Current and Prospective Industry Applications of AI in Finance*

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1 Introduction

In this note, we provide several current and prospective industry applications of Artificial Intelligence (AI) in finance in a non-technical and big-picture fashion. In particular, we discuss which AI tools are being used to make which types of financial decisions, on what time scales, to address which financial functions, and where and at what level human involvement is being integrated. (AI) is currently being applied to serve a number of objectives across the financial system. A few prominent examples are:

1. **Sentiment Indicators.** Social-media data-analytics companies use AI techniques to provide sentiment indicators to a number of groups in the financial industry. Specifically, investor sentiment indicators are being developed and offered to banks, hedge funds, high-frequency trading traders, social trading and investment platforms.

2. **Trading Signals.** ML can help firms to enhance productivity and to curb costs by quickly scanning and making decisions based on a multitude of sources of information than a human is capable of. But by identifying and relying on patterns that were predictive of outcomes in the past, these tools are also susceptible to fake information. For example, there were market moves across equities, bonds, foreign exchange, and commodities in April 2013 after trading algorithms reacted to a fake news Tweet

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1 AI is defined as the theory and development of computer systems able to perform tasks that traditionally have required human intelligence.

2 Social trading refers to 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."

3 ML is defined as a method of designing a sequence of actions to solve a problem that optimize automatically through experience and with limited or no human intervention.
about two explosions at the White House. This type of problems tends to be exacerbated with a more widespread usage of ML.\footnote{Tero Karpp, and Kate Crawford (2015), "Social Media, Financial Algorithms and the Hack Crash," Theory Culture & Society 33(1): 73-92.}

3. **Fraud Detection.** Seeking to increase productivity and at the same time reduce costs and risks, while complying with regulations, some firms use AI for fraud detection in financial institutions.\footnote{Bart van Liebergen (2017), "Machine Learning: A Revolution in Risk Management and Compliance?". The Capco Institute Journal of Financial Transformation, April} Firms can also use ML for credit monitoring and risk mitigation purposes. Below we consider four categories of industry’s applications of AI. These are: (i) customer-oriented (or “front-office”) applications, including credit scoring, insurance, and chatbots\footnote{Chatbots refer to virtual assistance programmes that interact with clients in natural language.} (ii) operations-oriented (or ”back-office”) applications, including capital optimization, model risk management and market impact analysis; (iii) trading and portfolio management in financial markets; and (iv) applications of AI by financial institutions for regulatory compliance (“RegTech”)\footnote{RegTech refers to 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 even encompass SupTech} or by public authorities for supervision (“SupTech”).\footnote{SupTech refers to applications of FinTech by supervisory authorities.} For each of these cases, a few examples of current and prospective applications are given, with estimates (whenever possible) of the current state of the art of the adoption of technologies in financial industry.

## 2 Customer-oriented Applications

AI is increasingly being adopted in the front office of many financial institutions. Large-scale client data are fed into learning algorithms to assess credit quality and to price loan contracts. Similarly, such data are used to assess risks for selling and pricing insurance policies. Finally, client interactions are increasingly carried out by AI interfaces with so-called chatbots, or virtual assistance programs that interact with clients via a Natural Language Processing (NLP)\footnote{NLP is an interdisciplinary field of computer science, AI, and computational linguistics that focuses on programming computers and algorithms to parse, process, and understand human language.}

### 2.1 Credit Scoring

Credit scoring tools that use ML are designed to speed up lending decision making processes, while potentially limiting any incremental risks. 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 have served as the foundation of most credit scoring models. These models use tools such as regression, decision trees, and other statistical tools to generate a credit score by using a limited amount of structured data.
Recently, banks and other lenders are turning to additional, unstructured and semi-structured data sources, including social media activity, mobile phone usage and text message activity, to capture a more nuanced view of creditworthiness, and improve the rating accuracy of loans. Applying ML algorithms to this constellation of new data has enabled an assessment of qualitative factors such as consumption behavior and consumers’ willingness to pay. The ability to leverage additional data on such measures allows for a greater, faster, and cheaper segmentation of borrower quality and ultimately leads to a quicker credit decision. However, the use of personal data also inevitably raises certain policy issues, in particular those related to data privacy and data protection.

