Artificial Intelligence in Risk Management and Financial Stability: Overview and Lessons for West African Bank Supervisors (WABS)

By
K.S. Katata Ph.D
Research, Policy, and International Relations Department
Nigeria Deposit Insurance Corporation (NDIC)

6.0 Introduction

A foremost Stanford-based Artificial Intelligence (AI) expert, Andrew Ng, described AI as "the new electricity" that will revolutionise every sector of the global economy (Ng, 2017). This statement is not far from the truth, at least in banking and financial services. Present-day forecasts about how FinTech could alter banking services can be grouped into data access & open banking, digitization, machine learning/AI, and personalization (McWilliams, 2019**)**.

First coined in 1955[1], AI simply refers to the computer's ability to acquire and apply knowledge without the intervention of the programmer. AI enables the banking and financial industry to meet the demands of customers in smarter, more convenient, and safer ways while accessing, spending, saving, or investing their money (Schroer, 2019). AI, along with associated technologies, is being used for several financial services applications (FSB, 2017). It is being used for several traditional banking issues with solutions that vary based on size, location, and the type of financial institution. A pertinent point put forward by Maskey (2018) is that several financial institutions in developing countries, though presently attempting to improve their data infrastructure, can utilize AI. Neural networks, an AI type, assist banks and other financial services by automating complex processes and decisions, leading to lower costs, improving accuracy, greater customer service, and leads to a competitive edge (Accenture, 2019). A survey of large banks revealed 93 different AI solutions were deployed in 13 different departments of banks (Sloane, 2018). AI is a disruptive technology that will benefit the banking industry with potential cost savings of up to US$1 trillion by 2030 (Maskey, 2018).

China is planning to be a leader in AI by 2030 (Fischer, 2018), and its financial sector is at the forefront of innovations in AI. Not only China but other countries like Canada, Russia, and the United Arab Emirates (UAE) have also already identified AI as a key technology for the future (Fischer, 2018). For instance, Mark Carney[2] state rising usage of AI and big data could lead to significant disproportions between the high-skilled workers who benefit from the advances and those who are sidelined by them[3]. Bank of England has a dedicated webpage with several articles on using FinTech and AI to shape financial services[4]. The US banking system regulators are also scrutinizing developments in retail financial markets, including AI and big data (McWilliams, 2018).

[1] https://www.forbes.com/sites/gilpress/2016/12/30/a-very-short-history-of-artificial-intelligence-ai/#7c0c8bf66fba

[2] The Central Bank of England Governor and Head of Financial Stability Board

[3] https://www.independent.co.uk/news/uk/home-news/mark-carney-marxism-automation-bank-of-england-governor-job-losses-capitalism-a8304706.html

[4] https://www.bankofengland.co.uk/research/FinTech

The World Economic Forum (WEF) collaboration with Deloitte, prepared a comprehensive document on how AI is altering financial services (WEF, 2018).[5] The Forum state that AI has been recognized as a key feature of the Fourth Industrial Revolution, and financial firms around the globe are heavily injecting funds into AI projects while governments and regulators try to understand and contain the weighty uncertainties as a result of AI being essential to institutions and markets. However, a key feature to note is that AI requires other related technologies like big data as opposed to being a completely independent solution.

A 2020 global survey jointly conducted by the Cambridge Centre for Alternative Finance (CCAF) at the University of Cambridge Judge Business School, Ernst & Young, and the World Economic Forum was aimed at providing some empirical data and information on the growing landscape of AI-enabled Financial Services. The study shows that the global financial services sector was experiencing significant digital transformation based on the advancement in the AI field according to the survey sample of 151 firms (FinTechs 54% of the sample and incumbent financial institutions 46%). The findings reveal the growing embracing of AI in finance, leveraging AI to overhaul current solutions and create new products and services.[6]

According to Danielsson, Macrae, and Uthemann (2017), some finance functions are tailor-made for AI, such as financial risk management and bank supervision. However, the authors state that AI can lead to financial system instability because it can increase the types of risks that lead to financial crises. Amongst other challenges, AI suffers from a lack of a universally-accepted definition (WEF, 2018). Also, a key issue affecting smaller firms from adopting AI for financial services is the lack of available talent (Maskey, 2018) because bigger firms have more funds to attract the required skilled personnel.

