machine collusion. It is possible to reach a collusive outcome without human intervention or even user awareness thanks to the dynamic adaptive capacity of self-learning and deep learning AI models. These models are capable of recognising mutual interdependencies and adapting to the behaviour and actions of other market participants or other AI models.

Figure 2. Impact of AI on business models and activity in the financial sector



By lowering credit underwriting costs and making it easier to extend credit to "thin file" consumers, artificial intelligence (AI) models in lending may help advance financial inclusion. Artificial intelligence (AI) has the potential to improve underwriting decision-making, streamline data processing for the evaluation of potential borrowers' creditworthiness, and strengthen loan portfolio management. Additionally, it may make credit ratings available to "unscored" consumers with sparse credit histories, assisting in the funding of SMEs and maybe encouraging underbanked populations to become financially included.

AI-based models have a lot of potential, but there are also hazards associated with them. These include the possibility of prejudiced, discriminatory, or unfair lending practices, as well as the use of incomplete data (such as that related to gender or ethnicity) in lending. AI-driven models not only unintentionally create or reinforce prejudices, but they also make it more difficult to identify discrimination in credit allocation and make it challenging to understand and explain model outputs to rejected applicants. These difficulties are made worse by the credit that BigTech extends because of their ability to access enormous amounts of client data, which raises concerns about potential anti-competitive behavior and market concentration in the technology sector of service delivery (such as cloud computing).

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management and code defect detection. However, it should be highlighted that smart contracts, which rely on straightforward software code, have been around for much longer than AI applications. Many of the proposed advantages of using AI in DLT systems are still theoretical at this point, and the majority of smart contracts that are used in a meaningful way today have nothing to do with AI approaches.

Future decentralized applications in decentralized finance (or "DeFi") may be supported by AI. Examples include automated credit rating based on user internet data, trading and investment advising services based on financial data, and insurance underwriting. Fully autonomous chains might theoretically be created using AI-based smart contracts that are self-learned1 and dynamically adjust without the need for human involvement. The adoption of AI could facilitate further disintermediation by replacing off-chain third-party sources of information with AI inference directly on-chain. It should be highlighted, nevertheless, that issues with low-quality or insufficient data inputs seen in blockchain-based systems, as well as the garbage in, garbage out dilemma, may not always be solved by AI-based systems. Depending on the magnitude of the DeFi market, this in turn creates serious concerns for investors, market integrity, and system stability. AI has the potential to increase the many dangers seen in DeFi marketplaces and complicate already difficult-to-manage autonomous DeFi networks in the absence of a single regulatory entry point or oversight frameworks that facilitate accountability and compliance.

Key overriding risks and challenges, and possible mitigating actions

AI's application in finance has the potential to create new, significant risks and issues while also amplifying existing ones in the financial markets due to its capacity to learn and adapt dynamically and totally autonomously to changing situations. Risks already exist when data is used insufficiently or of low quality, which can lead to biases and discriminatory outcomes that would eventually hurt financial customers. The investment requirements of AI techniques may result in concentration risks and associated competitive issues, perhaps creating a reliance on a small number of dominant competitors. Market integrity and compliance issues could emerge from the absence of proper model governance that takes into account the specific nature of AI, and from the lack of defined accountability structures. There are risks related to supervision and supervisory systems as well, which may require modifications in light of this new technology. Artificial intelligence (AI)-related novel hazards are associated with the unexpected effects of AI-based models and systems on market integrity and stability. The challenge of comprehending how AI-based algorithms produce results (explainability) leads to significant hazards. A variety of operational hazards associated with these techniques could threaten the financial system's resilience during difficult times, although growing use of AI in finance could also result in enhanced market interconnection.

Big data utilization in AI-powered applications may present a significant non-financial risk due to issues and concerns with data quality, data privacy and confidentiality, cyber security, and fairness considerations. AI techniques have the ability to either strengthen prejudice, unfair treatment, and discrimination in the financial services industry or aid prevent discrimination based on human interactions, depending on how they are applied. AI biases and discrimination can arise via using ML models with low-quality, faulty, or insufficient data, or inadvertently through proxies and inference (e.g., determining a person's gender by examining purchase activity data). Apart from safeguarding consumer interests financially, the utilization of big data and machine learning models may give rise to competition concerns. These concerns may include elevated levels of market provider concentration in specific areas or heightened likelihoods of covert collusions.

The most well-known problem with machine learning models is their inability to explain how and why they produce the outcomes they do, a problem known as "explainability" and linked to several significant hazards. If supervisors and model users are unable to foresee the potential detrimental effects of the actions guided by machine learning models on the markets, then the extensive use of opaque models may have unexpected repercussions. Any deliberate opaqueness on the part of businesses to safeguard their advantage exacerbates the lack of explainability and raises concerns about the oversight of ML and AI models as well as the flexibility of users to modify their tactics in response to unsatisfactory performance or stressful situations.