In addition to facilitating a potentially more accurate, segmented assessment of creditworthiness, the use of ML algorithms in credit scoring may also make it possible for a far 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 ML 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. As an example, high-frequency online data on payments transactions can help us to assess the creditworthiness of individuals and small businesses.

While this trend may benefit financial markets with shallow credit markets, it could also potentially lead to an unsustainable increase in credit outstanding in countries with deep credit markets. It should be particularly noted that to this date it has not yet been fully established that ML-based credit scoring models actually outperform traditional ones in terms of assessing creditworthiness.

Recently, a number of FinTech start-up companies have begun to target customers not traditionally served by banks. In addition to more commonly known online lenders that lend in the U.S., one firm is also 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 also drawing on the vast amount 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 are viewed as a first step toward

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13 FinTech refers to 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.
developing a credit history.

**AI** allows a massive amount of data to be processed 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 their 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 learning algorithms could potentially result in a lack of transparency to consumers. This **black box** aspect of **ML** algorithms may in turn raise certain policy concerns. When using **ML** 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 a resulting credit decision. Additionally, the use of new alternative data sources, such as online behavior or non-traditional financial information, could introduce a certain type of bias into the credit decision. Specifically, consumer advocacy groups have argued that **ML** tools can yield a combination of borrower characteristics that simply predicts race or gender, which are factors that fair lending laws prohibit from consideration in many jurisdictions. In particular, these learning algorithms might rate a borrower from an ethnic minority at a higher risk of default because similar borrowers have traditionally been given less favourable loan conditions.

### 2.2 Pricing, Marketing and Managing Insurance Policies

The insurance industry is increasingly utilizing **ML** to analyze complex data in an effort to lower costs and improve profitability. Since analyzing 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** applications in **InsurTech** is particularly wide spread in the U.S., UK, Germany and China. Many applications involve measures to improve the underwriting process, assist agents in sorting through vast data sets that insurance companies have collected to identify cases that pose higher risk. This potentially reduces claims and improves profitability. Some insurance companies are actively using **ML** to improve the pricing or marketing of insurance products by incorporating real-time, highly granular data, such as online shopping behavior or telemetrics (sensors in connected devices, such as car odometers). Firms usually have access to those data.

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15 InsurTech is the application of FinTech to insurance markets.


through partnerships, acquisitions, or noninsurance activities. In many cases, firms need to ask for an active consent of the user whenever data protection regulation asks them to.

AI 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 systems based on NLP. These applications can learn from training sets of past claims to highlight key considerations for human decision-makers. ML techniques can be used to determine repair costs and automatically categorize the severity of a vehicle accident damage. In addition, AI may help reduce claims processing times and operational costs. Insurance companies are also exploring how AI 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 is estimated that global InsurTech investment totalled $1.7 billion in 2016. At the same time, 26% of insurers provide monetary or non-monetary support (for example, coaching) to digital start-ups, and 17% of insurers have an in-house venture capital fund or investment vehicle targeting technology. While the use of ML has the potential to produce more accurate pricing and risk assessment for insurance companies, there may also be consumer protection issues that inevitably arise from potential data errors or an exclusion of certain groups.

2.3 Chatbots

Chatbots are virtual assistants that help customers to transact or solve financial problems. These automated programmes use NLP to interact with clients in NLP (by text or voice), and use ML 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 a widespread usage, especially among younger generations, and they have become more sophisticated. The current generation of Chatbots used by financial services firms is simple, generally providing balance information or alerts to customers, or answering simple questions to clients. It is interesting to note that the increased adoption of Chatbots appears to be highly correlated with an increased usage of messaging applications.

Chatbots are steadily moving toward giving advice to clients and prompting customers to act in a certain way. In addition to assisting customers of financial institutions in making financial decisions, financial institutions can also 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.

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20 Internet of things refers to 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.
in some areas, Asian financial institutions and regulators have developed more sophisticated Chatbots that are currently in use. The insurance industry has also explored the use of Chatbots to provide real-time insurance advice.

