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Artificial intelligence and machine learning in financial services

Market developments and financial stability implications

1 November 2017

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Executive Summary

Artificial intelligence (AI) and machine learning are being rapidly adopted for a range of applications in the financial services industry. As such, it is important to begin considering the financial stability implications of such uses. Because uses of this technology in finance are in a nascent and rapidly evolving phase, and data on usage are largely unavailable, any analysis must be necessarily preliminary, and developments in this area should be monitored closely.

Many applications, or "use cases", of AI and machine learning already exist. The adoption of these use cases has been driven by both supply factors, such as technological advances and the availability of financial sector data and infrastructure, and by demand factors, such as profitability needs, competition with other firms, and the demands of financial regulation. Some of the current and potential use cases of AI and machine learning include:

- Financial institutions and vendors are using AI and machine learning methods to assess credit quality, to price and market insurance contracts, and to automate client interaction.
- Institutions are optimising scarce capital with AI and machine learning techniques, as well as back-testing models and analysing the market impact of trading large positions.
- Hedge funds, broker-dealers, and other firms are using AI and machine learning to find signals for higher (and uncorrelated) returns and optimise trading execution.
- Both public and private sector institutions may use these technologies for regulatory compliance, surveillance, data quality assessment, and fraud detection.

With the FSB FinTech framework,[1] our analysis reveals a number of potential benefits and risks for financial stability that should be monitored as the technology is adopted in the coming years and as more data becomes available. In some cases, these observations are also contained in the FSB report on regulatory and supervisory issues around FinTech.[2] They are:

- The more efficient processing of information, for example in credit decisions, financial markets, insurance contracts, and customer interaction, may contribute to a more efficient financial system. The RegTech and SupTech applications of AI and machine learning can help improve regulatory compliance and increase supervisory effectiveness.
- At the same time, network effects and scalability of new technologies may in the future give rise to third-party dependencies. This could in turn lead to the emergence of new systemically important players that could fall outside the regulatory perimeter.
- Applications of AI and machine learning could result in new and unexpected forms of interconnectedness between financial markets and institutions, for instance based on the use by various institutions of previously unrelated data sources.

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[1] FSB (2016), "Fintech: Describing the Landscape and a Framework for Analysis," March [unpublished].

[2] FSB (2017), "*Financial Stability Implications from FinTech, Supervisory and Regulatory Issues that Merit Authorities Attention*," June.

- The lack of interpretability or "auditability" of AI and machine learning methods could become a macro-level risk. Similarly, a widespread use of opaque models may result in unintended consequences.
- As with any new product or service, there are important issues around appropriate risk management and oversight. It will be important to assess uses of AI and machine learning in view of their risks, including adherence to relevant protocols on data privacy, conduct risks, and cybersecurity. Adequate testing and 'training' of tools with unbiased data and feedback mechanisms is important to ensure applications do what they are intended to do.

Overall, AI and machine learning applications show substantial promise if their specific risks are properly managed. The concluding section gives preliminary thoughts on governance and development of models, as well as auditability by institutions and supervisors.

Introduction

This report analyses possible financial stability implications of the use of artificial intelligence (AI) and machine learning in financial services. It was drafted by a team of experts from the FSB Financial Innovation Network (FIN). The report draws on discussions with firms;[3] academic research; public and private sector reports; and ongoing work at FSB member institutions.[4] The report analyses potential financial stability implications of the growing use of AI by financial institutions. Given the relative novelty of many applications, and the paucity of data on adoption, it is necessarily a horizon-scanning piece.

The report is structured as follows. In section 1, the key concepts of the report are defined, and some background is given on the development of AI and machine learning for financial applications. Section 2 describes supply and demand factors driving the adoption of these techniques in financial services. Section 3 describes four sets of use cases: (i) customer-focused applications; (ii) operations-focused uses; (iii) trading and portfolio management; and (iv) regulatory compliance and supervision. Section 4 contains a micro-analysis of the effects of adoption on financial markets, institutions and consumers. Section 5 gives a macro-analysis of effects on the financial system. Finally, section 6 concludes with an assessment of implications for financial stability.

1. Background and definitions

Researchers in computer science and statistics have developed advanced techniques to obtain insights from large disparate data sets. Data may be of different types, from different sources, and of different quality (structured and unstructured data). These techniques can leverage the ability of computers to perform tasks, such as recognising images and processing natural languages, by learning from experience. The application of computational tools to address tasks traditionally requiring human sophistication is broadly termed ‘artificial intelligence’ (AI). As a field, AI has existed for many years. However, recent increases in computing power coupled with increases in the availability and quantity of data have resulted in a resurgence of interest in potential applications of artificial intelligence.[5] These applications are already being used to diagnose diseases, translate languages, and drive cars; and they are increasingly being used in the financial sector as well.

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3 FIN held two workshops on this topic. The first workshop was held on 4 April 2017 in San Francisco. The second workshop was held on 27 June 2017 in Basel. The participants at these workshops included representatives from 7 financial institutions, six artificial intelligence firms, three large tech firms and two industry organisations from North America, Europe and Asia. In addition, drafting team members and the FSB secretariat conducted bilateral conversations with relevant private sector contacts across a range of jurisdictions.

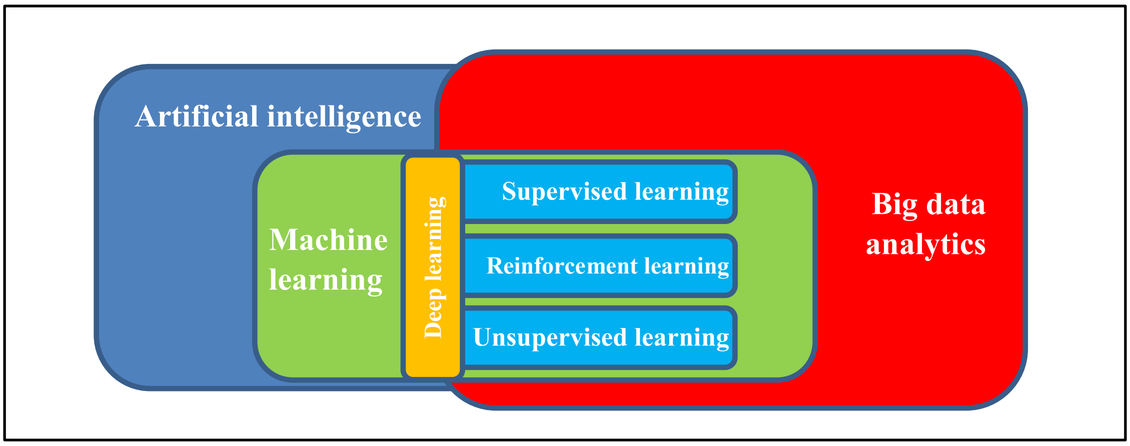
4 The report draws on some examples from specific private firms involved in FinTech. These examples are not exhaustive and do not constitute an endorsement by the FSB for any firm, product or service. Similarly, they do not imply any conclusion about the status of any product or service described under applicable law. Rather, such examples are included for purposes of illustration of new and emerging business models in the markets studied.

5 Various financial regulatory authorities have defined the big data phenomenon as a confluence of factors, including the ubiquitous collection of data from a variety of sources, the plummeting cost of data storage and powerful capacity to analyse data. See, e.g., U.S. Federal Trade Commission Report, January (2016,), “Big Data: A tool for Inclusion or Exclusion?” January, p. 1; EBA, EIOPA and ESMA (2016), “European Joint Committee Discussion Paper on the Use of Big Data by Financial Institutions,” JC 2016 86, p. 7.

There are many terms that are used in describing this field, so some definitions are needed before proceeding. 'Big data' is a term for which there is no single, consistent definition, but the term is used broadly to describe the storage and analysis of large and/or complicated data sets using a variety of techniques including AI.[6] Analysis of such large and complicated datasets is often called 'big data analytics.' A key feature of the complexity relevant in big data sets analytics often relates to the amount of unstructured or semi-structured data contained in the datasets.

This report defines AI as the theory and development of computer systems able to perform tasks that traditionally have required human intelligence. AI is a broad field, of which 'machine learning' is a sub-category.[7] Machine learning may be defined as a method of designing a sequence of actions to solve a problem, known as algorithms,[8] which optimise automatically through experience and with limited or no human intervention.[9] These techniques can be used to find patterns in large amounts of data (big data analytics) from increasingly diverse and innovative sources. Figure 1 gives an overview.

Figure 1: A schematic view of AI, machine learning and big data analytics



Many machine learning tools build on statistical methods that are familiar to most researchers. These include extending linear regression models to deal with potentially millions of inputs, or using statistical techniques to summarise a large dataset for easy visualisation. Yet machine

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6 Jonathan Stuart Ward and Adam Barker (2013), "*Undefined By Data: A Survey of Big Data Definitions*" Cornell University, arXiv:1309.5821.

7 Examples of AI applications that are not machine learning include the computer science fields of ontology management, or the formal naming and defining of terms and relationships by computers, as well as inductive and deductive logic and knowledge representation. In this report, for completeness, we often refer to "AI and machine learning," with the understanding that many of the important recent advances are in the machine learning space.

8 An algorithm may be defined as a set of steps to be performed or rules to be followed to solve a mathematical problem. More recently, the term has been adopted to refer to a process to be followed, often by a computer.

9 Arthur Samuel (1959), "Some Studies in Machine Learning Using the Game of Checkers," IBM Journal: 211-229; Tom Mitchell (1997), *Machine Learning*, New York: McGraw Hill; Michael Jordan and Tom Mitchell (2015), "Machine learning: Trends, perspectives, and prospects," *Science* 349(6245): 255-260. Samuel defined machine learning as the "field of study that gives computers the ability to learn without being explicitly programmed," while Mitchell defines it as the "the question of how to build computers that improve automatically through experience."

learning frameworks are inherently more flexible; patterns detected by machine learning algorithms are not constrained to the linear relationships that tend to dominate economic and financial analysis. In general, machine learning deals with (automated) optimisation, prediction, and categorisation, not with causal inference.[10] In other words, classifying whether the debt of a company will be investment grade or high yield one year from now could be done with machine learning. However, determining what factors have driven the level of bond yields would likely not be done using machine learning.

There are several categories of machine learning algorithms. These categories vary according to the level of human intervention required in labelling the data:

- In 'supervised learning', the algorithm is fed a set of 'training' data that contains labels on some portion of the observations. For instance, a data set of transactions may contain labels on some data points identifying those that are fraudulent and those that are not fraudulent. The algorithm will 'learn' a general rule of classification that it will use to predict the labels for the remaining observations in the data set.
- 'Unsupervised learning' refers to situations where the data provided to the algorithm does not contain labels. The algorithm is asked to detect patterns in the data by identifying clusters of observations that depend on similar underlying characteristics. For example, an unsupervised machine learning algorithm could be set up to look for securities that have characteristics similar to an illiquid security that is hard to price. If it finds an appropriate cluster for the illiquid security, pricing of other securities in the cluster can be used to help price the illiquid security.
- 'Reinforcement learning' falls in between supervised and unsupervised learning. In this case, the algorithm is fed an unlabelled set of data, chooses an action for each data point, and receives feedback (perhaps from a human) that helps the algorithm learn. For instance, reinforcement learning can be used in robotics, game theory, and self-driving cars.[11]
- 'Deep learning' is a form of machine learning that uses algorithms that work in 'layers' inspired by the structure and function of the brain. Deep learning algorithms, whose structure are called artificial neural networks, can be used for supervised, unsupervised, or reinforcement learning.

Recently, deep learning has led to remarkable results in diverse fields, such as image recognition and natural language processing (NLP). Deep learning algorithms are capable of discovering generalisable concepts, such as encoding the concept of a 'car' from a series of images. An investor might deploy an algorithm that recognises cars to count the number of cars in a retail parking lot from a satellite image in order to infer a likely store sales figure for a particular period. NLP allows computers to 'read' and produce written text or, when combined

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[10] Here, prediction is understood as identifying something as likely before the event based on experience. Causal inference and forecasting are done from a scientific perspective on the basis of analysis of the past.

[11] This categorisation of machine learning algorithms is taken from Kolanovic, Marko and Rajesh Krishnamachari (2017), "Big Data and AI Strategies: Machine Learning and Alternative Data Approach to Investing," JP Morgan, May; and Internet Society (2017), "Artificial Intelligence and Machine Learning: Policy Paper," Internet Society White Paper, April.

with voice recognition, to read and produce spoken language. This allows firms to automate financial service functions previously requiring manual intervention.

Machine learning can be applied to different types of problems, such as classification or regression analysis. Classification algorithms, which are far more frequently deployed in practice, group observations into a finite number of categories. Classification algorithms are probability-based, meaning that the outcome is the category for which it finds the highest probability that it belongs to. An example might be to automatically read a sell-side report and label it as 'bullish' or 'bearish' with some probability, or estimate an unrated company's initial credit rating. Regression algorithms, in contrast, estimate the outcome of problems that have an infinite number of solutions (continuous set of possible outcomes). This outcome can be accompanied with a confidence interval. Regression algorithms can be used for the pricing of options. Regression algorithms can also be used as one intermediate step of classification algorithm.

It is important to note what machine learning cannot do, such as determining causality. Generally speaking, machine learning algorithms are used to identify patterns that are correlated with other events or patterns. The patterns that machine learning identifies are merely correlations, some of which are unrecognisable to the human eye. However, AI and machine learning applications are being used increasingly by economists and others to help understand complex relationships, along with other tools and domain expertise.