The advantages, challenges, and risks of AI, therefore, call for understanding as well as monitoring by banking sector regulators (FSB, 2017), the potential benefits of AI to developing economies provide the impetus for its adoption by banking supervisors as led by China, UAE, and USA. Also, as stated by Wall (2018), the progress of AI in banking will not only challenge the supervisors to be current with the industry they regulate, but it will also provide prospects for them to more efficiently and effectively carry out their supervisory roles. This is a gap that this paper attempts to fill by drawing the attention of bank supervisors and deposit insurers to this very important development.

The paper is structured as follows: Section 6.1 presents a review of the literature on AI and associated technologies. The section also presents some statistics on AI-based payments and projections. Section 6.2 presents the role of AI in risk management and bank supervision, while the role of AI in financial stability is discussed in Section 6.3. Section 6.4 concludes and proffers recommendations for banking system supervisors, regulators, and deposit insurers

6.1 Theoretical and Empirical Literature Review

[5] 200+ subject matter expert interviews with leaders across incumbents and innovators and seven global workshops that brought together stakeholders from different backgrounds according to WEF

[6] https://www.ey.com/en_gl/innovation/why-ai-will-redefine-the-financial-services-industry-in-two-years

In this section, we provide a brief review of the literature on empirical issues of AI and associated technologies, including some statistics on AI-based payments and projections. The most commonly used AI technologies in finance and banking are also presented in the section.

6.1.1 The Concept of Artificial intelligence and related technologies

AI has no "generally-accepted" definition, but Fisher (2018) defines it as the capability of a computer system to do tasks that normally require human intelligence. FSB (2017) define AI as "human intelligence exhibited by machines." AI can be defined as the ability of IT systems to obtain and use knowledge without the explicit intervention of the programmer. WEF (2018) and Deloitte (2018) view AI as "A suite of technologies, enabled by adaptive predictive power and exhibiting some degree of autonomous learning, that have made dramatic advances in our ability to use machines to automate and enhance: pattern recognition, foresight, customization, decision-making, and interaction." According to WEF, several applications that are AI-powered utilise a mixture of this automation and enhancements.

As explained by Deloitte (2018), the lack of a standard definition is because AI is not really a technological concept but an approach that mimics human behavior. The techniques that are associated with AI and relevant to financial services are deep learning, machine learning, speech recognition & natural language processing, and visual recognition (Deloitte, 2018). On the other hand, WEF (2018) view AI as unable to stand alone but require other technologies in a mutually-reinforcing relationship so as to offer the desired services and benefits. WEF (2018) argue that advances in AI, blockchain, cloud computing, and quantum computing will reinforce and be mutually beneficial to each other. AI applications in the financial sector fall under the fold of "FinTech," while both machine learning and AI are stimulating the birth of a related field known as "Regtech" that is designed to make regulatory compliance faster, easier, and more efficient (Bauguess, 2017). A basic understanding of what these technologies are is, therefore important.

Arner, Barberis, and Buckley (2015) define FinTech as technology-enabled financial solutions, the new marriage of information technology and financial services. FinTech has also been defined as technology-enabled innovation in financial services that could lead to new business models, applications, processes, or products with an accompanying influence on financial services (FSB, 2017b). BCBS (2018) defines BigTech, an important term that is related to FinTech, as large internationally active technology companies that usually provide web services to consumers over the internet or IT systems and also maintain infrastructure like data storage that other firms use. Examples of BigTech given by BCBS (2018) are Google, Amazon, Facebook, and Apple (collectively known as GAFA), the three largest Chinese technology firms (Baidu, Alibaba, and Tencent), as well as traditional IT firms like Microsoft and IBM that are very relevant to the financial system. BCBS (2018) also defines RegTech (Regulatory Technology) as any kind of FinTech solution used for regulatory compliance and reporting by banks and other regulated financial entities.