3 Operations-oriented Applications

Financial institutions are adopting AI tools for a number of operational (or back-office) applications, such as (i) capital optimization by banks; (ii) model risk management (back-testing and model validation); and (iii) market impact analysis (modeling of trading out of big positions).

3.1 Capital Optimization

Capital optimization, which is the maximization of profits given scarce capital, is a traditional function in running a bank that heavily relies on quantitative analyses. AI tools are built on the foundations of computing capabilities, big data, and mathematical concepts of optimization to increase the efficiency, accuracy, and speed of capital optimization. Optimization of bank’s regulatory capital with ML is of interest to both academic and business professionals recently. In 2012, most banks have conducted meaningful programmes to optimize risk-weighted assets (RWA) and have seen 5 to 15% RWA savings.\(^{22}\) Capital optimization is also being undertaken in the area of derivatives margin optimization such as margin valuation adjustment (MVA).\(^{23}\) New regulations around clearing and bilateral margining have increased the demand for sophisticated techniques for optimizing capital and initial margin.\(^{24}\) AI could assist banks in optimizing MVA, and recent research indicates that effort is being made in this area.\(^{25}\) In the context of the MVA optimization, ML tries to reduce the initial margin for derivatives by a combination of: (a) executing pairs of offsetting derivative trades; (b) executing offsetting strategies with the same dealer; (c) novating trades from one dealer portfolio to another.\(^{26}\) ML 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 optimization is a reduction in the traditionally calibrated regulatory capital and a larger reliance on the non-optimizable capital regulatory tools.

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\(^{23}\) MVA is a method to determine the funding cost of the initial margin posted for a derivatives transaction.


\(^{26}\) Novation is a process of replacing a contract or a series of contracts with a new one(s), whereas a third party takes the place of an original party. This has the effect of canceling agreements that have been already offset with other agreements.
3.2 Risk Management (Back-testing and Model Validation) and Stress Testing

Back-testing\textsuperscript{27} and model validation\textsuperscript{28} are areas where progress with AI will likely be soon to become more pronounced\textsuperscript{29}. Banks are considering ML 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. Recently, US and European prudential regulators focused on back-testing and validation used by banks by providing guidance on model risk management\textsuperscript{30}. Using a range of financial settings for back-testing allows for consideration of shifts in market behavior and other trends, hopefully reducing the potential for underestimating risk in such scenarios.

Some applications have already shown promising results. For instance, one global corporate and investment bank is using UL algorithms\textsuperscript{31} in model validation. Its equity derivatives business has used this type of ML 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. UL algorithms help model validators in the ongoing monitoring of internal and regulatory stress-testing models, as they can help to determine whether these models are performing within acceptable tolerances or drifting away from their original purpose. They can also provide an additional input to operational risk models by indicating the vulnerability of institutions to cyber-attacks.

Similarly, AI techniques are also being applied to stress testing. The increased use of stress testing following the financial crisis has posed challenges to banks as they work to analyze a large amount of data for regulatory stress tests. One provider of AI 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 at limiting the number of variables used in scenario analysis for the loss given default and probability of default models. By using UL methods to review a large amount of data, the tools can be used to assess any bias associated with selection of variables, thereby leading to better models with greater transparency.

\textsuperscript{27}Backtesting assesses the viability of a trading strategy or pricing model by discovering how it would play out using historical data.

\textsuperscript{28}Model validation is defined 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.

\textsuperscript{29}Louie Woodall (2017), "Model risk managers eye benefits of machine learning," Risk, April.


\textsuperscript{31}UL is a subset of ML in which the data provided to the algorithm does not contain labels.
3.3 Market Impact Analysis (Trading Out of Big Positions)

AI can complement conventional market impact models. Firms can use AI to obtain more information from sparse historical models, or help identify non-linear relationships in order flow. ML can be used to create “trading robots” that 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 minimizing 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 an ML approach to minimize a 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. AI tools may help by augmenting models already in use, or by introducing a ML approach to minimize 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.