Many machine learning techniques are hardly new. Indeed, neural networks, the base concept for deep learning, were first developed in the 1960s.[12] However after an initial burst of excitement, machine learning and AI failed to live up to their promises and funding dissipated for over a decade, in part because of the lack of sufficient computing power and data. There was renewed funding and interest in applications in the 1980's, during which many of the research concepts were developed for later breakthroughs.[13]

By 2011 and 2012, driven by the vast increase in the computational power of modern computers, machine learning algorithms, especially deep learning algorithms, began to consistently win image, text, and speech recognition contests. Noticing this trend, major tech companies began to acquire deep learning start-ups and rapidly accelerate deep learning research.[14] Also new is the scale of collection of big data, for example the ability to capture data on the scale of every single credit card transaction or every word on the web, and even 'mouse' hovers over websites. Other advances have also helped, such as increased interconnectedness of information technology resources with cloud computing architecture, with which big data can now be organised and analysed. Using data sets of this size and complexity and with the increase in computing power, machine learning algorithms results have improved, some of which are highlighted in the sections that follow. This has also spurred large

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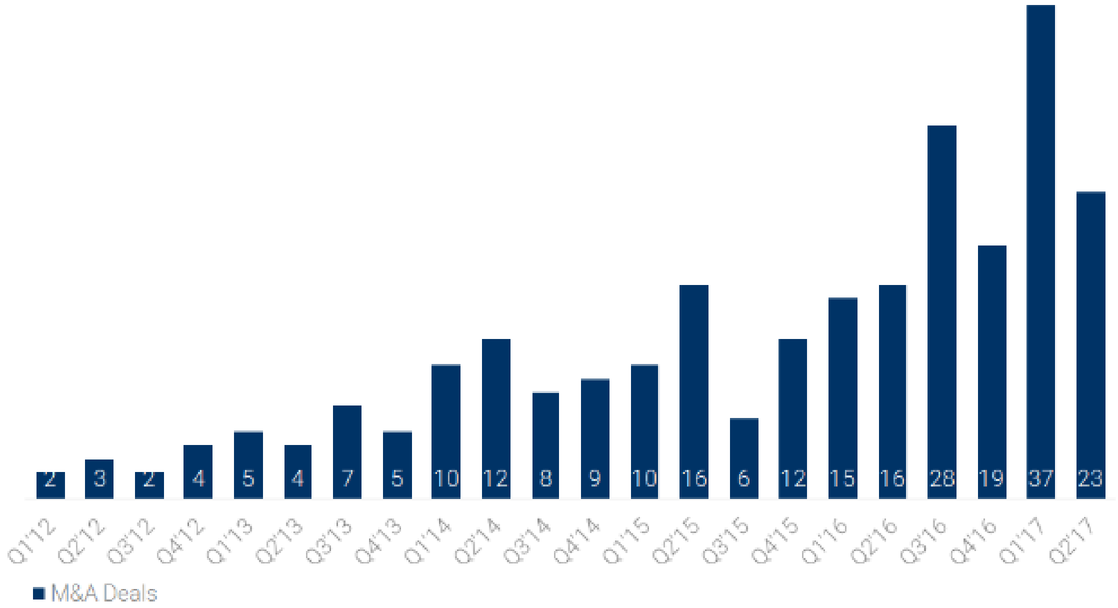
[12] The 'K-Nearest-Neighbour' algorithm, which is the simple, intuitive machine learning algorithm taught at the start of many undergraduate Computer Science classes, was proposed in its modern form in 1967. See Thomas Cover and Peter Hart (1967), "Nearest Neighbor Pattern Classification," *IEEE transactions on information theory*. 13.1: 21-27.

[13] See Luke Dormehl (2016), *Thinking Machines: The Quest for Artificial Intelligence--and Where It's Taking Us Next*, London: Penguin Books.

[14] Tim Dettmers (2015), "Deep Learning in a Nutshell: History and Training," *Parallel Forall,* December. Accessed on May 30, 2017. Web. https://devblogs.nvidia.com/parallelforall/deep-learning-nutshell-history-training/

investments in AI start-ups. The World Economic Forum reported that global investment in AI start-ups rose from $282 million in 2011, to $2.4 billion in 2015.[15] The number of merger and acquisition (M&A) deals in AI has also accelerated over this period (figure 2).

Figure 2: Global artificial intelligence merger and acquisition activity, 2012-2017



Source: CB Insights (2017), "The Race For AI: Google, Baidu, Intel, Apple In A Rush To Grab Artificial Intelligence Startups," Research Brief, July.

Many applications tend more toward 'augmented intelligence,' or an augmentation of human capabilities, rather than a replacement of humans. Even as advancements in AI and machine learning continue, including in the area of deep learning, most industries are not attempting to fully replicate human intelligence. As noted by one industry observer "…a human in the loop is essential: we are, unlike machines, able to take into account context and use general knowledge to put AI-drawn conclusions into perspective."[16]

2. Drivers

A variety of factors that have contributed to the growing use of FinTech generally have also spurred adoption of AI and machine learning in financial services.[17] On the supply side, financial market participants have benefitted from the availability of AI and machine learning

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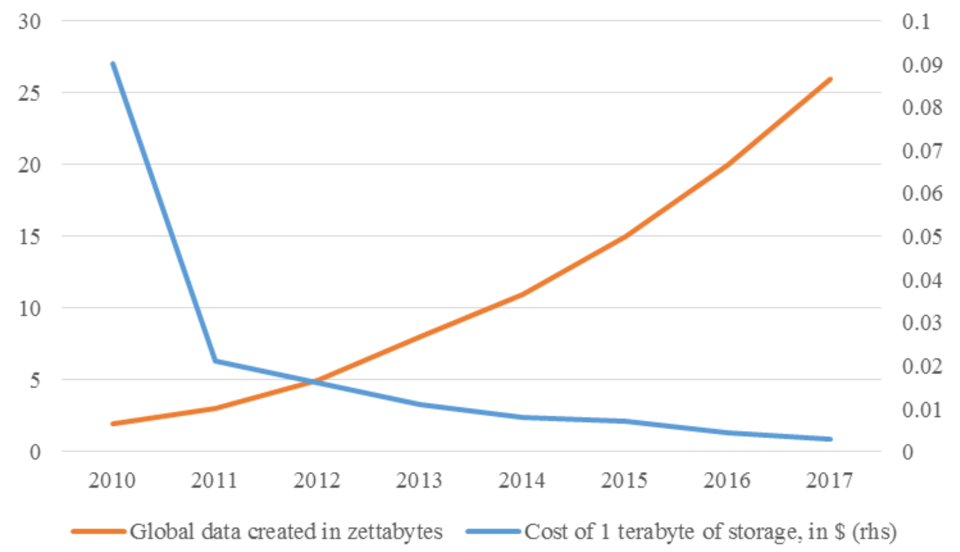
15 See Slaughter and May and ASI Data Science (2017), "Superhuman Resources: Responsible deployment of AI in business," Joint White Paper, June.

16 See Finextra and Intel (2017), "The Next Big Wave: How Financial Institutions Can Stay Ahead of the AI Revolution," May.

17 See FSB FinTech Issues Group (2017), p.10. AI and machine learning are also being adopted widely in sectors such as health care, manufacturing, marketing, and many other areas.

tools developed for applications in other fields. These include availability of computing power owing to faster processor speeds, lower hardware costs, and better access to computing power via cloud services.[18] Similarly, there is cheaper storage, parsing, and analysis of data through the availability of targeted databases, software, and algorithms. There has also been a rapid growth of datasets for learning and prediction owing to increased digitisation and the adoption of web-based services.[19] The declining cost of data storage and estimates of the volume of global data sets are shown in figure 3.

Figure 3: Costs of storage and global data availability, 2009-2017



Source: Reinsel, Gantz and Rydning (2017); Klein (2017). One zettabyte is equal to one billion terabytes.

The same tools driving advances in machine learning in search engines and self-driving cars, can be adopted in the financial sector. For example, entity recognition tools that enable search engines to understand when a user is referring to Ford Motor Company, rather than fording a river, are now used to quickly identify news or social media chatter relevant to publicly traded firms. As more firms adopt these tools, the financial incentives to access new or additional data and to develop faster and more accurate AI and machine learning tools may increase. In turn, such adoption and development of tools may affect incentives for yet other firms.

A variety of technological developments in the financial sector have contributed to the creation of infrastructure and data sets. The proliferation of electronic trading platforms has been accompanied by an increase in the availability of high quality market data in structured formats.[20] In some countries, such as the United States, market regulators allow publicly traded firms to use social media for public announcements. In addition to making digitised financial

[18] See IOSCO (2017), "Research Report on Financial Technologies (Fintech)," February, p. 6 on growth of computing power.

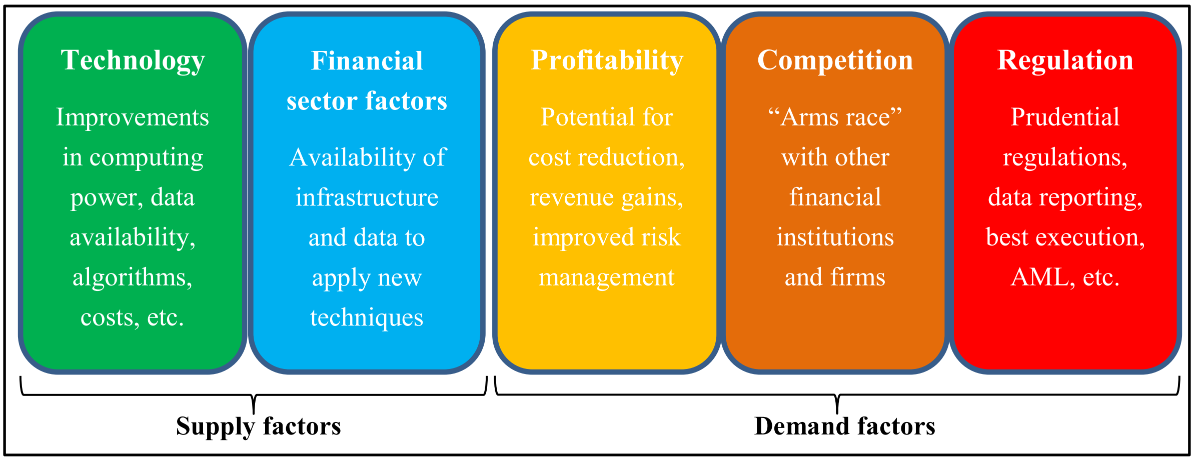
[19] Institute of International Finance (2017), "Deploying RegTech Against Financial Crime," Report of the IIF RegTech Working Group, March; David Reinsel, John Gantz and John Rydning (2017), "Data Age 2025: The Evolution of Data to Life-Critical," IDC White Paper, April; Andy Klein (2017), "Hard Drive Cost Per Gigabyte," Backblaze, July.

[20] See IOSCO (2017), p. 41 for description of APIs and FIX protocols to assist in price discovery and market liquidity in corporate bond markets.

data available for machine learning, the computerisation of markets has made it possible for AI algorithms to interact directly with markets, putting in real-time complex buy and sell orders based on sophisticated decision-making, in many cases with minimal human intervention. Meanwhile, retail credit scoring systems have become more common since the 1980s,[21] and news has become machine readable since the 1990s. With the growth of data in financial markets as well as datasets – such as online search trends, viewership patterns and social media that contain financial information about markets and consumers – there are even more data sources that can be explored and mined in the financial sector.

On the demand side, financial institutions have incentives to use AI and machine learning for business needs. Opportunities for cost reduction, risk management gains, and productivity improvements have encouraged adoption, as they all can contribute to greater profitability. In a recent study, industry sources described priorities for using AI and machine learning as follows: optimising processes on behalf of clients; working to create interactions between systems and staff applying AI to enhance decision-making; and developing new products and services to offer to clients.[22] In many cases these factors may also drive 'arms races' in which market participants increasingly find it necessary to keep up with their competitors' adoption of AI and machine learning, including for reputational reasons (hype).

Figure 4: Supply and demand factors of financial adoption of AI and machine learning



There is also demand due to regulatory compliance.[23] New regulations have increased the need for efficient regulatory compliance, which has pushed banks to automate[24] and adopt new analytical tools that can include use of AI and machine learning. Financial institutions are seeking cost effective means of complying with regulatory requirements, such as prudential

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[21] Examples include the FICO score in the US and Canada, Schufa scoring in Germany and firm-specific scores in Japan.

[22] Finextra and Intel (2017).

[23] From the perspective of technology companies offering AI and machine learning solutions for regulatory compliance by financial institutions, these factors can be considered supply-side.

[24] It is important to distinguish between 'automation' or 'intelligent automation' and use of AI and machine learning. This is a distinction that goes back to the use of algorithms to spread out orders in the 1990s. Most of those rule-based algorithms are not considered machine learning algorithms by the financial community, in contrast to the types of algorithms used today that do 'learn' from financial data, news and other data sources.

regulations, data reporting, best execution of trades, and rules on anti-money laundering and combating the financing of terrorism (AML/CFT). Correspondingly, supervisory agencies are faced with responsibility for evaluating larger, more complex and faster-growing datasets, necessitating more powerful analytical tools to better monitor the financial sector. Figure 4 shows how these supply and demand factors fit together.