Machine learning (ML) is one of the sub-paradigms of AI (BCBS, 2018) that enables IT systems to automatically discover patterns in data and use them to make decisions (Deloitte, 2018). Most definitions of ML are based on the idea that machines can somehow learn (Bauguess, 2017) and produce forecasts using data and experience without explicit specification of all the information required by the IT system to execute the task or be explicitly programmed. ML includes a range of techniques that can be used for several purposes, including prediction, classification, structural discovery, and finding data points that are not common (Wall, 2017).

According to Wall (2018), a likely issue with several ML methods like regression analysis is that the assumptions made about the data structure being considered may not be nearly correct even for a few problems and may even be inappropriate for others. As a remedy to these issues, deep learning was developed by computer scientists modeled according to how the human brain operates so that computers can learn for themselves. Deep learning is, therefore, a subset or type of ML (Deloitte, 2018) and is a class of algorithms that utilise several layers of learning algorithms to infer relationships and meaning out of a large set of data (FSB, 2017). Wall (2018) view deep learning as using algorithms based on the arrangement and function of the brain called artificial neural networks. Examples of deep learning applications are image recognition and natural language processing (NLP). Neural networks are designed based on the organization of the human brain. Artificial neural networks are simply algorithms that learn but are designed as a series of interconnected layers (Accenture, 2019).

A well-regarded aspect of AI is cognitive computing, regarded as the "human aspect of AI" (WEF, 2018). Sommer (2017) defines cognitive computing as a fusion of computer science and cognitive science that attempts to make computers function like the human brain through self-teaching algorithms built using data mining, visual recognition, and natural language processing techniques. Srikanth (2017) views it as the replication of human thought processes in a computerized model using a blend of unstructured and structured data from proprietary and public sources.

6.1.2 Empirical Review of AI-based payments and projections

Globally, AI attracted investments of over US$24 billion globally in 2018, which was a twelvefold increase since 2013 (Kaya, 2019). The biggest share was from the USA, followed by Chinese startups. AI has been predicted to have global revenues of over $47 billion by 2020, compared to $8 billion in 2016, according to research firm IDC[7]. Also, US banks saved $41.1 billion in 2018 using AI, and AI's business value is seen to reach $300 billion globally by 2030[8].

A 2018 GARP/SAS[9] online survey with over 2,000 respondents from across the financial services industry, including banking, investment banking, and asset management, found that 81% of risk professionals are already getting a lot of benefits from AI. AI includes computer vision, forecasting, machine learning, natural language processing, and optimization. The survey showed that AI usage was mostly by the risk management department at 48% of the responses, followed by finance at 14%, and IT at 9%. The users of AI include director-level and above titles at 28%, while team leader/senior manager showed 36%, with an analyst at 31%. The survey also revealed that AI technologies were mostly used for forecasting, then optimization, next is ML, followed by robotic process automation, then natural language processing, and with virtual agents as the least used function.

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[7] https://www.gsb.stanford.edu/insights/andrew-ng-why-ai-new-electricity

[8] https://www.businessinsider.com/jpmorgan-artificial-intelligence-machine-learning-2019-7?IR=T

[9] *Global Association of Risk Professionals (GARP), survey can be found at https://www.sas.com/en_is/news/press-releases/2019/february/artificial-intelligence-risk-garp-survey.html*

In a 2018 web article, Abramovich, Executive Editor, Enterprise Thought Leadership, Adobe, provide the following statistics on AI: 80% of all emerging technologies will be based on AI by 2021; Demand for AI skill, which has doubled in the past 2 years., is not adequate; and the market for wearable AI will reach $180 billion by 2025[10].