ML is often used to identify groups of bonds that behave similarly to each other. For example, one firm uses ML 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. 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, ML can be used to help identify how the timing of trades can minimize a 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 actual trade progresses, using SL techniques to make short-term predictions to determine those tweaks. Banks are also testing RL to teach AI tools to react to order imbal-

34 SL is a subset of ML in which an algorithm is fed a set of “training” data that contains labels on the observations.
ance and queue position in the limit order book.\(^{35}\)

4 Trade Execution and Portfolio Management

AI is an active area of research and development (R&D) for asset managers and trading firms. In addition to significant R&D, some firms now use ML 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 discuss the implications of AI on trade execution (which is sell-side) and portfolio management (which is buy-side).

4.1 Trade Execution

Trading firms are looking to AI to use data to improve their ability to sell to clients. For example, analyzing past trading behavior can help anticipate a client’s next order. Trading generates a large quantity of data, and this scale is typically required by ML tools to work effectively. If the current trend of using 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 can more pro-actively manage risk exposures. In particular, ML can serve as a basis for risk modeling by exchanges to determine when members’ trading account positions may have increased risk profiles that warrant an 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 optimize their use of capital by centralizing the risks that arise from various parts of their businesses.

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

4.2 Portfolio Management

In portfolio management, AI tools are being used to identify new signals on price movements and to make a more effective use of the vast amount of available data and market research than with current models. ML 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.

\(^{35}\)RL is a subset of ML 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 to learn.
Among asset managers, ML is used most extensively by systematic ("quant") funds, most of which are hedge funds. While these players have been using quantitative techniques long before the recent advances in DL, they are widely viewed as some of the most avid adopters of these techniques. 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 ML to be effective, both traders and quants need to have a good oversight and a good understanding of the tools used. Many quant funds are not comfortable with fully automating and implementing a model if they cannot understand how a particular prediction is carried out. The focus of ML tools among quant funds reflects how ML is fundamentally an approach to generating predictive power from data, which distinguishes it from investment approaches that use a greater discretion and judgment.

At the moment, ML 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%. In turn, some portion of the trading is based on ML. It is hard to quantify precisely what proportion use ML for several reasons:

1. Firms are hesitant to share proprietary information.

2. When firms do share information on their use of ML, there is not always a standard definition or understanding of what is included in the concept.

3. Some investments or trades may be made on a discretionary basis but informed (to varying extents) by the use of ML. For some quant funds, ML tools inform investment strategies that are implemented by a person. Other firms provide information generated by ML to asset managers. For example, one firm’s ML engine shows how asset prices have behaved historically in response to market events. In other cases, it appears that firms are using ML 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%.

One contact in the industry estimates that "pure" ML players have about $10 billion in assets under management, but that this figure is growing rapidly. In addition to the use by fund managers, specialized firms are making available to asset managers ML 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 learning strategies may follow a

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5 Regulatory Compliance and Supervision

AI 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. The total RegTech market is expected to reach $6.45 billion by 2020 growing at a compound annual growth rate (CAGR) of 76%. SupTech is the use of these technologies by public sector regulators and supervisors. Within SupTech, the objective of AI applications is to enhance efficiency and effectiveness of supervision and surveillance. While there can often be interchangeable in the terms, the two applications are discussed here separately. Some of the examples below are from the academic literature. While not yet being applied by regulatory or supervisory bodies, they represent prospective applications in this sector. The applications 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.

5.1 Regulatory Compliance

For analyzing unstructured data, RegTech can use ML combined with NLP. Besides being applied to monitor behavior and communicate with traders on transparency and market conduct, ML together with NLP can interpret data inputs such as e-mails, spoken word, instant messaging, documents, and metadata. This in turn raises the issue about the limits of 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 a new set of regulations. For instance, 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 Transferable Securities (UCITS) Directive, and the Alternative Investment Fund Managers Directive (AIFMD). Firms could potentially leverage NLP and other ML tools to interpret these regulations in a common language. They could then analyze and codify the rules for automation into integrated risk and reporting systems to help firms to 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 a challenging area where AI is applied.

37Luke Smolinski (2017), ”Wolfe aims to shake up research with AI push,” Risk.net, 23 May.
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. ML is increasingly used in remote KYC of financial services firms to perform identification 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. ML-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 as well. 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. Nonetheless, concerns about their accuracy have kept some financial services from incorporating these tools.