A number of developments could impact future adoption of a broad range of financial applications of AI and machine learning. These developments include continued growth in the number of data sources and the timeliness of access to data; growth in data repositories, data granularity, variety of data types; and efforts to enhance data quality. Continued improvement in hardware, as well as AI and machine learning software as a service, including open-source libraries, will also impact continued innovation. Development in hardware includes processing chips and quantum computing that enable faster and more powerful AI. These developments could enable cheaper and broader access to AI and machine learning tools that are increasingly powerful. They could make more sophisticated real-time insights possible on larger datasets, such as real-time databases of online user behaviour or internet-of-things (IoT) sensors located around the world.

At the same time, sophisticated software services are becoming more widely available. Some of the software services are open source libraries made available in the past few years that provide researchers with off-the-shelf-tools for machine learning. There are also a growing variety of vendors that provide machine learning for financial market participants, including some firms that scrape news and/or metadata and enable users to identify the specific features (webpages viewed, etc.) that correlate with the events they are interested in predicting. As services emerge to provide, clean, organise, and analyse these data for financial insights, the cost to users of incorporating sophisticated insights may fall significantly. Thus, at the same time, risks related to multiple users of the same information and techniques across the financial sector could grow (see section 4).

The legal framework for relevant data will likely also impact the adoption of AI and machine learning tools. Breaches of personal data or uses of data that are not in the interests of consumers may be expected to lead to added data protection legislation (see annex A). In addition, the development of new data standards, new data reporting requirements, or other institutional changes in financial services can impact the adoption of AI and machine learning in specific markets.

3. Selected use cases

Financial stability implications depend critically on the uses of AI and machine learning. To assess these implications, questions to be considered would include which AI and machine learning tools are being used to make which types of decisions, on what time scales, to address which financial functions, and where and at what level human involvement is being integrated.

AI and machine learning are being adopted for a number of purposes across the financial system. Examples include:

- *Sentiment indicators*: Social media data analytics companies use AI and machine learning techniques to provide 'sentiment indicators' to a number of financial services players. Investor sentiment indicators are being developed and sold to banks, hedge funds, high-frequency trading traders, and social trading and investment platforms.[25]

- *Trading signals*: Machine learning can help firms to increase productivity and to reduce costs by quickly scanning and making decisions based on more sources of information than a human can (see section 3.3). Therein also lies a limitation of machine learning technology: by identifying and relying on patterns that were predictive of outcomes in the past, these tools are susceptible to false information.[26] For example, there were market moves across equities, bonds, foreign exchange, and commodities in April 2013 after trading algorithms reacted to a fraudulent news Tweet announcing two explosions at the White House. These types of issues may be exacerbated with more widespread use of machine learning.[27]
- *AML/CFT and fraud detection*: Seeking to increase productivity and simultaneously reduce costs and risks, while complying with regulations, some firms use AI for AML/CFT and fraud detection at financial institutions.[28] Firms can also use machine learning for credit monitoring and risk mitigation purposes, (see section 3.4).

This section considers four sets of use cases of AI and machine learning. These are: (i) customer-focused (or 'front-office') uses, including credit scoring, insurance, and client-facing chatbots; (ii) operations-focused (or 'back-office') uses, including capital optimisation, model risk management and market impact analysis; (iii) trading and portfolio management in financial markets; and (iv) uses of AI and machine learning by financial institutions for regulatory compliance ('RegTech') or by public authorities for supervision ('SupTech'). For each of the use cases, a few examples of active or potential use cases are given, alongside estimates (where available) of the current adoption of technologies. The implications at the micro and macro level are reserved for sections 4 and 5.

3.1 Customer-focused uses: credit scoring, insurance and client-facing chatbots

AI and machine learning are already being applied in the front office of financial institutions. Large-scale client data are fed into new algorithms to assess credit quality and thus to price loan contracts. Similarly, such data can help assess risks for selling and pricing insurance policies. Finally, client interactions may increasingly be carried out by AI interfaces with so-called 'chatbots,' or virtual assistance programs that interact with users in natural language. This section considers each in turn.

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[25] See IOSCO (2017), p. 28. Social trading refers to a range of trading platforms that allow users to compare trading strategies or copy the trading strategy of other investors (see glossary).

[26] Of course, humans are also prone to error and manipulation. Machine learning algorithms may be superior to humans in detecting patterns that have not occurred before. At the same time, the use of such algorithms for automation could allow for a quicker and more large-scale dispersion of effects than for functions performed by individual human users.

[27] Tero Karpp, and Kate Crawford (2015), "Social Media, Financial Algorithms and the Hack Crash," *Theory Culture & Society* 33(1): 73-92.

[28] Bart van Liebergen (2017), "Machine Learning: A Revolution in Risk Management and Compliance?" *The Capco Institute Journal of Financial Transformation*, April.

3.1.1 Credit scoring applications

Credit scoring tools that use machine learning are designed to speed up lending decisions, while potentially limiting incremental risk. Lenders have long relied on credit scores to make lending decisions for firms and retail clients. Data on transaction and payment history from financial institutions historically served as the foundation of most credit scoring models. These models use tools such as regression, decision trees, and statistical analysis to generate a credit score using limited amounts of structured data. However, banks and other lenders are increasingly turning to additional, unstructured and semi-structured data sources, including social media activity, mobile phone use and text message activity, to capture a more nuanced view of creditworthiness, and improve the rating accuracy of loans. Applying machine learning algorithms to this constellation of new data has enabled assessment of qualitative factors such as consumption behaviour and willingness to pay. The ability to leverage additional data on such measures allows for greater, faster, and cheaper segmentation of borrower quality and ultimately leads to a quicker credit decision.[29] However, the use of personal data raises other policy issues, including those related to data privacy and data protections.[30]

In addition to facilitating a potentially more precise, segmented assessment of creditworthiness, the use of machine learning algorithms in credit scoring may help enable greater access to credit. In traditional credit scoring models used in some markets, a potential borrower must have a sufficient amount of historical credit information available to be considered 'scorable.' In the absence of this information, a credit score cannot be generated, and a potentially creditworthy borrower is often unable to obtain credit and build a credit history. With the use of alternative data sources and the application of machine learning algorithms to help develop an assessment of ability and willingness to repay, lenders may be able to arrive at credit decisions that previously would have been impossible.[31] While this trend may benefit economies with shallow credit markets, it could lead to non-sustainable increases in credit outstanding in countries with deep credit markets.[32] More generally, it has not yet been proved that machine learning-based credit scoring models outperform traditional ones for assessing creditworthiness.

Over the past several years, a host of FinTech start-up companies targeting customers not traditionally served by banks have emerged. In addition to more commonly known online lenders that lend in the United States, one firm is using an algorithmic approach to data analysis and has expanded to overseas markets, particularly China, where the majority of borrowers do not have credit scores. Another firm, based in London, is working to provide credit scores for individuals with 'thin' credit files, using its algorithms and alternative data sources to review loan applications rejected by lenders for potential errors. Additionally, some companies are

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29 Stefan Lessmann, Bart Baesens, Hsin-Vonn Seow, and Lyn Thomas (2015), "Benchmarking state-of-the art classification algorithms for credit scoring: An update of research," *European Journal of Operational Research* 247(1): 124-136.

30 See CGFS and FSB (2017), p. 26.

31 As an example, high-frequency online data on payments transactions can help to assess the creditworthiness of individuals and small businesses.

32 For empirical evidence on the differential impact of credit inclusion on financial stability, see Ratna Sahay, Martin Čihák, Papa N'Diaye, Adolfo Barajas, Srobona Mitra, Annette Kyobe, Yen Nian Mooi, and Seyed Reza Yousefi (2015), "Financial Inclusion: Can It Meet Multiple Macroeconomic Goals?" IMF Staff Discussion Note 15/17. One conclusion is that in countries with deep credit markets, greater credit-based financial inclusion can be associated with new vulnerabilities.

drawing on the vast amounts of data housed at traditional banks to integrate mobile banking apps with bank data and AI to assist with financial management and make financial projections, which may be first steps to developing a credit history.

There are a number of advantages and disadvantages to using AI in credit scoring models. AI allows massive amounts of data to be analysed very quickly. As a result, it could yield credit scoring policies that can handle a broader range of credit inputs, lowering the cost of assessing credit risks for certain individuals, and increasing the number of individuals for whom firms can measure credit risk. An example of the application of big data to credit scoring could include the assessment of non-credit bill payments, such as the timely payment of cell phone and other utility bills, in combination with other data. Additionally, people without a credit history or credit score may be able to get a loan or a credit card due to AI, where a lack of credit history has traditionally been a constraining factor as alternative indicators of the likelihood to repay have been lacking in conventional credit scoring models.

However, the use of complex algorithms could result in a lack of transparency to consumers. This 'black box' aspect of machine learning algorithms may in turn raise concerns. When using machine learning to assign credit scores make credit decisions, it is generally more difficult to provide consumers, auditors, and supervisors with an explanation of a credit score and resulting credit decision if challenged. Additionally, some argue that the use of new alternative data sources, such as online behaviour or non-traditional financial information, could introduce bias into the credit decision.[33] Specifically, consumer advocacy groups point out that machine learning tools can yield combinations of borrower characteristics that simply predict race or gender, factors that fair lending laws prohibit considering in many jurisdictions (see annex B). These algorithms might rate a borrower from an ethnic minority at higher risk of default because similar borrowers have traditionally been given less favourable loan conditions.

The availability of historical data across a range of borrowers and loan products is key to the performance of these tools. Likewise, the availability, quality, and reliability of data on borrower-product performance across a wide range of financial circumstances is also key to the performance of these risk models. Also, the lack of data on new AI and machine learning models, and the lack of information about the performance of these models in a variety of financial cycles, has been noted by some authorities.[34]

3.1.2 Use for pricing, marketing and managing insurance policies

The insurance industry is using machine learning to analyse complex data to lower costs and improve profitability. Since analysing data to drive pricing forms the core of insurance business, insurance-related technology, sometimes called 'InsurTech,' often relies on analysis of big data. Adoption of AI and machine learning applications in InsurTech is particularly high in the United States, UK, Germany and China.[35] Many applications involve improvements to the

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[33] For a thorough treatment, see Cathy O'Neil (2016), *Weapons of Math Destruction: How Big Data Increases Inequality and Threatens Democracy*, London: Allen Lane.

[34] See U.S. Treasury Department (2016), "Opportunities and Challenges in Online Marketplace Lending," May; CGFS and FSB (2017), "FinTech Credit: Market Structure, Business Models and Financial Stability Implications," May.

[35] Jim Struntz (2017), "AI on the insurance frontline," Accenture Insurance Blog, July.

underwriting process, assisting agents in sorting through vast data sets that insurance companies have collected to identify cases that pose higher risk, potentially reducing claims and improving profitability.[36] Some insurance companies are actively using machine learning to improve the pricing or marketing of insurance products by incorporating real-time, highly granular data, such as online shopping behaviour or telemetrics (sensors in connected devices, such as car odometers). Firms usually have access to those data through partnerships, acquisitions, or non-insurance activities. In many cases, firms need to ask for an active consent of the user whenever data protection regulation asks them to.

AI and machine learning applications can substantially augment some insurance sector functions, such as underwriting and claims processing. In underwriting, large commercial underwriting and life or disability underwriting can be augmented by AI systems based on NLP. These applications can learn from training sets of past claims to highlight key considerations for human decision-makers. Machine learning techniques can be used to determine repair costs and automatically categorise the severity of vehicle accident damage.[37] In addition, AI may help reduce claims processing times and operational costs.[38] Insurance companies are also exploring how AI and machine learning and remote sensors (connected through the 'internet of things') can detect, and in some cases prevent, insurable incidents before they occur, such as chemical spills or car accidents.

It seems likely that these methods will achieve greater adoption. According to private sector estimates, global InsurTech investment totalled $1.7 billion in 2016. At the same time, 26 per cent of insurers provide monetary or non-monetary support (for example, coaching) to digital start-ups, and 17 per cent of insurers have an in-house venture capital fund or investment vehicle targeting technology.[39] While the use of machine learning has the potential to produce more accurate pricing and risk assessment for insurance companies, there may be consumer protection concerns that stem from potential data errors or the exclusion of some groups (see section 5).

3.1.3 Client-facing chatbots

Chatbots are virtual assistants that help customers transact or solve problems. These automated programmes use NLP to interact with clients in natural language (by text or voice), and use machine learning algorithms to improve over time. Chatbots are being introduced by a range of financial services firms, often in their mobile apps or social media. While many are still in the trial phase, there is potential for growth as chatbots gain increasing usage, especially among the younger generations, and become more sophisticated. The current generation of chatbots in use by financial services firms is simple, generally providing balance information or alerts to

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36 See International Association of Insurance Supervisors, "FinTech Developments in the Insurance Industry," 21 February 2017.

37 PWC (2016), "Top Issues: AI in Insurance: Hype or reality?" March.

38 IAIS (2017), "Report on FinTech Developments in the Insurance Industry," February.

39 Accenture, "The Rise of Insurtech," 2017.

customers, or answering simple questions. It is worth observing that the increasing usage of chatbots is correlated with the increased usage of messaging applications.[40]

Chatbots are increasingly moving toward giving advice and prompting customers to act. In addition to assisting customers of financial institutions in making financial decisions, financial institutions can benefit by gaining information about their customers based on interactions with chatbots. While outdated infrastructure for client data storage has slowed the development of chatbots in financial institutions in many jurisdictions, Asian financial institutions and regulators have developed more sophisticated chatbots that are currently in active use. The insurance industry has also explored the use of chatbots to provide real-time insurance advice.