Explainability is incompatible not just with the internal governance, risk management, and control systems of financial service providers, but also with the laws and regulations now in place. Users' comprehension of how their models impact markets or contribute to market shocks is restricted, and it may increase systemic risks associated with pro-cyclicality. Crucially, users' incapacity to modify their strategies under pressure could aggravate flash crash-like situations by increasing market volatility and illiquidity during times of extreme stress. The problems with explainability are exacerbated by a widespread deficiency in technical literacy and by the incompatibility between the complexity inherent in AI models and the requirements of human-scale interpretation and reasoning that correspond with human cognition. Regulatory challenges in terms of transparency and auditing of such models in many financial services use cases.

In order to better understand the behavior of AI-powered models in both calm and turbulent market settings and to effectively manage the risks involved, financial market practitioners must continue to work toward improving these models' explainability. Depending on the kind of AI employed, opinions on the maximum explainability that may be attained in AI-driven models vary. It will be necessary to strike a delicate balance between the model's predictability and interpretability. Requirements for

disclosure about the usage of AI-powered models and processes should assist reduce explainability issues and give consumers more comfort and confidence when utilizing AI-driven services.

To guarantee that AI systems operate in a reliable and resilient manner, potential risks need to be continuously evaluated and controlled. Carefully training and retraining machine learning (ML) models using datasets big enough to capture non-linear correlations and tail events in the data (including manufactured ones) can strengthen the robustness of AI systems. Throughout their lives, AI models must be continuously monitored, tested, and validated. This is necessary to detect and address "model drifts," or concept or data drifts, which might impair the model's predictive ability. When tail events, like the COVID-19 crisis, cause discontinuity in the datasets, such model drifts occur and are nearly impossible to correct because the data employed does not reflect them. The role of human judgement is crucial at all phases of AI deployment, from input of datasets to review of model outputs, and can help prevent the risk of interpreting meaningless correlations detected from patterns in activity as causative linkages. In the event that AI-based systems stop serving their intended purpose, automated control mechanisms, also known as "kill switches," can be used as a last resort to quickly shut them down. However, this approach is also less than ideal because it introduces operational risk and guarantees a lack of resilience in situations where the primary business system must be shut down when the financial system is under stress.

To reinforce current model governance arrangements, explicit governance frameworks that define distinct responsibilities for AI-based systems at every stage of their development and implementation should be implemented. Internal model governance committees or model review boards of financial services providers are responsible with the creation of model governance rules and methods for model building, documentation, and validation for any time of model. With the increased use of AI by financial institutions, such boards are anticipated to proliferate. They may also undergo a "upgrading" of their responsibilities and duties, as well as modifications to certain procedures to account for the complexity of AI-based models (e.g., frequency of model validation).

The importance of transparent accountability measures is growing as AI models are used in high-value decision-making use cases (such as loan access). Additionally, there are risks associated with outsourcing AI approaches to outside parties, including those related to responsibility and competitive dynamics (such as concentration and dependency risks). The act of outsourcing AI models or infrastructure can potentially result in vulnerabilities linked to heightened market positional convergence risk. These vulnerabilities may in turn cause herding behavior and convergence in trading strategies, as well as the possibility of a significant portion of the market being impacted simultaneously. Ultimately, this could lead to periods of illiquidity during stressful times.

The increasing intricacy of certain creative applications of artificial intelligence in finance may pose a threat to the technology-neutral approach that many governments employ to regulate financial market goods. The application of cutting-edge AI techniques may result in potential contradictions with the current legal and regulatory frameworks (e.g. given the lack of explainability or the adaptive nature of deep learning models). Furthermore, there could be a chance that national, international, and sector-specific laws pertaining to AI will become fragmented.

As AI applications become more commonplace in finance, skill sets for developing and managing new risks from AI will need to be strengthened. The financial industry's use of AI could lead to a large number of job losses inside the sector, creating employment difficulties.

AI in finance ought to be viewed as a tool that enhances rather than replaces human expertise. The benefits of the technology could be realized while preserving controls over accountability and final decision-making in a "human and machine" combination where AI informs human judgment rather than replaces it (decision-aid instead of decision-maker). Human primacy in decision-making may need to be appropriately emphasized, especially for higher-value use cases (loan decisions, for example).

Policy considerations

The application of AI in finance must be compliant with regulatory goals of fostering financial stability, safeguarding financial customers, and fostering competition and market integrity. This is the responsibility of policy makers and regulators. In addition to safeguarding investors and financial consumers, policymakers should think about fostering fair, transparent, and orderly markets and encouraging AI innovation in the industry. To encourage and facilitate the application of responsible AI, emerging hazards resulting from the application of AI techniques must be recognized and addressed. It might be necessary to clarify and modify current regulatory and supervisory requirements as needed to overcome some of the apparent incompatibilities of current arrangements with AI applications.