5.2 Macroprudential Surveillance and Data Quality Assurance

AI 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. ML 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. In addition to the applications of AI, there are a number of potential applications of distributed ledger technology (DLT), cloud computing and digital identity to regulatory reporting. Similarly, AI could help trade repositories (TRs) to 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 a full use of TR data. Application of ML 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 ML algorithms could help identify data gaps, data inconsistencies, and fat-finger errors, as well as match likely pairs of trans-

40Macroprudential analysis is the study of the soundness and vulnerabilities of a financial system to identify risks to it.
41FSB (2017), Review of OTC derivatives market reforms: Effectiveness and broader effects of the reforms, at p. 28.
actions 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 ML algorithm able to recognize 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.\footnote{AMF (2017), "AMF creates FinTech lab and signs partnership with R3," press release, April.}

### 5.3 Central Banks and Prudential Authorities

ML 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.\footnote{David Bholat, Stephen Hansen, Pedro Santos, and Cheryl Schonhardt-Bailey (2015), Text mining for central banks, Bank of England CCBS Handbook No. 33.}

In a recent Banca d’Italia (BdI) study, textual sentiment 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 potential threats posed 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.\footnote{Kathleen Weiss Hanley and Gerard Hoberg (2016), "Dynamic Interpretation of Emerging Systemic Risks," working paper, October.}

Other studies are able to predict and anticipate market outcomes and economic conditions, including volatility and growth.\footnote{Harry Mamaysky and Paul Glasserman (2016), "Does Unusual News Forecast Market Stress?" Columbia Business School Research Paper No. 15-70, April.}

Use of ML combined with NLP can be used to identify patterns for further attention from supervisors in large and complex data. ML 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 behavioral data like communications and to compare normal trading scenarios with those that may have substantial deviations, triggering the need for further analysis.\footnote{Samuel Fraiberger (2016), "News Sentiment and Cross-Country Fluctuations," February.}

Central banks can use AI to assist with monetary policy assessments. A 2015 survey of central banks’ use of AI in monetary policy assessments found that AI can...

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).

Recent research highlights how these methods could be used. Researchers at Columbia University have recently combined newly developed ML 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 market innovation by comparing trends of policy efficacy over time. 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 utilizes a dataset containing variables from different sectors of the economy. In order to select the statistically most relevant predictors they use automatic regression variable selection. At the Office of Financial Research (OFR), researchers are evaluating the potential for ML tools to identify new financial innovations receiving more attention from market participants in financial publications. OFR researchers have also used ML to extract sentiment and key topics from financial publications in order to evaluate the relationship between news, attention, and financial stability.

5.4 Surveillance and Fraud Detection

Some regulators are using AI for fraud and anti-money laundering (AML) and combating the financing of terrorism (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 visualize 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 in the analysis of suspicious transactions to identify those transactions that warrant further

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50 Monica Andini, Emanuele Ciani, Guido de Blasio, Alessio Dlgnazio, and Viola Salvestrini (2017), "Targeting policy-compliers with Machine Learning: An application to a tax rebate program in Italy,” Banca dltalia working paper.
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. ML is being used to identify complex patterns and highlight the suspicious transactions that are potentially more serious and warrant closer investigation. Coupled with ML methods to analyze the granular data from transactions, client profiles, and a variety of unstructured data, ML 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 ML algorithms to detect possible fraud and misconduct. Certain risk assessment tools are beginning to move into the AI space. In particular, 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. For instance, the SEC staff uses ML to identify patterns in the text of SEC filings. With SL, these patterns can be compared to past investigation 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 prioritize an investigation. For investment advisers, the SEC staff compiles structured and unstructured data. UL algorithms are used to identify unique or outlier reporting behaviors - including both topic modeling and tonality analysis. See Bauggess (2017). The output from this first stage is then combined with past investigation outcomes and fed into a second-stage, ML algorithm to predict the presence of idiosyncratic risks at each investment advisor. See Bauggess (2017). In Australia, ASIC has also used ML software to identify misleading marketing in a particular sub-sector, such as unlicensed accountants in the provision of financial advice.