3.2 Operations-focused uses

Financial institutions can use AI and machine learning tools for a number of operational (or back-office) applications. Some of these applications include: (i) capital optimisation by banks; (ii) model risk management (back-testing and model validation); and (iii) market impact analysis (modelling of trading out of big positions). This section considers each of these in turn.

3.2.1 Capital optimisation use case

Capital optimisation, or the maximisation of profits given scarce capital, is a traditional function in running a bank that heavily relies on mathematical approaches. AI and machine learning tools build on the foundations of computing capabilities, big data, and mathematical concepts of optimisation to increase the efficiency, accuracy, and speed of capital optimisation. Optimisation of bank's regulatory capital with machine learning has been a topic of interest from both academic and business professionals over the last several years. In 2012, a private sector observer noted that most banks said they had conducted meaningful programmes to optimise risk-weighted assets (RWA) and had seen 5 to 15 per cent RWA savings.[41] Capital optimisation is also being done in the area of derivatives margin optimisation such as margin valuation adjustment (MVA).[42] New regulations around clearing and bilateral margining have increased the demand for sophisticated techniques for optimising capital and initial margin.[43]

AI and machine learning could assist banks in optimising MVA, and recent research suggests that work is being done in this area.[44] In the context of MVA optimisation, machine learning tries to reduce the initial margin for derivatives by a combination of: (a) executing pairs of

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[40] According to one estimate, usage of the top 4 messaging services now surpasses the top 4 social network apps. See BI Intelligence (2016), "Messaging apps are now bigger than social networks," September.

[41] McKinsey (2012), "Capital management, Banking's new imperative," McKinsey Working papers on Risk, Number 38, November 2012.

[42] Margin valuation adjustment tries to determine the funding cost of the initial margin posted for a derivatives transaction.

[43] Kondratyev A, and G. Giorgidze, (2017), "MVA Optimisation with Machine Learning Algorithms, 23," Social Science Research Network, January 2017.

[44] M Heusser and P Varhol, (2016) "An Intro to Genetic Algorithms," InfoWorld, December 2016; Qinghai Bai (2010), "Analysis of Particle Swarm Optimisation Algorithm," Computer and Information Science 3(1), February. The first paper discusses genetic algorithms, which are a method that optimises an output or outputs with successive derived equations based on predetermined hypotheses. The second discusses particle swarm optimisation, which is a method and algorithm based on swarm intelligence, derived from research on the movement behaviour of flocks of birds and schools of fish. Both offer machine learning techniques to optimise funding costs in the constraints of the leverage ratio-implied capital charge.

offsetting derivative trades; (b) executing offsetting strategies with the same dealer; (c) novating trades from one dealer portfolio to another. Machine learning finds the best combination of the initial margin reducing trades at a given time based on the degree of initial margin reduction in the past under different combinations of those trades. A likely implication of these advances in RWA and MVA optimisation is a reduction in the traditionally calibrated regulatory capital and larger reliance on the non-optimisable capital regulatory tools.

3.2.2 Model risk management (back-testing and model validation) and stress testing

Academics and practitioners often cite back-testing and model validation as areas where progress with AI and machine learning will likely be soon visible.[45] Banks are considering machine learning to make sense of large, unstructured and semi-structured datasets and to police the outputs of primary models. Back-testing is important because it is traditionally used to evaluate how well banks' risk models are performing. In the last years, US and European prudential regulators focused on back-testing and validation used by banks by providing guidance on model risk management.[46] Using a range of financial settings for back-testing allows for consideration of shifts in market behaviour and other trends, hopefully reducing the potential for underestimating risk in such scenarios.[47]

Some applications are already live. For instance, one global corporate and investment bank is using unsupervised learning algorithms in model validation. Its equity derivatives business has used this type of machine learning to detect anomalous projections generated by its stress-testing models. Each night, these models produce over three million computations to inform regulatory, internal capital allocations and limit monitoring. A small fraction of these computations are extreme, and knocked out of the normal distribution of results by a quirk of the computation cycle or faulty data inputs. Unsupervised learning algorithms help model validators in the ongoing monitoring of internal and regulatory stress-testing models, as they can help determine whether those models are performing within acceptable tolerances or drifting from their original purpose. They can also provide additional input to operational risk models, such as the vulnerability of organisations to cyber-attacks.

Similarly, AI and machine learning techniques are also being applied to stress testing. The increased use of stress testing following the financial crisis has posed challenges for banks as they work to analyse large amounts of data for regulatory stress tests. One provider of AI and machine learning tools has worked closely with a large financial institution to develop tools to assist them in modelling their capital markets business for bank stress testing. The tools developed aim to limit the number of variables used in scenario analysis for the loss given default and probability of default models. By using unsupervised learning methods to review

[45] Louie Woodall (2017), "Model risk managers eye benefits of machine learning," Risk, April.

[46] For example, see Federal Reserve Board (2011), "Supervisory guidance on model risk management," SR Letter 11-7, April; FDIC (2017), "Supervisory guidance on model risk management," FIL-22-2017, June; ECB (2017), "Guide to the Targeted Review of Internal Models," February.

[47] Model validation is defined in industry guidance as "the set of processes and activities intended to verify that models are performing as expected, in line with their design objectives, and business uses [to identify] potential limitations and assumptions, and assesses their possible impact." See Clayton Mitchell (2016), "Model Validation: For Elements of Determining the Accuracy of Your Model," British Bankers Association, January.

large amounts of data, the tools can document any bias associated with selection of variables, thereby leading to better models with greater transparency.

3.2.3 Market impact analysis (modelling of trading out of big positions)

AI and machine learning can complement conventional market impact models.[48] Firms can use AI to obtain more information from sparse historical models, or help identify non-linear relationships in order flow. Machine learning can be used to create 'trading robots' that then teach themselves how to react to market changes. Market impact analysis involves evaluating the effect of a firm's own trading on market prices. Since firms are concerned about the impact of trades, especially of large trades, on market prices, more accurate estimation of this impact is key to timing trades and minimising trading execution costs.

Firms are investigating using AI tools to assess the market impact of a given trade. The effect of a firm's own trading on market prices is notoriously hard to model, especially for less liquid securities, where data on comparable past trades are scarce. AI tools may help by augmenting models already in use, or by introducing a machine learning approach to minimise trading impact on prices and liquidity. For the most active systematic funds, as much as two-thirds of the gain on trades are estimated to be lost to market impact costs.[49] AI tools may help by augmenting models already in use, or by introducing a machine learning approach to minimise trading impact on prices and liquidity for trading both into and out of large market positions, or as a part of every-day trading strategies.

Machine learning is often used to identify groups of bonds that behave similarly to each other.[50] By doing so, they can rely on many more data points, providing better estimates of price movements when the market is thin. The resulting tool groups bonds into broad, intuitively similar buckets and then, using cluster analysis, collects the most comparable products together in each bucket, to score the liquidity of individual bonds.

Also, AI can be used to help identify how the timing of trades can minimise market impact. Market impact models can be developed that describe how the effect of a trade depends on previous trades as a starting point. The models attempt to avoid scheduling trades too closely together to avoid having a market impact greater than the sum of its parts. These models can be used to set out the best possible trading schedules for a range of scenarios and then tweak the schedule as the real trade progresses, using supervised learning techniques to make the short-term predictions determining those tweaks. Banks are also testing reinforcement learning to teach artificial intelligence tools to react to order imbalance and queue position in the limit order book.

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[48] Sebastian Day (2017), "Quants turn to machine learning to model market impact," RISK Magazine, April.

[49] Day (2017).

[50] For example, one firm uses machine learning to assess the liquidity of bonds. Every bond is quantitatively measured against a range of common features such as currency, duration, time to maturity and amount outstanding. Those measurements determine its position within a theoretical multi-dimensional space. For example, trading 500 lots of an obscure US Treasury bond, the tool will identify other US Treasury bonds the shortest distance away within that space. The tool will then use their combined pool of data to calibrate the parametric model.

3.3 Trading and portfolio management

AI and machine learning techniques are active areas of research and development for asset managers and trading firms. In addition to significant research and development (R&D), some firms now use machine learning to devise trading and investment strategies. The extent to which AI investment strategies are autonomous or incorporate human oversight varies on a case-by-case basis. In this section, we distinguish between trading execution (primarily sell-side) and portfolio management (buy-side).

3.3.1 AI and machine learning in trading execution

Trading firms are looking to AI and machine learning to use data to improve their ability to sell to clients. For example, analysing past trading behaviour can help anticipate a client's next order. Trading generates large quantities of data, and this scale is typically required by machine learning tools to work effectively. If the current trend to increasing use of voice-to-text services continues, this will generate additional data from trades executed over the phone, which can be integrated with the pool of data from electronic platforms.

AI and machine learning can more pro-actively manage risk exposures. Machine learning can serve as a basis for risk modelling by exchanges to determine when members' trading account positions may have increased risk profiles that may warrant intervention. For large trading firms such as banks, the use of a central risk trading book, or risk management techniques based on big data analysis, have enabled these firms to manage risks and optimise their use of capital by centralising the risks that arise from various parts of their businesses.

AI and machine learning can help compliance with trading regulations. A RegTech application of AI to trading is voice-to-text technology powered by deep learning. This helps firms meet pre-trade and post-trade transparency requirements for non-equity markets.[51]

3.3.2 Scope for the use of AI and machine learning in portfolio management

In portfolio management, AI and machine learning tools are being used to identify new signals on price movements and to make more effective use of the vast amount of available data and market research than with current models. Machine learning tools work on the same principles as existing analytical techniques used in systematic investing. The key task is to identify signals from data on which predictions relating to price level or volatility can be made, over various time horizons, to generate higher and uncorrelated returns.

Among asset managers, machine learning is used most extensively by systematic ('quant') funds, most of which are hedge funds.[52] An AI unit tends to sit within a larger team at an asset manager to aid with portfolio construction. One view in the industry is that for AI and machine learning to be effective, both traders and quants need to have good oversight and understanding of the tools used. Many quant funds state that they are not comfortable fully automating and

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[51] Under the Markets in Financial Instruments Directive (MiFID II), for instance, dealers designated as 'systematic internalisers' will be unable to quote prices to a client for some bilateral trades unless they also simultaneously broadcast the same quote to the wider market – a task that is realisable if the quote is provided on a screen, but more difficult via a phone.

[52] While these players have been using quantitative techniques since long before the recent advances in deep learning, they are widely regarded as some of the most avid adopters of these techniques.

implementing a model if they cannot understand how a particular prediction is made. The concentration of machine learning tools among quant funds reflects how machine learning is fundamentally an approach to generating predictive power from data, which distinguishes it from investment approaches that use greater discretion and judgment.

At the moment, machine learning likely only drives a minor subset of quant funds' trades. Quant funds manage on the order of $1 trillion in assets, out of total assets under management (AUM) invested in mutual funds globally in excess of $40 trillion. The market share of quant funds has not changed drastically in the years since the crisis, but between 2013 and 2016 the proportion of trades carried out by quant funds, on one measure, approximately doubled from 13% to 27%.[53] In turn, some portion of the trading is based on machine learning. It is hard to quantify precisely what proportion use machine learning for several reasons:

- Firms are hesitant to share proprietary information.
- When firms share information on their use of machine learning, there is not always a standard definition or understanding of what is included within the concept.
- Some investments or trades may be made on a discretionary basis but informed (to varying extents) by the use of machine learning.[54]

One contact in the industry estimates that 'pure' AI and machine learning players have about $10 billion in assets under management, but that this figure is growing rapidly.[55]

In addition to the use by fund managers, specialist firms are making available to asset managers machine learning tools to gain insight from the vast volume of news and market research available. In other cases, asset managers are themselves building indicators, using AI capability supplied by third parties. One general issue is that useful trading signals derived from AI and machine learning strategies may follow a decay function over time, as data are more widely used and hence become less valuable for gaining an edge over other investors. [56]

3.4 AI and machine learning in regulatory compliance and supervision

AI and machine learning techniques are being used by regulated institutions for regulatory compliance, and by authorities for supervision. RegTech is often regarded as the subset of FinTech that focus on facilitating regulatory compliance more efficiently and effectively than existing capabilities.[57] The total RegTech market is expected to reach $6.45 billion by 2020,

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[53] Tabb Group, referenced in Gregory Zuckerman and Bradley Hope (2017), "The Quants Run Wall Street Now," *Wall Street Journal*, 22 May.

[54] For some quant funds, machine learning tools inform investment strategies that are implemented by a person. Other firms provide information generated by machine learning to asset managers. For example, one firm's machine learning engine shows how asset prices have behaved historically in response to market events. In other cases, it appears that firms are using machine learning systems to manage portfolios and to execute trades automatically. One firm runs an automated fund using an evolutionary computation approach, using a large network of central processing units to randomly generate trillions of trading "genes;" from which the system selects and "breeds" the best-performing 0.01%.

[55] This is based on bilateral discussions by the FSB secretariat with an investor focused on AI and machine learning funds.

[56] See for example Luke Smolinski (2017), "Wolfe aims to shake up research with AI push," Risk.net, 23 May.