The Bank of England (BoE) and the Financial Conduct Authority (FCA) jointly conducted a survey in 2019 to better appreciate the use of ML in UK financial services (BoE, 2019). The survey solicited information from about 300 firms that, include banks, credit brokers, e-money institutions, financial market infrastructure firms, investment managers, insurers, non-bank lenders, and principal trading firms. A total of 106 responses were received. The aim of the survey was to understand the nature of ML implementation, the sectors using it, and for how long. The survey also gathered details on the methodological features of specific ML use cases, like the models and data as well as risks and governance. The major discoveries of the survey are: ML is progressively used in UK financial services; ML is mostly used in anti-money laundering (AML), fraud detection, customer services, credit risk management, as well as general insurance pricing and underwriting. Furthermore, regulation is not seen as a barrier, but legacy IT systems and data limitations are the major constraints. Also, ML does not necessarily produce new risks but could magnify existing ones. Finally, most users apply their existing model risk management framework to ML applications.

6.1.3 Empirical Review of AI Use cases by banks and Other Financial Services Providers

AI is aiding the financial services industry to reorganize and enhance processes from credit decisions to quantitative trading and financial risk management. "the banking industry must react and evolve to not get wiped out by an extinction event such as digital disruption." according to Citibank's global head of bank research Ronit Ghose [11] during EMEA Media Summit.

AI will impact the future evolution of financial services in three main ways (Saxena, 2019)[12]. First, AI enables banks to make new financial products in less time and with fewer resources, thereby requiring minimal monitoring than what is manually obtained. Second, AI will allow banks and other financial institutions to attend to customers who will not be served without it. That is because about two billion people in the world are under-banked (World Bank Global Findex Database of 2017)[13]. AI can help in this instance because traditional banking channels don't necessarily service these customers, but AI can help in addressing this issue. Third, AI can assist banks and other financial institutions in interacting more intensely with users because their customer can engage the bank when he/she desires, unlike traditional brick-and-mortar models or non-AI bank apps that may require human interaction.

Accenture (2019) discusses the uses and risks of neural networks in financial services, specifically in banking, insurance, and capital markets. The banking applications of AI include efficient information retrieval from invoices to authenticate a transaction; fraud detection for credit

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[10] https://cmo.adobe.com/articles/2018/9/15-mindblowing-stats-about-artificial-intelligence-dmexco.html#gs.pnmyf1
[11] https://www.finextra.com/newsarticle/33062/ai-big-tech-and-the-cloud-will-damage-the-banking-industry-if-not-embraced---citibank
[12] Apoorv Saxena, is the global head of AI and machine-learning services for JPMorgan Chase, discusses the bank's AI initiatives with Wharton Business School, University of Pennsylvania.
[13] https://globalfindex.worldbank.org/

transactions, overdraft forecasts using past customers' transaction data, and improved anti-money laundering checks based on satellite and street imagery to confirm addresses as a part of knowing your customer.

Das (2019) describes how deep learning models have been proven to be used for the discovery of relationships and nonlinearities in data that are not easily uncovered using standard econometric techniques. The deep learning models use pattern recognition in a way such that financial problems are presented in pattern recognition form that translates to a higher level of predictability than without them. Das further state that deep learning techniques are used to train pricing models by utilising data on inputs and market prices, making theoretical models like those used for option pricing irrelevant.

Das (2019) also discusses other interesting practical applications of AI in banking. Das describes how Mizuho Financial Group developed a humanoid robot called Pepper in partnership with IBM to handle customer inquiries in the Tokyo branch for its retail banking operations. AI-based customer service assistant is also undergoing trial-testing by the Royal Bank of Scotland to interrelate with staff and customers. The author state that chatbots are rapidly altering the interface and relationship between banks and their customers.