6 Micro-financial Analysis

From the viewpoint of a micro-finance, the application of AI to financial services may have an important impact on financial markets, institutions and consumers. In this section, potential changes to incentives and

53Topic modeling is a method of UL by letting data define key themes in text.
54Tonality analysis is a method to gauge the negativity of a piece of text by counting terms with a negative connotation.
behavior and how they may affect financial stability are discussed.

6.1 Financial Markets

Since AI has the potential to substantially enhance the efficiency of information processing, thereby reducing information asymmetries, applications of AI has the potential to strengthen the information function of the financial system. The mechanisms whereby this improvement may occur include:

1. **AI may enable certain market participants to collect and analyze 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, such as the case in sentiment analysis. This could reduce information asymmetries and thus contribute to the efficiency and stability of financial markets.  

2. **AI may lower market participants’ trading costs.** Moreover, AI 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 programmes in areas such as credit scoring or financial market activities, the ensuing correlated risks may entail financial stability risks. If ML-based traders outperform others, this could in the future result in many more traders adopting similar ML 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 a greater adoption of such trading strategies. As with any herding behavior in the market, this has the potential to amplify financial shocks. Moreover, advanced optimization techniques and predictable patterns in the behavior of automated trading strategies could be used by insiders or by cybercriminals to manipulate market prices.

6.2 Financial Institutions

AI has 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:

1. **AI may enhance machine-based processing of various operations in financial institutions, thus increasing revenues and reducing costs.** For example, if AI helps to identify customers’ needs and better target or tailor products to profitable customers, financial institutions could more efficiently allocate resources

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57Rachel Wolcott (2017), ”“Hacking the algo”: when automated traders are victims, not villains,” Thomson Reuters Regulatory Intelligence, August.
Automating routine business processes can result in lower operating costs.

2. **AI** can be used for risk management through earlier and more accurate estimation of risks. For example, to the extent that **AI** 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** could be used to anticipate and detect fraud, suspicious financial transactions, default, and the risk of cyber-attacks, which could result in better risk management. But **AI** based tools might also miss new types of risks and events because they could potentially be “overtrained” on past events. While **AI** tools holds potential to improve risk management, the recent deployment of these strategies means that they remain untested at addressing risk under shifting financial conditions.

3. The data intensity and open-source\(^{58}\) character of research in **AI** may encourage collaboration between financial institutions and other industries, such as e-commerce and sharing economy businesses. Nonetheless, use of **AI** risks creating a "black box" 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. For an article describing the problems of black boxes in **AI** decision-making, see Knight (2017).\(^{59}\) Moreover, the communication mechanism used by such tools may be incomprehensible to humans, thus posing monitoring challenges for the human operators of such solutions. For example, the recent publicity around the Facebook **AI** agents illustrates this possibility. See Griffin (2017)\(^{60}\) If in doubt, users of such **AI** 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** based decisions lead to losses to financial intermediaries across the financial system, there mould be a lack of clarity around responsibility. Several regulators have suggested that final responsibility always lies with 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)\(^{61}\) For example, if a specific **AI** application developed by a third party resulted in large losses, is the institution that conducted the trading solely responsible for

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


60 Andrew Griffin (2017), "Facebook’s AI creating its own language is more normal than people think, researchers say,” The Independent, 3 August.

the losses? Or would regulators or other parties be able to pursue potential claims against the application developer? Could more widespread use of AI, 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 DL. 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. Finally, the lack of transparency around applications may be problematic for both institutions and regulators when it may not be possible to understand how undesirable events occurred and when steps may need to be taken to prevent recurrence.

Any uncertainty in the governance structure in the use of AI might increase the risks to financial institutions. For a central banker’s speech illustrating the issue of AI and its governance, see Kuroda (2017).\footnote{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.} If each investor makes their investment without fully understanding the applications and his/her potential losses in tail events, the aggregate risks could be underestimated. In addition, any uncertainty in the governance structure could substantially increase the costs of allocating losses, including the possible costs of litigation. In this regard, financial institutions applying AI to their businesses need to establish well-designed governance and maintain auditability.