[57] FCA (2015), "Call for Input: Supporting the development and adoption of RegTech," November; Institute of International Finance (2015), "Regtech: exploring solutions for regulatory challenges," October.

growing at a compound annual growth rate (CAGR) of 76%.[58] SupTech is the use of these technologies by public sector regulators and supervisors. Within SupTech, the objective of AI and machine learning applications is to enhance efficiency and effectiveness of supervision and surveillance. While there can be overlap in the terms,[59] the two applications are discussed here separately. Some of the examples below are from the academic community. While not yet being applied by regulatory or supervisory bodies, they represent potential applications in this sector. The use cases are grouped by the function for which they are used, namely regulatory compliance; regulatory reporting and data quality; monetary policy and systemic risk analysis; and surveillance and fraud detection.

3.4.1 RegTech: applications by financial institutions for regulatory compliance

For analysing unstructured data, RegTech can use machine learning combined with NLP. Besides being applied to the monitoring of behaviour and communication of traders for transparency and market conduct, machine learning together with NLP can interpret data inputs such as e-mails, spoken word, instant messaging, documents, and metadata. This in turn begs the issue of the boundaries for the employee surveillance policy. Some regulated institutions are experimenting with cases seeking to enhance their ability to comply with product suitability requirements.

NLP could be used by asset management firms to cope with new regulations. In the EU, investment managers have to comply with specific requirements in the Markets in Financial Instruments Directive (MiFID II), the Undertakings for Collective Investments in Transferrable Securities (UCITS) Directive, and the Alternative Investment Fund Managers Directive (AIFMD). Firms could potentially leverage NLP and other machine learning tools to interpret these regulations into a common language. They could then analyse and codify the rules for automation into the integrated risk and reporting systems to help firms comply with the regulations. This could bring down the cost, effort and time needed to interpret and implement new and updated regulations for fund managers.

Knowing the identity of customers ('know your customer' or KYC) is another area where AI and machine learning are applied to address one of the biggest pain points in the financial industry, both with regards to user experience and regulator expectations. The KYC process is often costly, laborious, and highly duplicative across many services and institutions. Machine learning is increasingly used in remote KYC of financial services firms to perform identity and background pre-checks. It is predominantly used in two ways: (1) evaluating whether images in identifying documents match one another, and (2) calculating risk scores on which firms determine which individuals or applications need to receive additional scrutiny. Machine learning-based risk scores are also used in ongoing periodic checks based on public and other data sources, such as police registers of offenders and social media services. Use of these sources may enable risk and trust to be assessed quickly and often cheaply. Firms can use risk scores on the probability of customers raising "red flags" on KYC checks to help make decisions on whether to proceed with the time and expense of a full background check.

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[58] Frost & Sullivan (2017), "Global Forecast of RegTech in Financial Services to 2020," March.

[59] For instance, some authors use RegTech to refer to applications used by regulators, as well. See Douglas W. Arner, Jànos Barberis and Ross P. Buckley (2017), "FinTech, RegTech and the Reconceptualization of Financial Regulation," *Northwestern Journal of International Law and Business* 37(3): 371-413.

Nonetheless, concerns about their accuracy have kept some financial services from incorporating these tools.

3.4.2 Uses for macroprudential surveillance and data quality assurance

AI and machine learning methods may help to improve macroprudential surveillance by automating macroprudential analysis and data quality assurance. A series of new reporting requirements across jurisdictions has led to a greater volume and frequency of reported data, as well as greater resources required from financial institutions to complete reporting on time. In some cases (for example, transactions data in MiFID, AIFMD templates, etc.), the volume of data received can be challenging for the authorities receiving the data, such that it cannot be used to its full potential using traditional methods. Moreover, substantial errors, blank fields, and other data quality issues are often more prevalent in new datasets, and additional checks and data quality assurance are needed. Machine learning can help improve data quality, for example, by automatically identifying anomalies (potential errors) to flag them to the statistician and/or the data-providing source. This may allow for both lower-cost and higher-quality reporting and more efficient and effective data processing and macroprudential surveillance of data by authorities.[60]

Similarly, AI and machine learning could help trade repositories (TRs) tackle data quality issues, increasing the value of TR data to authorities and the public. Authorities report that overcoming data quality issues continues to be a key challenge to making full use of TR data.[61] Application of machine learning techniques may help TRs – for over-the-counter (OTC) derivatives or (where applicable) other types of transactions, such as exchange-traded derivatives or securities financing transactions – improve data quality. Specifically, appropriately trained machine learning algorithms could help identify data gaps, data inconsistencies, and fat-finger errors, as well as match likely pairs of transactions and/or interpolate missing data. The same techniques can be used by authorities, themselves. In this context, the Autorité des marchés financiers du Québec reports that it has successfully tested in its FinTech Laboratory a supervised machine learning algorithm able to recognise distinct categories from unstructured free text fields in OTC derivatives data, such as the floating leg of swaps. Implementation of alerts based on this algorithm is underway to automatically detect transactions that are not compliant with mandatory clearing requirements.[62]

3.4.3 SupTech: uses and potential uses by central banks and prudential authorities

Machine learning can be applied to systemic risk identification and risk propagation channels. Specifically, NLP tools may help authorities to detect, measure, predict, and anticipate, among other things, market volatility, liquidity risks, financial stress, housing prices, and unemployment.[63] In a recent Banca d'Italia (BdI) study, still in progress, textual sentiment

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[60] In addition to the applications of AI and machine learning, there are a number of potential applications of distributed ledger technology (DLT), cloud computing and digital identity to regulatory reporting. These RegTech applications are beyond the scope of this paper. See IIF (2017) for more detail.

[61] See e.g. FSB (2017), *Review of OTC derivatives market reforms: Effectiveness and broader effects of the reforms*, at p. 28

[62] AMF (2017), "AMF creates Fintech lab and signs partnership with R3," press release, April.

[63] David Bholat, Stephen Hansen, Pedro Santos, and Cheryl Schonhardt-Bailey (2015), *Text mining for central banks*, Bank of England CCBS Handbook No. 33.

derived from Twitter posts is used as a proxy for the time-varying retail depositors' trust in banks. The indicator is used to challenge the predictions of a banks' retail funding model, and to try to capture possible threats to financial stability deriving from an increase of public distrust in the banking system. Furthermore, at the BdI, in order to extract the most relevant information available on the web, newspaper articles are processed through a suitable NLP pipeline that evaluates their sentiment. In another study, academics developed a model using computational linguistics and probabilistic approaches to uncover semantics of natural language in mandatory US bank disclosures. The model found risks as early as 2005 related to interest rates, mortgages, real estate, capital requirements, rating agencies and marketable securities.[64] Other studies are able to predict and anticipate market outcomes and economic conditions, including volatility[65] and growth.[66]

Use of machine learning combined with NLP can be used to identify patterns for further attention from supervisors in large and complex data. Machine learning can also be used with NLP to link trading databases to other information on market participants. This could include, for example, the ability to integrate and compare trading activity information with behavioural data like communications and to compare normal trading scenarios with those that may have substantial deviations, triggering the need for further analysis.[67]

Central banks can use AI to assist with monetary policy assessments. A 2015 survey of central banks' use of and interest in big data reported, among other things, that central banks expected a growing use of big data for macroeconomic and financial stability purposes. The most prevalent expected use was for economic forecasting, in particular for economic indicators such as inflation and prices. For instance, 39% of central banks expect to 'nowcast,' or predict in real time, retail home prices using big data. AI can be used to forecast unemployment, GDP, industrial production, retail sales, tourism activity, and the business cycle (for example, with sentiment indicators and nowcasting techniques).[68, 69]

Recent research highlights how these methods could be used. Researchers at Columbia University have recently combined newly developed machine learning approaches with observational studies to enable public authorities and market participants to: (i) 'score' policy choices and link them to indicators of financial sector performance; (ii) simulate the impact of policies under varying economic and political conditions; and (iii) detect the rate of change of

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64 See Kathleen Weiss Hanley and Gerard Hoberg (2016), "Dynamic Interpretation of Emerging Systemic Risks," working paper, October.

65 See Harry Mamaysky and Paul Glasserman (2016), "Does Unusual News Forecast Market Stress?" Columbia Business School Research Paper No. 15-70, April.

66 See Samuel Fraiberger (2016), "News Sentiment and Cross-Country Fluctuations," February.

67 See Bart van Liebergen, "Machine Learning: A Revolution in Risk Management and Compliance?" The CAPCO Institute Journal of Financial Transformation, 2017. See also, Singapore Monetary Authority development of algorithms to detect and identify trading accounts suspected of syndicated activity, Ravi Menon, Managing Director, MAS, "Financial Regulation – The Forward Agenda," March 20, 2017.

68 See Irving Fisher Committee on Central Bank Statistics (2015), "Central banks' use of and interest in "big data,"" October.

69 A growing body of existing research done by academics and others suggests that machine learning tools do in fact make it possible to better detect, measure, predict, anticipate, and even nowcast market outcomes. See the following for more examples: Cindy K. Soo (2013), "Quantifying Animal Spirits: News Media and Sentiment in the Housing Market," University of Pennsylvania The Wharton School, January; Hal Varian and Hyunyoung Choi (2009), "Predicting the Present with Google Trends" Google Research Blog, April.

market innovation by comparing trends of policy efficacy over time.[70] With the aim of studying the redistributive effects of fiscal policy over different municipalities, a study from the BdI employs a dynamic factor model and utilises a dataset containing variables from different sectors of the economy. In order to select the statistically most relevant independent variables they use automatic regression variable selection.[71] At the Office of Financial Research (OFR), researchers are evaluating the potential for machine learning tools to identify new financial innovations receiving more attention from market participants in financial publications. OFR researchers have also used machine learning to extract sentiment and key topics from financial publications in order to evaluate the relationship between news, attention, and financial stability.

3.4.4 Uses by market regulators for surveillance and fraud detection

Some regulators are using AI for fraud and AML/CFT detection. The Australian Securities and Investments Commission (ASIC) has been exploring the quality of results and potential use of NLP technology to identify and extract entities of interest from evidentiary documents. ASIC is using NLP and other technology to visualise and explore the extracted entities and their relationships. In order to fight criminal activities carried out through the banking system (such as money laundering), BdI collects detailed information on bank transfers and correlates this information with information from newspaper articles. The correlation involves both structured and unstructured data for file sizes of more than 50 gigabytes. In the same vein, the Monetary Authority of Singapore (MAS) is exploring the use of AI and machine learning in the analysis of suspicious transactions to identify those transactions that warrant further attention, allowing supervisors to focus their resources on higher risk transactions. Investigating suspicious transactions is time consuming and often suffers from a high rate of false positives, due to defensive filings by regulated entities. Machine learning is being used to identify complex patterns and highlight the suspicious transactions that are potentially more serious and warrant closer investigation. Coupled with machine learning methods to analyse the granular data from transactions, client profiles, and a variety of unstructured data, machine learning is being explored to uncover non-linear relationships among different attributes and entities, and to detect potentially complicated behaviour patterns of money laundering and the financing of terrorism not directly observable through suspicious transactions filings from individual entities.

Market regulators can also use these techniques for disclosure and risk assessment. The US Securities and Exchange Commission (SEC) staff leverages "big data" to develop text analytics and machine learning algorithms to detect possible fraud and misconduct. Certain risk assessment tools are beginning to move into the AI space.[72] For instance, the SEC staff uses

[70] Sharyn O'Halloran, Sameer Maskey, Geraldine McAllister, David K. Park and Kaiping Chen (2015), "Big Data and the Regulation of Financial Markets," IEEE/ACM International conference on Advances in Social Networks Analysis and Mining.

[71] Monica Andini, Emanuele Ciani, Guido de Blasio, Alessio D'Ignazio, and Viola Salvestrini (2017), "Targeting policy-compliers with Machine Learning: An application to a tax rebate program in Italy," Banca d'Italia working paper, forthcoming.

[72] The SEC staff has noted that it extracts words and phrases from narrative disclosures in forms and filings and using human written rules to define patterns in document to systematically measure and assess how emerging growth companies are availing themselves of JOBS Act provisions. See Scott Bauguess (2017), "The Role of Big Data, Machine Learning and

machine learning to identify patterns in the text of SEC filings. With supervised learning, these patterns can be compared to past examination outcomes to find risks in investment manager filings. The SEC staff notes that these techniques are five times better than random at finding language that merits a referral to enforcement. While the results can generate false positives that can be explained by non-nefarious actions and intent, these nonetheless provide increasingly important signals to prioritise examination.[73] For investment advisers, the SEC staff compiles structured and unstructured data. Unsupervised learning algorithms are used to identify unique or outlier reporting behaviours – including both topic modelling and tonality analysis.[74] The output from this first stage is then combined with past examination outcomes and fed into a second-stage, machine learning algorithm to predict the presence of idiosyncratic risks at each investment advisor.[75] In Australia, ASIC has also used machine learning software to identify misleading marketing in a particular sub-sector, such as unlicensed accountants in the provision of financial advice.[76]

4. Micro-financial analysis

From a micro-financial point of view, the application of AI and machine learning to financial services may have an important impact on financial markets, institutions and consumers.[77] In this section, potential changes to incentives and behaviour and how they may affect financial stability, for better or worse, are considered.