Rosenshine (2019) argues the effect AI has on the financial services industry and states that out of the diverse range of applications, it has the most promise in the financial sector. Rosenshine state that 61% of financial services industry participants are presently either using AI or plan to adopt its application within the next 12 months. The financial sector is leading others in the use of AI, such as ML for fraud detection, chatbots for enhanced customer services, and Big Data analytics for better decision-making and risk management.

Artificial intelligence and machine learning (AI/ML) have made it possible to create new insights and monitoring tools in the financial sector due to the vast amount of data being created as well as advances in computing power (McWilliams, 2019). ML models are increasingly used by banks and FinTechs to help banks in making credit decisions, fraud detection, and improve customer services. According to Brainard (2018), AI is also used by banks for credit origination, insurance pricing, fraud detection, capital optimization, and portfolio management.

J.P. Morgan, a leading global Systemically Important Bank (SIB), has an AI Research team comprised of various AI experts that also partners with various teams to quicken the implementation of AI within the bank[14]. J.P. Morgan explores cutting-edge research in the fields of AI/ML, as well as related fields like cryptography, to develop solutions that are most impactful to its clients and businesses.[15] Its interest is in Anomaly Detection to identify unusual patterns in order to minimize and mitigate risk, as well as Intelligent Pricing to complement traditional pricing models, enabling more accurate prediction.[16] JP Morgan is reported to have a budget of $11.4 billion in 2019 for AI and ML.[17]

[14] https://www.jpmorgan.com/global/technology/artificial-intelligence
[15] https://www.jpmorgan.com/global/technology/artificial-intelligence#research-agenda
[16] https://www.jpmorgan.com/global/technology/applied-AI-and-ML
[17] https://www.businessinsider.com/jpmorgan-artificial-intelligence-machine-learning-2019-7?IR=T

HSBC, another global SIB, is partnering with a Canadian AI firm to analyse data from clients for its global banking decision[18]. The bank is also testing a new AI system to tackle more 'sophisticated' financial crime by spotting odd behaviour faster[19].

Wells Fargo implemented a new AI solution to leverage data better and customize their services (Maskey, 2018). Also, both JPMorgan Chase and Wells Fargo launched AI-based mobile banking apps to make customer relationship management easier and to attract new clients (Maskey, 2018).

AI is used in credit solutions by banks to make smarter underwriting decisions by using a variety of features that more precisely assess traditionally underserved borrowers in the credit decision-making process (Schroer, 2019). For managing risk, Schroer (2019) states that the financial markets are using ML to create more models to recognize trends, identify risks, preserve manpower and ensure improved information for future planning. The firms listed by Schroer used by financial and banking institutions for improved predictions and management risk include Kensho (which provides ML and data analytics to J.P. Morgan, Bank of America, Morgan Stanley, and S&P Global) and Ayasdi. The author also reports AI is also being used by banks in the area of cybersecurity and fraud detection by top US banks.

6.1.4 Empirical Review of AI Use Cases by Banking Sector Supervisors

The FSB (2017) recognizes existing and possible use cases of AI/ML in financial services, including customer-focused; operations-focused; trading and portfolio management in financial markets, and uses by financial institutions like banks as RegTech or by supervisors for supervision as SupTech.

In mid-2016, the Bank of England (BoE) launched the FinTech accelerator scheme to advance its understanding of FinTech concepts, products, and firms as well as to gain further insight into the evolving issues and questions that may arise for policymakers, regulators, and operators (Hauser, 2017). According to Hauser, BoE has completed 9 Proofs-of-Concept (PoCs) with 10 firms. The PoCs are focused on most areas of central banking but can be placed into four main broad technologies: distributed ledgers; data storage and analysis; ML; and cyber security. Even though Hauser elaborated on these four areas, we will only discuss ML (and AI) as they are the focus of this paper. The BoE ML PoC uses algorithms to discover patterns and learn iteratively from data. In the short term, this could be used as a counterpart and reinforce the analysis and supervisory activity of the BoE. It is probably the most challenging and experimental area of FinTech in the BoE Accelerator program. Hauser (2017) describes the ML PoCs, one which investigated algorithms planned to analyse high-resolution limit order book data from trading exchanges.