Lastly, there may be important third-party dependencies. In the development of AI 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 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 are used for "mission-critical" applications of financial institutions.

### 6.3 Consumers and Investors

If AI reduces the costs and enhance the efficiency of financial services, consumers could enjoy a number of benefits.

1. Consumers and investors could enjoy lower fees and borrowing costs if AI reduces the costs for various financial services.

2. Consumers and investors could have wider access to financial services. For example, applications of AI for robo-advice\footnote{Robo-advisors refer to applications that combine digital interfaces and algorithms, and can also include ML, 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.} might facilitate peoples use of various asset markets for their investments. Moreover,
AI, through advanced credit scoring for FinTech lending, might make wider sources of funds available to consumers and small and medium enterprises (SMEs).

3. AI could facilitate more “customized” and “personalized” financial services through big data analytics. For example, AI 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. Moreover, since AI analytics could analyze 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 would be important for consumer protection purposes.

On issues of data privacy and information security,\textsuperscript{64} 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 algorithms may create outcomes that implicitly correlate with those indicators, for example, based on geography or other characteristics of individuals. There is an ongoing research on how to address and mitigate these biases. This is a key area in the broader discussion on AI ethics.

### 6.4 Regulatory Considerations

As AI 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 forum of regulators deserve attention. 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:

1. 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.\textsuperscript{65}

2. 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.\textsuperscript{66}


\textsuperscript{66}Senior Supervisors Group (2015), Algorithmic Trading Briefing Note, April.
Some national regulators note that, from a supervisory perspective, firms developing algorithmic models based on AI 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 behavior. 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 U.S. securities self-regulatory organization.\(^\text{67}\)

Similarly, the Basel Committee on Banking Supervision (BCBS) notes that a sound development process should be consistent with the firms 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 behavioral expectations of the firm. In order to support new model choices, firms should be able to demonstrate developmental evidence of theoretical construction; behavioral 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.\(^\text{68}\)

### 7 Macro-financial Analysis

Widespread adoption of AI 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 to financial services has potential to enhance the efficiency of the economy and to contribute to growth through the following mechanisms.\(^\text{69}\)

1. Enhancing the efficiency of financial services: more efficient risk management of individual banks’ loan portfolio and insurers’ liabilities may benefit the aggregate system. AI could help process information on the fundamental value of assets, thus allocating funds to investors and projects more effectively. Moreover, if AI increases 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.

2. Facilitating collaboration and realizing new “economies of scope.” Were AI to facilitate collaboration between financial services and various industries, such as e-commerce and ”sharing economy” industries, this could realize 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, 

\(^{67}\text{FINRA (2015), FINRA Rule 3110 (Supervision), June.}\)


\(^{69}\text{Carolyn Wilkins (2017), ”Blame It on the Machines?” speech to the Toronto Region Board of Trade, Toronto, Ontario, 18 April.}\)
"who buys what, when, and where?") would encourage cooperation between e-commerce and financial services.

3. Stimulating investments in AI related areas: Many firms, including non-financial businesses, appear eager to apply AI to their business. The growth in investments in AI-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 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.

7.1 Market Concentration and Systemic Importance of Institutions

AI 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 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 its implementation requires significant investments (for acquiring and maintaining infrastructure and skilled workers).

For the possible impact of AI on banks’ systemic importance, there are a number of key scenarios. If AI “unbundle” traditional banking services 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 narrower set of activities, rather than continuing to offer universal services. 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 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 would generally increase or decrease the degree of concentration.

7.2 Potential Market Vulnerabilities

Use of AI 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 ML-powered robo-advisors give more customized advice to individuals, their investment activities may become more tailored to individual preferences and perhaps less correlated with other

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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 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 ML may be less predictable than current rule-based applications and may interact in unexpected ways. To the extent that firms using AI 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 models, and interpretation of market shocks may be hampered. Finally, high frequency trading (HFT) applications of AI could be new sources of vulnerabilities. If a similar investment strategy based on AI is widely used in HFT, it might increase market volatility through large sales or purchases executed almost simultaneously.