4.1 Possible effects of AI and machine learning on financial markets

Since AI and machine learning have the potential to substantially enhance the efficiency of information processing, thereby reducing information asymmetries, applications of AI and machine learning have the potential to strengthen the information function of the financial system.[78] The mechanisms whereby this improvement may occur include:[79]

a) AI and machine learning may enable certain market participants to collect and analyse information on a greater scale. In particular, these tools may help market participants to understand the relationship between the formulation of market prices and various factors,

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AI in Assessing Risks: a Regulatory Perspective," Speech by Acting Director and Acting Chief Economist, Division of Economics and Risk Analysis, OpRisk North America, June 21.

73 See Bauguess (2017). See also Gerard Hoberg and Craig M. Lewis (2015), "Do Fraudulent Firms Produce Abnormal Disclosure?" Working paper.

74 Topic modelling lets the data define the themes of each filing. Tonality analysis gauges the negativity of a filing by counting terms with a negative connotation. See Bauguess (2017).

75 See Bauguess (2017).

76 See Greg Medcraft (2017), "The Fourth Industrial Revolution: Impact on Financial Services and markets," speech, March.

77 See FSB FinTech Issues Group (2017), p. 14; 18-19 for a description of comparable impact that FinTech has generally.

78 For a seminal reference on the functions of the financial system, see Robert Merton and Zvi Bodie (2005), "Design of financial systems: Towards a synthesis of function and structure," *Journal of Investment Management* 3(1): 1–23.

79 The Bank of Japan held an AI conference on April 13, 2017, and the market views described in this chapter are in line with those expressed in this conference.

such as in sentiment analysis. This could reduce information asymmetries and thus contribute to the efficiency and stability of markets.[80]

b) AI and machine learning may lower market participants' trading costs. Moreover, AI and machine learning may enable them to adjust their trading and investment strategies in accordance with a changing environment in a swift manner, thus improving price discovery and reducing overall transaction costs in the system.

Nonetheless, if many market participants come to use similar AI and machine learning programmes in areas such as credit scoring or financial market activities, the consequent correlated risks may entail financial stability risks. If machine learning-based traders outperform others, this could in the future result in many more traders adopting similar machine learning strategies (even if this may also reduce the profitability of such strategies). While there is no evidence of this occurring to date, this could become relevant with greater adoption of such trading strategies. As with any herding behaviour in the market, this has the potential to amplify financial shocks. Moreover, advanced optimisation techniques and predictable patterns in the behaviour of automated trading strategies could be used by insiders or by cybercriminals to manipulate market prices.[81]

4.2 Possible effects of AI and machine learning on financial institutions

AI and machine learning have the potential to enhance the efficiency and profitability of financial institutions, while reducing their costs and risks, through various channels. Greater profitability could aid the build-up of buffers and ultimately benefit system-wide stability:

a) AI and machine learning may enhance machine-based processing of various operations in financial institutions, thus increasing revenues and reducing costs. For example, if AI and machine learning help to identify customers' needs and better target or tailor products to profitable customers, financial institutions could more efficiently allocate resources toward serving those customers that account for substantial fees or have the potential for future growth. Automating routine business processes may allow for lower operating costs.

b) AI and machine learning can be used for risk management through earlier and more accurate estimation of risks. For example, to the extent that AI and machine learning enable decision-making based on past correlations among prices of various assets, financial institutions could better manage these risks. Tools that mitigate tail risks could be especially beneficial for the overall system. Also, AI and machine learning could be used for anticipating and detecting fraud, suspicious transactions, default, and the risk of cyber-attacks, which could result in better risk management. But AI and machine learning based tools might also miss new types of risks and events because they could potentially 'overtrain' on past events. While AI and machine learning tools hold potential to improve risk management, the recent deployment of these strategies means that they remain untested at addressing risk under shifting financial conditions.

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[80] See IOSCO (2017), p. 28.

[81] Rachel Wolcott (2017), "'Hacking the algo:' when automated traders are victims, not villains," Thomson Reuters Regulatory Intelligence, August.

c) The data intensity and open-source character of research in AI and machine learning may encourage collaboration between financial institutions and other industries, such as e-commerce and sharing economy businesses.

Nonetheless, use of AI and machine learning risks creating 'black boxes' in decision-making that could create complicated issues, especially during tail events. In particular, it may be difficult for human users at financial institutions – and for regulators – to grasp how decisions, such as those for trading and investment, have been formulated.[82] Moreover, the communication mechanism used by such tools may be incomprehensible to humans, thus posing monitoring challenges for the human operators of such solutions.[83] If in doubt, users of such AI and machine learning tools may simultaneously pull their 'kill switches,' that is manually turn off systems. After such incidents, users may only turn systems on again if other users do so in a coordinated fashion across the market. This could thus add to existing risks of system-wide stress and the need for appropriate circuit-breakers.

In addition, if AI and machine learning based decisions cause losses to financial intermediaries across the financial system, there may be a lack of clarity around responsibility.[84] For example, if a specific AI and machine learning application developed by a third party resulted in large losses, is the institution that conducted the trading solely responsible for the losses? Or would regulators or other parties be able to pursue potential claims against the application developer? Could more widespread use of AI and machine learning, including by non-traditional market players, impact the nature of supervision? Furthermore, there are open questions about (identifying) potential collusion among trading applications that rely on deep learning. Specifically, if algorithms interact in ways that would be considered collusion if done by human agents, then as with human agents, proof of intent may be an issue. In this light, there may be a number of legal uncertainties (see annex A). Finally, the lack of transparency around applications may be problematic for both institutions and regulators when it may not be possible to understand how undesired events occurred and when steps may need to be taken to prevent a recurrence.

Any uncertainty in the governance structure in the use of AI and machine learning might increase the risks to financial institutions.[85] If each investor makes their investment without fully understanding the applications and his or her possible losses in tail events, the aggregate risks could be underestimated. In addition, any uncertainty in the governance structure could substantially increase the costs for allocating losses, including the possible costs of litigation. In this regard, financial institutions applying AI and machine learning to their businesses need to establish well-designed governance and maintain auditability.

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82 For an article concisely describing the problems of black boxes in AI decision-making, see Will Knight (2017), "The Dark Secret at the Heart of AI," MIT Technology Review, April.

83 For example, the recent publicity around the Facebook AI agents illustrates this possibility. See Andrew Griffin (2017), "Facebook's AI creating its own language is more normal than people think, researchers say," The Independent, 3 August.

84 Several regulators argue that final responsibility always lies at the regulated entity, who should perform robust due diligence for all contracted services. In many jurisdictions, financial entities may contract services from third-party providers but remain responsible for compliance with relevant rules. See BCBS (2017), "Implications of fintech developments for banks and bank supervisors - consultative document," August.

85 For a central banker's speech illustrating the issue of AI and its governance, see Haruhiko Kuroda (2017), "AI and the Frontiers of Finance," speech by the Governor of the Bank of Japan at the Conference on "AI and Financial Services/Financial Markets," Tokyo, April.

Finally, there may be important third-party dependencies. In the development of AI and machine learning to date there is a high reliance on a relatively small number of third-party technological developers and service providers. This third-party reliance could be relevant for market participants and financial institutions in the future. For instance, if a major provider of AI and machine learning tools were to become insolvent or suffer an operational risk event, this could lead to operational disruptions at a large number of financial institutions at the same time. These risks may become more important in the future if AI and machine learning are used for 'mission-critical' applications of financial institutions.

4.3 Possible effects of AI and machine learning on consumers and investors

If AI and machine learning reduce the costs and enhance the efficiency of financial services, consumers could obtain a number of benefits.

a) Consumers and investors could enjoy lower fees and borrowing costs if AI and machine learning reduce the costs for various financial services.

b) Consumers and investors could have wider access to financial services. For example, applications of AI for robo-advice might facilitate people's use of various asset markets for their investments. Moreover, AI and machine learning, through advanced credit scoring for FinTech lending, might make wider sources of funds available to consumers and small and medium enterprises (SMEs).

c) AI and machine learning could facilitate more 'customised' and 'personalised' financial services through big data analytics. For example, AI and machine learning might facilitate the analysis of big data, thus clarifying the characteristics of each consumer and/or investor and allowing firms to design well-targeted services. Nonetheless, the use of consumers' data may entail issues of data privacy and information security.[86] Moreover, since AI and machine learning analytics could analyse the characteristics of each customer through public data, it would be necessary to consider how the output of customer analysis should be protected, while protecting the anonymity of each consumer and facilitating the safe and efficient use of big data for better services. In addition, establishing well-designed governance structures for financial service providers using AI and machine learning would be important for consumer and investor protection purposes.

Avoiding discrimination in credit scoring, credit provision, and insurance is also an important topic. Even where data on sensitive characteristics such as race, religion, gender, etc. are not collected, AI and machine learning algorithms may create outcomes that implicitly correlate with those indicators, for example, based on geography or other characteristics of individuals. There is ongoing research on how to address and mitigate these biases. This is a key area in the broader discussion on AI ethics (see annex B).

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[86] Since AI and machine learning analytics could analyse the characteristics of each customer through public data, it would be necessary to consider how the output of customer analyses and protecting the anonymity of each consumer and facilitating the safe and efficient use of big data for better services. In addition, establishing well-designed governance structures for financial service providers using AI and machine learning would be important for consumer protection purposes. On issues of data privacy and information security, see Haruhiko Kuroda (2016), "Information Technology and Financial Services: The Central Bank's perspective," Remarks by Governor Kuroda at the FinTech Forum, August 23.

4.4 Current regulatory considerations regarding the use of AI and machine learning

Because AI and machine learning applications are relatively new, there are no known dedicated international standards in this area. Yet in light of some of the potential risks identified above, a few efforts by international standards-setters and similar international fora of regulators deserve note. For example, several international standards-setters have considered risks associated with algorithmic trading, as it has become a pervasive feature of markets that may, among other things, amplify systemic risk. Examples include the following:

- The International Organization of Securities Commissions (IOSCO) reported on the impact of new technologies including algorithmic trading on market surveillance, and made recommendations to consider, including for data collection and cross-border cooperation.[87]
- The Senior Supervisors' Group (SSG), a forum for senior representatives of supervisory authorities from around the world, issued principles for supervisors to consider when assessing practices and key controls over algorithmic trading activities at banks.[88]

Some national regulators note that, from a supervisory perspective, firms developing algorithmic models based on AI and machine learning should have a robust development process in place. They need to ensure that possible risks are considered at every stage of the development process. This is particularly important in order to avoid market abuse and prevent the strategy from contributing to, or causing, disorderly market behaviour.[89] This requirement is part of MiFID II, which will come into force in the first quarter of 2018 in Europe. There are similar requirements for algorithms imposed on certain regulated entities by a US securities self-regulatory organisation.[90]

Similarly, the Basel Committee on Banking Supervision (BCBS) notes that a sound development process should be consistent with the firm's internal policies and procedures and deliver a product that not only meets the goals of the users, but is also consistent with the risk appetite and behavioural expectations of the firm. In order to support new model choices, firms should be able to demonstrate developmental evidence of theoretical construction; behavioural characteristics and key assumptions; types and use of input data; numerical analysis routines and specified mathematical calculations; and code writing language and protocols (to replicate the model). Finally, it notes that firms should establish checks and balances at each stage of the development process.[91]

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87 IOSCO (2011), "Regulatory Issues Raised by the Impact of Technological Changes on Market Integrity and Efficiency," July; IOSCO (2013), "Technological Challenges to Effective Market Surveillance Issues and Regulatory Tools," April

88 Senior Supervisors' Group (2015), "Algorithmic Trading Briefing Note," April.

89 These statements were made in discussions at the two workshops and in internal discussions in the FIN.

90 See FINRA (2015), "FINRA Rule 3110 (Supervision)," June.

91 See BCBS (2011), "Principles for the Sound Management of Operational Risk," June.

5. Macro-financial analysis

Widespread adoption of AI and machine learning could impact the financial system in a number of ways, depending on the nature of the application. From the perspective of economic growth, the application of AI and machine learning to financial services has potential to enhance the efficiency of the economy and to contribute to growth through the following mechanisms:[92]

(a) Enhancing the efficiency of financial services: more efficient risk management of individual banks' loan portfolio and insurers' liabilities may benefit the aggregate system. AI and machine learning could help process information on the fundamental value of assets, thus allocating funds to investors and projects more effectively. Moreover, if AI and machine learning increase the speed and reduce the costs of payment and settlement transactions, for example by executing trades at times when there are available counterparties with corresponding demand, this may stimulate transactions for real economic activities.

(b) Facilitating collaboration and realising new 'economies of scope:' Were AI and machine learning to facilitate collaboration between financial services and various industries, such as e-commerce and 'sharing economy' industries, this could realise new economies of scope and foster greater economic growth. For example, customer analysis based on transaction data attached to payment and settlement activities (for example, "who buys what, when, and where?") would encourage cooperation between e-commerce and financial services.

(c) Stimulating investments in AI and machine learning related areas: Many firms, including non-financial businesses, appear eager to apply AI and machine learning to their business. The growth in investments in AI and machine learning-related R&D can directly contribute to economy-wide investment and thus stimulate economic growth.

From a macro-financial viewpoint, the short- to medium-term effects of the adoption of AI and machine learning on financial structure and markets could be more mixed. There are a number of potential effects on the systemic importance of market participants, the degree of concentration, and market vulnerabilities, which are elaborated below.

5.1 Market concentration and systemic importance of institutions

AI and machine learning may affect the type and degree of concentration in financial markets in certain circumstances. For instance, the emergence of a relatively small number of advanced third-party providers in AI and machine learning could increase concentration of some functions in the financial system. Similarly, access to big data could be a source of systemic importance, especially if firms are able to leverage their proprietary sources of big data to obtain substantial economies of scope. Finally, the most innovative technologies may be mainly affordable to large companies because the development of uses requires significant investments (for acquiring and maintaining the infrastructure and the skilled workers).