Another PoC is designed to discover irregularities in anonymised regulatory data from credit unions which pooled conventional data science techniques (including clustering and classification algorithms) with a feature that enables users to highlight suspicious or safe items while allowing the program to 'learn' from the user and adjust the risk scores accordingly. The third ML PoC should expand the findings of the second PoC to more diverse data sets that include transaction data. The fourth and final PoC in this category examines the extent to which analysis of the large

[18] https://www.finextra.com/newsarticle/33951/hsbc-ramps-up-artificial-intelligence-efforts-with-element-ai-partnership

[19] https://www.telegraph.co.uk/business/2019/06/30/hsbc-tests-new-ai-system-tackle-sophisticated-crime/

quantities of weakly-structured textual data on regulated firms to learn whether those insights can complement the analysis of more formal data reporting.

According to Broeders and Prenio (2018), ML at the Monetary Authority of Singapore is used for detecting potential money laundering cases faster. That is because manually creating a network for identifying potential anti-money laundering violations takes about two years. However, utilising AI and ML for the same task can be executed only in a few minutes. Moreover, AI and ML can detect patterns in data that humans cannot.

Broeders and Prenio (2018) also report the use of machine-readable regulation by the UK Financial Conduct Authority (FCA) and Monetary Authority of Singapore (MAS) for data collection, while AI, ML, and Neural Networks are utilized by FCA, MAS, Central Bank of the Republic of Austria (OeNB) and Netherlands Bank (DNB) for data analytics. Data collection applications include data management, supervisory reporting, and virtual assistance, while data analytics applications entail market surveillance, misconduct analysis as well as micro-prudential and macro-prudential supervision. Also, economists, statisticians, and computer scientists from various departments use Big Data & ML at the Bank of Italy for both macroeconomic and microeconomic issues that combine structured data with unstructured textual data to detect anti-money laundering activities.

6.1.5 Empirical Review of Factors that enable AI adoption

It is useful to briefly deliberate the factors that lead to the acceptance of FinTech as an encompassing solution of AI**.** According to Das (2019), the long-run driver for disruptive FinTech is due to the high cost of financial intermediation, which has historically been steady at about 2% of the cost of the transaction amounts since 1880 until the present time. Some of the reasons put forward for this high cost of financial intermediation include the lack of effective competition on the supply side and the lack of knowledge of the consumers on the demand side. For the reason why the adoption of AI is slow, Ng proposes data scarcity and lack of available talent as the main factors[20]. That is because AI algorithms are built by highly talented specialists, and the algorithms require vast amounts of data to be useful, which is not always readily available.

For Culkin and Das (2017), AI has been accepted mainly due to "deep learning" neural networks use when the following three useful factors combine: (1) the efficiency of quantitative analysis for neural nets calibration; (2) advancement in software and hardware for very large (deep) neural nets computational analysis; and (3) the proliferation of big data to use in training these models.

6.2 The Role of AI in Financial Risk Management and Bank Supervision

The aim of this section is to understand how AI influences the risk management and supervision of banks. ML tools can be used to improve market integrity by monitoring potential market abuse practices. The potential of ML can be seen such that authorities like the ECB and the U.S. Fed are using Natural Language Processing (a form of AI) to help them identify financial stability risks[21].

Deep learning, an AI technique combined with granular data, could assist bank supervisors in discovering otherwise tough-to-detect relationships in the banking system (Wall, 2016). Detecting

[20] https://www.gsb.stanford.edu/insights/andrew-ng-why-ai-new-electricity

[21] https://www.frontiersin.org/articles/10.3389/frai.2019.00014/full

these associations could provide supervisors with a greater understanding of how individual banks operate as well as their links across other institutions and the overall financial system.