Regarding leverage, liquidity, and maturity transformation, the adoption of AI by financial market participants such as hedge funds and market makers may also have both positive and negative impacts. AI could increase liquidity in financial markets through enhanced speed and efficiency of trading activities. AI could be used to detect excessive risks and overly-complicated transactions and to design more effective hedging strategies for risk management by individual financial institutions. 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. To the extent that these tools enable the growth of new credit platforms to directly connect lenders and borrowers (broadly called FinTech credit), 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 in order to minimize 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 may increase risks. Specifically, it may allow for much tighter liquidity buffers, higher leverage, and faster maturity transformation than in cases where AI had not been used for such an optimization.

7.3 Networks and Interconnectedness

Applications of AI 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 that 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. If a critical segment of financial institutions relies 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, a collective adoption of AI tools may inevitably give birth to a new kind of risks.

### 7.4 Other Economic Implications

AI applications in insurance markets could reduce the degree of moral hazard and adverse selection. But it could also undermine the risk pooling function of insurance. Moral hazard and adverse selection are inherent problems in insurance. Nonetheless, if AI is used to continuously adjust insurance fees in accordance with a changing behavior of policyholders, this may reduce moral hazard. If AI is utilized to offer customized insurance policies reflecting detailed characteristics of each person, it may also decrease adverse selection. On the other hand, these applications 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 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 an undesirable discrimination and even reinforce human prejudices. This calls for a wider societal debate on the desired extent of risk sharing, how the algorithms are conceived, and which information is admissible.

Meanwhile, AI can continue to be a useful tool for financial institutions (RegTech) and supervisors (SupTech). Many of the applications discussed in section on Regulatory Compliance and Supervision could result in improvement in risk management, compliance, and systemic risk monitoring, while potentially reducing regulatory burdens. Yet, if a similar type of AI is used without appropriately ”training” it or introducing feedback, reliance on such systems may introduce new risks. For example, if AI 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 is 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 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

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71 Andrew Haldane (2009), "Rethinking the financial network," speech at the Financial Student Association, April.
72 IAIS (2017).
occurs, regulatory compliance is expected of the firm at all times. If AI tools are used to determine whether a particular activity is reportable or not, mistakes would still result in an regulatory action being taken, 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 with human judgment and other available analytical tools and methods may be more effective, particularly to facilitate inference drawn from a causal analysis. More generally, the greater adoption of AI in finance may benefit also from more of a "systems" perspective in financial regulation to contribute to financial stability in an increasingly complex system. If optimization 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.

8 Conclusions

The use of AI technology is changing the provision of some financial services. While data on the extent of adoption in various markets is currently still quite limited, discussion with market participants suggests that some segments of the financial system are actively employing AI. These applications are thus currently more widely used than other key FinTech innovations, such as distributed ledger technology or smart contracts. In particular, fraud detection, capital optimization, and portfolio management applications of AI technology appear to be growing rapidly. Most market participants expect that AI will continue to be adopted further in financial industry. Because of this, it is important to start thinking about the financial stability implications now rather than after the potential implications have been realized. The analysis is necessarily incomplete and will benefit from greater understanding of applications over time. The use of AI in financial industry may indeed confer major benefits to 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 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 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 applications 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 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 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 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 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 techniques are difficult or impossible to interpret. The lack of interpretability may be overlooked in various situations, including, for example, if the models performance exceeds that of more 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 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 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. Industry representatives noted the challenges posed by conducting audits effectively, including sufficient skills in-house to understand and supervise AI 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 applications. Yet, the scarcity of resources

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75It is for this very reason that Statistical Learning (as opposed to ML) literature emphasizes model interpretatibility in a a trade-off with model complexity.
with the required skills and knowledge can be an issue. 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. Assessing AI 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 applications is accompanied with a 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 may be important conditions not only for risk management as noted above, but also for a greater trust from the general public as well as regulators and supervisors in critical financial services. The applications of AI should continue to be monitored diligently. As the underlying technologies develop further, there is potential for a more widespread usage, beyond the applications discussed in this note. It is important to continue monitoring these innovations and to update their assessments in the immediate future.