For the possible impact of AI and machine learning on banks' systemic importance, there are a number of key scenarios. If AI and machine learning 'unbundle' traditional banking services

[92] For a central bank's view focusing on the impacts of AI on the economy more broadly, see Carolyn Wilkins (2017), "Blame It on the Machines?" speech to the Toronto Region Board of Trade, Toronto, Ontario, 18 April.

and entice new firms to offer financial services, this might reduce the systemic importance of individual large universal banks. These banks could focus on a more narrow set of activities, rather than continuing to offer universal services.[93] However, taken as a group, universal banks' vulnerability to systemic shocks may grow if they increasingly depend on similar algorithms or data streams. On the other hand, if a large bank, which already has public trust, successfully adopts AI and machine learning so as to strengthen its market power, its systemic importance could increase. Whether other market participants provide similar services on competitive terms may also be affected by market entry costs and regulation. Thus, it is difficult to assess whether AI and machine learning would generally increase or decrease the degree of concentration.

5.2 Potential Market Vulnerabilities

Use of AI and machine learning for trading could impact the amount and degree of 'directional' trading. Under benign assumptions, the divergent development of trading applications by a wide range of market players could benefit financial stability. For example, if machine learning-powered robo-advisors give more customised advice to individuals, their investment activities may become more tailored to individual preferences and perhaps less correlated with other trading strategies. By reducing the barriers to entry for retail consumers to invest, these applications could also expand the investor base in capital markets. Similarly, the use of AI and machine learning for new and uncorrelated trading strategies by hedge funds could also result in greater diversity in market movements. More efficient processing of information could help to reduce price misalignments earlier and hence mitigate the build-up of macro-financial price imbalances.

On the other hand, new trading algorithms based on machine learning may be less predictable than current rule-based applications and may interact in unexpected ways. To the extent that firms using AI or machine learning techniques can generate higher returns or lower trading costs, it is likely that incentives for adoption will increase. In the absence of data on the extent of market-wide use, market movements may be ascribed to AI and machine learning models, and interpretation of market shocks may be hampered. Finally, high frequency trading (HFT) applications of AI and machine learning could be new sources of vulnerabilities. If a similar investment strategy based on AI and machine learning is widely used in HFT, it might increase market volatility through large sales or purchases executed almost simultaneously.[94]

Regarding leverage, liquidity, and maturity transformation, the adoption of AI and machine learning by financial market participants such as hedge funds and market makers may also have both positive and negative impacts. AI and machine learning could increase liquidity in financial markets through enhanced speed and efficiency of trading activities. AI and machine learning could be used to detect excessive risks and overly-complicated transactions and to design more effective hedging strategies for risk management by individual financial

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[93] See Hiroshi Nakaso (2016), "FinTech – Its Impacts on Finance, Economies and Central Banking," speech, November 18.

[94] See, e.g., FSB FinTech Issues Group (2017), p.46: "we have found no empirical evidence so far on convergence of robo-advisors' algorithms or portfolios."

institutions.[95] To the extent these tools enable the growth of new credit platforms to directly connect lenders and borrowers (broadly called FinTech credit),[96] this could reduce reliance on bank loans, reduce banks' leverage, and achieve a more diversified risk-sharing structure in the overall financial system. On the other hand, to the extent that market participants use AI and machine learning in order to minimise capital or margins or maximise expected returns on capital (within the constraints of regulations, and without paying due attention to risks), the use of AI and machine learning may increase risks. Specifically, it may allow for much tighter liquidity buffers, higher leverage, and faster maturity transformation than in cases where AI and machine learning had not been used for such optimisation.

5.3 Networks and interconnectedness

Applications of AI and machine learning may enhance the interconnectedness of financial markets and institutions in unexpected ways. Institutions' ability to make use of big data from new sources may lead to greater dependencies on previously unrelated macroeconomic variables and financial market prices, including from various non-financial corporate sectors (e-commerce, sharing economy, etc.). As institutions find algorithms that generate uncorrelated profits or returns, there is a risk these will be exploited on a sufficiently wide scale that correlations actually increase. These potentially unforeseen interconnections will only become clear as technologies are actually adopted.

More generally, greater interconnectedness in the financial system may help to share risks and act as a shock absorber up to a point. Yet the same factors could spread the impact of extreme shocks.[97] If a critical segment of financial institutions rely on the same data sources and algorithmic strategies, then under certain market conditions a shock to those data sources – or a new strategy exploiting a widely-adopted algorithmic strategy – could affect that segment as if it were a single node. This may occur even if, on the surface, the segment is made up of tens, hundreds, or even thousands of legally independent financial institutions. As a result, collective adoption of AI and machine learning tools may introduce new risks.

5.4 Other implications of AI and machine learning applications

AI and machine learning applications in insurance markets could reduce the degree of moral hazard and adverse selection – but could also undermine the risk pooling function of insurance. Moral hazard and adverse selection are inherent problems in insurance. Nonetheless, if AI and machine learning are used to continuously adjust insurance fees in accordance with changing behaviour of the policyholders, this may reduce moral hazard. If AI and machine learning are utilised to offer customised insurance policies reflecting detailed characteristics of each person, it may also decrease adverse selection. On the other hand, these uses may pose various new challenges. For example, the more accurate pricing of risk may lead to higher premiums for riskier consumers (such as in health insurance for individuals with a genetic predisposition to

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[95] See the debates in the panel discussion entitled "FinTech and the Transformation of Financial Services" held in the International Monetary Fund on April 19, 2017.

[96] See CGFS and FSB (2017).

[97] Andrew Haldane (2009), "Rethinking the financial network," speech at the Financial Student Association, April.

certain diseases) and could even price some individuals out of the market. Even if innovative insurance pricing models are based on large data sets and numerous variables, algorithms can entail biases that can lead to non-desirable discrimination and even reinforce human prejudices. This warrants a societal discussion on the desired extent of risk sharing, how the algorithms are conceived, and which information is admissible.[98]

Meanwhile, AI and machine learning can continue to be a useful tool both for financial institutions (RegTech) and supervisors (SupTech). Many of the uses described in section 3.4 could result in improvements in risk management, compliance, and systemic risk monitoring, while potentially reducing regulatory burdens. Yet, if a similar type of AI and machine learning is used without appropriately 'training' it or introducing feedback, reliance on such systems may introduce new risks. For example, if AI and machine learning models are used in stress testing without sufficiently long and diverse time series or sufficient feedback from actual stress events, there is a risk that users may not spot institution-specific and systemic risks in time. These risks may be pronounced especially if AI and machine learning are used without a full understanding of the underlying methods and limitations.

Furthermore, as the current regulatory framework is not designed with the use of such tools in mind, some regulatory practices may need to be revised for the benefits of AI and machine learning techniques to be fully harnessed. For example, in MiFID II, where an obligation is placed on the firm to submit a report when a reportable event occurs, regulatory compliance is expected of the firm at all times. If AI and machine learning tools are used to deem if a particular activity is reportable or not, mistakes would still result in regulatory action, even if the tools can identify what information the regulators truly needs in order to reduce the risk of market disruption. In this regard, combining AI and machine learning with human judgment and other available analytical tools and methods may be more effective, particularly to facilitate causal analysis.[99] More generally, the greater adoption of AI, machine learning, and other technological advances in finance may benefit also from more of a 'systems' perspective in financial regulation to contribute to financial stability in an increasingly complex system.[100]

If optimisation solutions are adopted primarily by the private sector but not the public sector, there may be a risk that some individuals or firms may use them more successfully to 'game' regulatory rules or conduct regulatory arbitrage.

6. Conclusions and implications for financial stability

The use of AI and machine learning technology is changing the provision of some financial services. While data on the extent of adoption in various markets is quite limited, dialogue with market participants suggests that some segments of the financial system are actively employing AI and machine learning. These applications are thus currently more widely used than other

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98 See IAIS (2017).

99 Susan Athey (2017), "Beyond prediction: Using big data for policy problems," *Science* 355(6324): 483-485.

100 Andrei A. Kirilenko and Andrew W. Lo (2013), "Moore's Law versus Murphy's Law: Algorithmic Trading and Its Discontents," *Journal of Economic Perspectives*, 27(2) 51–72; Susan Athey (2017), "Beyond prediction: Using big data for policy problems," *Science* 355(6324): 483-485.

key FinTech innovations, such as distributed ledger technology or smart contracts. In particular, fraud detection, capital optimisation, and portfolio management applications appear to be growing rapidly. Most market participants expect that AI and machine learning will be adopted further. Because of this, it is important to start thinking about the financial stability implications now rather than after the potential implications have been realised.[101] The analysis is necessarily partial and will benefit from greater understanding of use cases over time. Moreover, many of the changes will not result in a material change to financial stability and hence fall outside the scope of this report.

The use of AI and machine learning in financial services may bring key benefits for financial stability in the form of efficiencies in the provision of financial services and regulatory and systemic risk surveillance. The more efficient processing of information on credit risks and lower-cost customer interaction may contribute to a more efficient financial system. The internal (back-office) applications of AI and machine learning could improve risk management, fraud detection, and compliance with regulatory requirements, potentially at lower cost. In portfolio management, the more efficient processing of information from AI and machine learning applications could help to boost the efficiency and resilience of financial markets – reducing price misalignments earlier and (under benign assumptions) reducing crowded trades. Finally, with use cases by regulators and supervisors, there is potential to increase supervisory effectiveness and perform better systemic risk analysis in financial markets.

At the same time, network effects and scalability of new technologies may in the future give rise to additional third-party dependencies. This could in turn lead to the emergence of new systemically important players. AI and machine learning services are increasingly being offered by a few large technology firms. Like in other platform-based markets, there may be value in financial institutions using similar third-party providers given these providers' reputation, scale, and interoperability. There is the potential for natural monopolies or oligopolies. These competition issues – relevant enough from the perspective of economic efficiency – could be translated into financial stability risks if and when such technology firms have a large market share in specific financial market segments. These third-party dependencies and interconnections could have systemic effects if such a large firm were to face a major disruption or insolvency.

Many current providers of AI and machine learning tools in financial services may fall outside the regulatory perimeter or may not be familiar with applicable law and regulation. Where financial institutions rely on third-party providers of AI and machine learning services for critical functions, and rules on outsourcing may not be in place or not be understood, these servicers and providers may not be subject to supervision and oversight. Similarly, if providers of such tools begin providing financial services to institutional or retail clients, this could entail financial activities taking place outside of the regulatory perimeter.

The lack of interpretability or 'auditability' of AI and machine learning methods has the potential to contribute to macro-level risk if not appropriately supervised by microprudential supervisors. Many of the models that result from the use of AI or machine learning techniques are difficult or impossible to interpret. The lack of interpretability may be overlooked in various situations, including, for example, if the model's performance exceeds that of more

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[101] See CGFS and FSB (2017); FSB (2017).

interpretable models. Yet the lack of interpretability will make it even more difficult to determine potential effects beyond the firms' balance sheet, for example during a systemic shock. Notably, many AI and machine learning developed models are being 'trained' in a period of low volatility. As such, the models may not suggest optimal actions in a significant economic downturn or in a financial crisis, or the models may not suggest appropriate management of long-term risks.

Should there be widespread use of opaque models, it would likely result in unintended consequences. For example, if multiple firms develop trading strategies using AI and machine learning models but do not understand the models because of their complexity, it would be very difficult for both firms and supervisors to predict how actions directed by models will affect markets. When the models' actions interact in the marketplace, it is quite possible that unintended, and possibly negative, consequences could result for financial markets. Similar unintended consequences may occur in applications aimed at credit scoring, capital optimisation, or cyber threat detection, where the build-up of risks may occur slowly.

As with the use of any new product or service, there are important issues around the appropriate risk management and oversight of AI and machine learning. In discussions with FSB members for this report, industry representatives noted the challenges posed by conducting audits effectively, including sufficient skills in-house to understand and supervise AI and machine learning models. Beyond the staff operating these applications, key functions such as risk management and internal audit and the administrative management and supervisory body should be fit for controlling and managing the use of applications. Yet, the scarcity of resources with the required skills and knowledge can be an issue.[102] On the supervisory side, auditing of models may require skills and expertise that supervisory institutions may not currently have. Some supervisors note a need to examine specifications developed in the scheduling and staging process of model development and to assess the governance structure around various stages of the model after its launch.[103]

Assessing AI and machine learning applications for risks, including adherence to any relevant protocols regarding data privacy, conduct risks, and cybersecurity, is important at this stage. It is important that progress in AI and machine learning applications is accompanied with further progress in the interpretation of algorithms' outputs and decisions. Increased complexities of models may strain the abilities of developers and users to fully explain, and/or, in some instances, understand how they work. Efforts to improve the interpretability of AI and machine learning may be important conditions not only for risk management as noted above, but also for greater trust from the general public as well as regulators and supervisors in critical financial services.

The uses of AI and machine learning should continue to be monitored. As the underlying technologies develop further, there is potential for more widespread use, beyond the use cases discussed in this report. It will be important to continue monitoring these innovations and to update this assessment in the future.

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102 FSB (2017), pp. 31-32.