World Economic Forum, WEF (2018) states that financial system supervision will be redesigned as advanced fraud detection and security features based on AI to limit the capacity of malevolent players to act without being detected. AI can bolster the resilience and efficiency of market infrastructure that includes advanced compliance and risk management. For example, using ML to develop applications that can track down possibly fraudulent activity and reveal false positive flags. ML can also predict loan or bank defaults with greater accuracy, which obviously can improve bank supervision.

Model validation and backtesting are processes that have a high cost to both the supervisors and supervised firms but with substantial bearings on the balance sheets of banks and financial system stability (WEF, 2018). That is because risk modelling is not a perfect process and is, therefore, prone to uncertainty and errors. ML systems can assist in model validation and backtesting through automated modelling such that banks and their supervisors can run millions of trial models a day, thereby reducing and improving both supervision by the regulators and its compliance by the players. Also, ML enables a wide variety of simulations on both new and unstructured data, which is useful for risk analysis and bank supervision.

AI and ML applications are designed to augment the competence and usefulness of supervision and surveillance (FSB, 2017). Generally, AI and ML techniques are used for regulatory compliance, monetary policy and systemic risk identification and risk propagation, regulatory reporting and data quality, and surveillance and fraud detection. Through the automation of macro-prudential analysis and data quality assurance, these techniques may also help to improve macro-prudential surveillance. Specifically, ML can help bank supervisors to detect, measure, predict, and anticipate several financial issues, including financial stress and unemployment. The growing use of AI for stress testing since the 2007 global financial crisis has been challenging to banks while analysing large quantities of data in compliance with regulatory stress tests. AI and ML procedures are also being used for stress testing by both banks and their supervisors (FSB, 2017). Bank supervisors can therefore, potentially improve their effectiveness and perform better systemic risk analysis using AI and ML tools.

Financial Stability Board (2017) further states that ML can be used to detect patterns for increased scrutiny from bank supervisors when the data is large and complex. AI and ML are also used by internal/back-office applications to improve fraud detection, risk management, and compliance with regulatory requirements at a possibly lower cost.

Several regulatory initiatives by the US, European Union, and UK bank supervisors are actively focused on banks' model risk management processes (Woodall, 2017). The consequential and greater than before interest in model risk managers has led to the automation of certain tasks, such as data cleansing and model validation, which ML can do well.

Toronto Centre, TC (2017) discusses how FinTech can impact financial services in the following four ways: by increasing competition, expanding consumer options, democratizing access to financial services, increasing efficiency due to innovation, creating new investment opportunities for established institutions, and improving financial supervision. According to TC, ML can be used for dynamic and predictive supervision such that supervisors can make supervisory decisions in an anticipatory way based on predictive behavioral analysis.

Wall (2018) discuss how ML can be a useful tool for financial supervisors to help them Identify issues requiring additional investigation. Using their gathered knowledge about the pertinent markets and/or institutions, the supervisors can assess the issues recognized by ML. Also, the unsupervised and supervised versions of ML can be useful for bank supervisors. Supervised ML can be used to identify possible violations of regulations, while the unsupervised version can assist by grouping observations into groups, thereby permitting additional investigation of the distinct groups and of those outliers that do not fit into any group.

Wall (2018) also discuss the application of ML to early warning systems (EWS) that seek to detect banks that are more likely to be distressed or fail. Wall state that bank supervisors have used insights from EWS to apportion additional supervisory resources to the banks that are more likely to use those resources.