A contextual and proportionate framework could be used to examine the application of regulatory and supervisory requirements on AI techniques, depending on the importance of the application and its potential to affect consumer outcomes and market functioning. This should promote the application of AI without unduly inhibiting creativity. However, the protection of investors and financial consumers,

as well as basic prudential and stability measures, are all important policy makers' tasks and should not be compromised by adopting proportionality.

Policy makers should consider intensifying their attention on greater data governance by financial sector enterprises, aiming to reinforce consumer protection across AI applications in finance. Considerations for specific requirements or best practices for data management in AI-based techniques could include things like data quality, the suitability of the dataset for the intended use of the AI model, and safety measures that guarantee the model's resilience in terms of avoiding potential biases. Two examples of best practices to reduce discrimination risks include appropriate sense checking of model results against baseline datasets and additional tests based on whether protected classes may be deduced from other qualities in the data. Authorities may take into consideration imposing more restrictions on the usage of personal data as well as providing opt-out choices.

Legislators ought to take into account the need for disclosure about the application of AI strategies in the rendering of financial services and the potential effects on client outcomes. To enable them to choose wisely among competing products, financial consumers should be aware of the usage of AI techniques in product delivery as well as the possibility of interacting with an AI system rather than a human being. Such disclosure should contain precise details on the AI system's capabilities and limits. Authorities should take into account the creation of appropriateness requirements for AI-driven financial services in order to assist enterprises in determining if potential clients possess a thorough awareness of how the usage of AI impacts product delivery.

Regulators ought to think about how to get beyond the perception that the laws and regulations now in place are incompatible with AI's seeming lack of explainability. The frameworks that financial services businesses now use for model governance and risk management may need to be updated and/or adjusted. in order to deal with the issues that the application of AI-based models raises. Supervisors may want to look into more technical methods of managing risk, such as adversarial model stress testing or outcome-based metrics (Gensler and Bailey, 2020[2]). The supervisory focus could be shifted from documentation of the development process and the process by which the model arrives at its prediction to model behavior and outcomes.

To foster trust in AI-driven systems, policy makers ought to think about mandating transparent model governance frameworks and responsibility attribution. Financial services providers could enhance current arrangements for AI-related operations by implementing explicit governance frameworks that clearly define roles and responsibilities for developing and managing AI-based systems from

conception to implementation. Internal model governance frameworks might be modified to properly account for risks arising from the application of AI, as well as to include consumer-intended results along with an evaluation of if and how these outcomes are achieved through the usage of AI technology. Supervisors' ability to monitor such activities may be aided by the aforesaid processes having sufficient documentation and audit trails.

In order to enable AI applications in finance gain trust, financial institutions should provide greater assurance about the robustness and resilience of AI models. This is because policy makers are trying to prevent the accumulation of systemic hazards. In order to guard against systemic risks and vulnerabilities that can appear during stressful times, models' performance needs to be evaluated in the most adverse market situations. Although they expose the company to new operational risks, the adoption of automatic control mechanisms (like kill switches) that set off models or initiate alerts under stressful situations may help reduce hazards.

Business continuity should be guaranteed by backup plans, models, and procedures in the event that the models malfunction or behave unexpectedly. Moreover, if banks were to calculate risk weights or capital using AI algorithms, regulators might take into account minimal or add-on buffers (Gensler and Bailey, 2020[2]).

To make sure that ML model-based decision-making is working as planned and in accordance with relevant laws and regulations, frameworks for suitable training, retraining, and rigorous testing of AI models could be developed and/or strengthened. To increase the dependability of these models during unforeseen crises, training datasets must be sufficiently big to capture non-linear correlations and tail events in the data, even if they are synthetic. Model drifts must be found and corrected, and this requires ongoing testing of ML models.

Human primacy in decision making might be appropriately emphasized when it comes to higher-value use cases, like loan decisions, which have a big impact on customers. Authorities ought to think about implementing procedures that let clients contest the results of AI models and seek remedies could also aid in increasing public confidence in these systems. One example of such a policy is the GDPR, which grants people the right "to obtain human intervention" and the opportunity to voice their opinions in the event that they disagree with an algorithm's conclusion (EU, 2016[3]).

The growing technological complexity of AI and the question of whether resources will need to be allocated to stay up with technological advancements could be taken into consideration by policy makers. The usage of AI has created new kinds of hazards and transformed several financial market activity; as a result, governmental priorities have increased in the last few years. Research and skill development for those involved in the finance sector as well as law enforcement agencies should receive funding.

The role of policy makers is vital in fostering innovation in the sector while ensuring that financial consumers and investors are appropriately protected and the marketplaces around such products and services remain fair, orderly and transparent. Policymakers ought to think about bolstering their current defenses against threats brought on by or intensified by the usage of AI. Fostering trust and confidence and encouraging the use of such cutting-edge methods can be achieved by open communication about the usage of AI and the security measures put in place to secure the system and its users. Given how simple it is to provide financial services across borders, policymakers and business may engage in a transdisciplinary conversation at both the national and international levels.