103 This statement derives from discussions at the two workshops and in internal discussions in the drafting team.

Glossary

Algorithm: a set of computational rules to be followed to solve a mathematical problem. More recently, the term has been adopted to refer to a process to be followed, often by a computer.

Artificial intelligence: the theory and development of computer systems able to perform tasks that traditionally have required human intelligence.

Augmented intelligence: augmentation of human capabilities with technology, for instance by providing a human user with additional information or analysis for decision-making.

Big data: a generic term that designates the massive volume of data that is generated by the increasing use of digital tools and information systems.

Chatbots: virtual assistance programmes that interact with users in natural language.

Cluster analysis: A statistical technique whereby data or objects are classified into groups (clusters) that are similar to one another but different from data or objects in other clusters.

Deep learning: a subset of machine learning, this refers to a method that uses algorithms inspired by the structure and function of the brain, called artificial neural networks.

FinTech: technologically enabled financial innovation that could result in new business models, applications, processes, or products with an associated material effect on financial markets and institutions and the provision of financial services.

InsurTech: the application of FinTech for insurance markets.

Internet of things: the inter-networking of physical devices, vehicles, buildings, and other items embedded with electronics, software, sensors, actuators, and network connectivity that enable these objects to collect and exchange data and send, receive, and execute commands.

Machine learning: a method of designing a sequence of actions to solve a problem that optimise automatically through experience and with limited or no human intervention.

Margin valuation adjustment: a method to determine the funding cost of the initial margin posted for a derivatives transaction.

Natural Language Processing (NLP): An interdisciplinary field of computer science, artificial intelligence, and computation linguistics that focuses on programming computers and algorithms to parse, process, and understand human language.

Open source: a designation for a computer programme in which underlying source code is freely available for redistribution and modification.

RegTech: any range of applications of FinTech for regulatory and compliance requirements and reporting by regulated financial institutions. This can also refer to firms that offer such applications, and in some cases can encompass SupTech (see below).

Reinforcement learning: a subset of machine learning in which an algorithm is fed an unlabelled set of data, chooses an action for each data point, and receives feedback (perhaps from a human) that helps the algorithm learn.

Robo-advisors: applications that combine digital interfaces and algorithms, and can also include machine learning, in order to provide services ranging from automated financial recommendations to contract brokering to portfolio management to their clients, without or with very limited human intervention. Such advisors may be standalone firms and platforms, or can be in-house applications of incumbent financial institutions.

Social trading: a range of trading platforms that allow users to compare trading strategies or copy the trading strategy of other investors. The latter is often referred to as 'copy trading' or 'mirror investing.'

SupTech: applications of FinTech by supervisory authorities.

Supervised learning: a subset of machine learning in which an algorithm is fed a set of 'training' data that contains labels on the observations.

Terabyte: a unit of data storage, equal to one trillion (10^{12}) bytes, or 1,000 gigabytes.

Tonality analysis: a method to gauge the negativity of a piece of text by counting terms with a negative connotation.

Topic modelling: a method of unsupervised learning lets the data define key themes in text.

Unsupervised learning: a subset of machine learning in which the data provided to the algorithm does not contain labels.

Zettabyte: a unit of data storage, equal to one sextillion (10^{21}) bytes, one trillion gigabytes, or one billion terabytes.

Annex A: Legal issues around AI and machine learning

AI and machine learning present a range of legal issues relating to privacy and data protection, consumer protection, anti-discrimination and liability issues, and cross-border issues.

The issues around data privacy relate to the ability to access the data being processed by AI and machine learning tools. While big data are widely used to generate profits, they can only do so with technology that converts the data into relevant services.[1] In financial services, AI and machine learning applications usually depend on access to, and use of, large amounts of data in a 'life cycle' that includes data collection, data compilation and consolidation, data mining and analytics.[2] The applicability of laws and regulations will be generally fact-driven and jurisdiction-specific. But certain legal issues are being commonly evaluated in the context of the use of AI and machine learning with big data, including the applicability of data ownership rights and data privacy protections and cross-border flows of data. Regulatory authorities are accelerating efforts to understand the implications for the financial sector.[3]

Data ownership rights and protections are being revised in several jurisdictions. Among OECD members, many have privacy protection laws, and the OECD has guidelines on the protection of privacy and cross-border uses.[4] The European Union (EU) recently enacted a General Data Protection Regulation (GDPR), due to come into force in 2018. Especially relevant with respect to the use of AI and machine learning are Article 11, which provides a right to "an explanation of the decision reached after [algorithmic] assessment," and allied articles providing for similar disclosures.[5] Other key articles relating to AI and machine learning are Article 9, which prohibits the processing of "special [sensitive] categories of personal data" as defined; Article 22, which provides for a data subject's qualified right not to be subject to a decision with legal or significant consequences <u>based solely on automated processing</u>; and Article 24, which provides that decisions shall not be <u>based on</u> special categories of personal data.[6]

Ownership of intellectual property in personal data and data protections may be of particular relevance when a data subject wishes to move their profile to a different data processor, or when a regulator steps in to transfer a service to another provider. In both cases, having intellectual property arrangements that conform with regulatory and client expectations may be challenging given the complexity of the subject area, including cross-border issues (see below).

Meanwhile, some authorities are exploring if consumers should have the ability to understand complex modelling techniques for credit systems.[7] New tools developed to improve interpretability of AI and machine learning models can aid firms and policymakers.[8] Consumer protection, anti-discrimination and liability issues are areas of emerging focus and future work, including on the use of big data analytics in risk management and macroprudential surveillance. A variety of consumer protection laws already apply to big data practices that might include the use of AI and machine learning, such as fair credit reporting, equal opportunity laws, and fair trade practices. Yet not all of these regulations may address AI and machine learning techniques using large quantities of data in digital form.

Anti-discrimination laws in particular may be relevant to AI and machine learning techniques. Machine learning models may result in discriminatory practices that may be unlawful, even where characteristics such as racial or gender information is not input directly; the development of non-discriminatory data mining techniques is an active but unsolved area of research.[9]

Regarding legal liability, there may be questions on the allocation of responsibility among suppliers, operators and users of AI and machine learning systems – for example the responsibility of a manufacturer or distributor of a financial product that is based on third party data input devices or algorithms.[10] There are difficult liability issues, including the extent to which humans may be entitled to rely on expert systems in a wide range of settings. Such liability issues will become increasingly important as artificial agents perform a broader range of tasks currently performed by humans, with the potential for mistakes and for legal disputes around damages.[11]

Finally, the growth of AI and machine learning applications could lead to cross-border issues. Currently, the development of these technologies in finance is concentrated in a small number of countries, while adoption may occur at financial institutions around the world. Regulators should keep in mind that cross-border supervision, cooperation and investigation and other regulatory issues may be expected to arise with AI and machine learning applications active across jurisdictions.

1 Nobuchika Mori (2017), "Will FinTech create shared values?" speech at Columbia Business School conference, May.

2 Defined in EIOPA (2017), "Opinion of the Occupational Pensions Stakeholder Group on JC Big Data," EIOPA-OPSG-17-06 15, March, pp. 6-7. See also U.S. Federal Trade Commission (2016), "Big Data: A Tool for Inclusion or Exclusion," January, p. 3.

3 See EIOPA (2017); U.S. Federal Register (2017), Vol. 82, No.33, and Bureau of Consumer Financial Protection: Docket No. CFPB Notice and Request for Information Regarding Use of Alternative Data and Modelling Techniques in the Credit Process, February 21, 2017 ("CFPB RFI"); European Banking Authority (2017), "Report on innovative uses of consumer data by financial institutions, June. See also FSB FinTech Issues Group (2017), p. 19.

4 OECD (2013), "Guidelines on the Protection of Privacy and Transborder Flows of Personal Data," July.

5 For instance, Articles 13, 14, and 15 require disclosure of the existence of automated decision-making, including profiling, referred to in Article 22(1) and (4) and, at least in those cases, "*meaningful information about the logic involved*," as well as the significance and the envisaged consequences of such processing for the data subject.

6 Note that Articles 9, 22 and 24 are all subject to exceptions. See Sandra Wachter, Brent Mittelstadt, and Luciano Floridi (2017), "Why a Right to Explanation of Automated Decision-Making Does Not Exist in the General Data Protection Regulation," *International Data Privacy Law*, Forthcoming; and Bryce Goodman and Seth Flaxman (2016), "European Union regulations on algorithmic decision-making and a 'right to explanation,'" paper presented at 2016 ICML Workshop on Human Interpretability in Machine Learning (WHI 2016), New York. Wachter et al. argue that these provisions confer no right to an ex-post explanation of decisions, though ex-post explanations may be crafted through jurisprudence or EDPB work. Goodman and Flaxman on the other hand argue the law will also effectively create a "right to explanation," whereby a user can ask for an explanation of an algorithmic decision that was made about them.

7 Michael Gordon and Vaughn Stewart (2017), "Insights on Alternative Data use on Credit Scoring," CPFB Law360, May.

8 See Pang Wei Koh and Percy Liang (2017), "Understanding Black-box Predictions via Influence Functions," Proceedings of the 34th International Conference on Machine Learning, Sydney; Marco Tulio Ribiero, Sameer Singh and Carlos Guestrin (2016), "'Why Should I Trust You?' Explaining the Predictions of Any Classifier," arXiv:1602.04938v3; and Fast Forward Labs (2017), "New Research on Interpretability," August.

9 See Bettina Berendt and Sören Preibusch (2014), "Better decision support through exploratory discrimination-aware data mining: foundations and empirical evidence," Artificial Intelligence and Law 22 (2): 175-209; Indrė Žliobaitė (2017), "Measuring discrimination in algorithmic decision making," Data Mining and Knowledge Discovery 31(4): 1060–1089; and Bruno Lepri, Jacopo Staiano, David Sangokoya, Emmanuel Letouze and Nuria Oliver (2016), "The Tyranny of Data? The Bright and Dark Sides of Data-Driven Decision-Making for Social Good," working paper, December.

10 See EIOPA (2017), pp. 6-7.

11 Laurence White and Samir Chopra (2011), *A Legal Theory for Autonomous Artificial Agents*, University of Michigan Press, chapter 4.

Annex B: AI ethics

The rapid development of AI has inspired both hope and concern about rapidly growing sophistication and capabilities. These discussions extend far beyond AI in financial services and have inspired new research in philosophy on 'machine ethics,' which concerns itself with ethical norms in the behaviour of artificial agents.[1] As artificial agents take on responsibilities in areas, such as executing financial transactions, driving cars, and controlling complex systems of devices, there are concerns about how to ensure ethical behaviour in the interests of users. Recently, Bostrom (2014) has discussed the implications of 'superintelligence,' or AI systems whose capabilities surpass those of humans, potentially resulting in new challenges and unintended consequences.[2] In 2015, a diverse group of technology and science luminaries including Stephen Hawking, Bill Gates, and Elon Musk signed an open letter urging more research into the benefits and risks of AI and another on the dangers of autonomous weapons.[3]

One issue is that AI and machine learning may reinforce biases. Some commentators point to the potential of big data analytics to entrench existing biases in college applications, job selection, prison sentencing, and credit provision.[4] For example, unsupervised learning algorithms may show fewer high-level job vacancies to female applicants, and sentencing algorithms may be harsher for ethnic minorities. Yet depending on programming choices, they may also present opportunities to reduce such discrimination.[5] Other writers note that the use of machine learning to filter news and social contacts or programming choices which disadvantage some languages may have far-reaching long-run consequences.[6]

There are a number of initiatives to further research on AI ethics and the ethical use of AI. For example, in September 2016, a group of large tech firms (Amazon, Facebook, Google, IBM and Microsoft) founded the Partnership on Artificial Intelligence, which aims to "*develop and share best practices on AI*," "*advance public understanding*" and "*identify and foster… AI for socially beneficial purposes*." Apple, eBay, SalesForce, Sony, the ACLU, Human Rights Watch, UNICEF, and a number of other organisations have since joined the partnership, and it has launched research around thematic pillars including "AI, labour and the economy" and "safety-critical AI".[7] Concurrently, the European parliament has debated the legal status of autonomous agents.[8] Finally, machine ethics remains a field of active research, which may yet yield further insights for broader public policy.

[1] Michael Anderson and Susan Leigh Anderson (eds., 2011), *Machine Ethics*, Cambridge University Press; Wendell Wallach and Colin Allen (2008), *Moral Machines: Teaching Robots Right from Wrong*. Oxford University Press.
[2] Nick Bostrom (2014), *Superintelligence: Paths, Dangers, Strategies*, Oxford: Oxford University Press.
[3] Future of Life Institute (2015), "Research Priorities for Robust and Beneficial Artificial Intelligence: an Open Letter," January; --- (2015), "Autonomous Weapons: an Open Letter from AI & Robotics Researchers," July.
[4] Cathy O'Neil (2016), *Weapons of Math Destruction: How Big Data Increases Inequality and Threatens Democracy*, London: Allen Lane.
[5] Executive Office of the President (2016), "Big Data: A Report on Algorithmic Systems, Opportunity, and Civil Rights," Washington, D.C., May.
[6] Robert Munro (2015), "The threat from AI is real, but everyone has it wrong," Operational Database Management Systems, August.
[7] Partnership on AI (2017), "Partnership on AI Strengthens Its Network of Partners and Announces First Initiatives," May.
[8] European Parliament Committee on Legal Affairs (2017), "Draft Report with recommendations to the Commission on Civil Law Rules on Robotics," January.

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