AI mechanism can be in charge of a system, self-correcting on its own while learning from its mistakes and achieving its stated human objectives (Danielsson, 2017). Also, AI systems are also designed to mimic human behaviour, using well-defined objectives that produce observed outcomes. This implies that AI is ideal for micro-prudential supervision and risk management. The underlying technical issues are clearly defined, as are both the high- and low-level objectives. Therefore both micro-prudential supervision and risk management are well-suited for AI because compliance is based on clearly identified rules and transactions that give rise to huge quantities of structured data. However, Danielsson et al. (2017) state that the very same characteristics that make AI so beneficial for these purposes are also why it could disrupt the financial system and increase systemic risk.

Danielsson (2017) discusses the impact of AI on micro-prudential supervision and risk management. Risk modelling, the first stage of risk management, is straightforward for AI. This step is concerned with processing market prices using rather simple statistical approaches. The next step is to create a risk management AI engine that has knowledge of positions, risk, and human capital. This engine combines a thorough knowledge of all the positions held by a bank with information on the individuals who decide on those positions. That is because most of the required information is already within the banks' existing IT infrastructure.

Once an AI engine has been updated with a bank's objectives, the system can then, on its own, produce standard risk management routines, produce asset allocation decisions, assist in establishing position limits and recommend bonuses or otherwise (Danielsson, 2017). The same tasks that AI executed for risk management can also be done for micro-prudential supervision. According to (Danielsson, 2017), it is AI that led to the birth of a new field called regulation technology, or 'RegTech.' Consequently, supervisory rules can be easily translated into computer language codes. Bank supervisors can use these to authenticate its rules for consistency and compliance while enabling banks, via the application programming interface, can respond better to regulations. Furthermore, both bank supervisors and the banks, using their respective AI systems, can automatically query each other to ensure compliance. The implication of this is that all the banks' generated data becomes optimally labeled and arranged in such a way that the data can be processed automatically by the supervisors to identify risk and other supervisory tasks.

Continuous usage and extensive adoption of AI for supervision and risk management may therefore increase systemic risk (Danielsson, 2017). That is because our focus is on the wrong places for risk, whereby AI for risk management and supervision is concerned with the risk that can be measured, not the one that matters. The issue here is that using statistical distribution, the risk is measurable and quantifiable, but uncertainty cannot be quantified. Due to the inability to train an AI engine based on unknown data, AI cannot therefore cope well with uncertainty. It should be noted that supervision and risk management are mostly focused on risk and not uncertainty. Consequently, uncertainty is mostly ignored by AI, which human risk managers and bank supervisors may also miss but are less likely to. Bank supervisors can also assess current and past knowledge using experience and theoretical frameworks, which AI cannot do.

According to UK's FCA, ML can be used for policy analysis and regulation, while AI enables new approaches to market analysis so that regulators can better apprehend the effect of policies and design more suitable interventions. Two likely areas that the agency would explore further are: using ML to forecast outcomes before they happen, like credit default or financial distress, and using ML as an aid in policy design for causal estimation such that it's able to approximate how the impact of policies differs across individuals[22].

6.3 The Role of AI in Financial stability

This section is largely due to FSB (2017). The growing use of AI and ML in financial services has the potential to increase the efficiency of the financial system while also probably creating new systemic risks by escalating interconnectedness and increasing banks' dependence on opaque models.

Recall the FSB (2017) recognize existing and possible use cases of AI and ML in financial services, including customer-focused; operations-focused; trading, and portfolio management in financial markets and uses by financial institutions like banks for as RegTech or by supervisors for supervision as SupTech.

For the customer-focused use cases, the FSB found that AI and ML applications can enhance market stability as banks possess a greater ability to examine big data to enhance their knowledge of their operations and to better forecast risks. It was, however, noted that because of data paucity on how the market would react to a rise in AI and ML usage, a shock could occur in the market. Actually, there could be incentives for market participants to apply AM and ML applications if their competitors are applying them for customer-focused uses and resulting in increased profits. This rise in market participants could result in market shock and introduce instability to the system.

In terms of operations-focused uses and trading and portfolio management, the FSB state that banks and trading firms would be able to better evaluate market impacts and shifts in market behavior associated with AI and ML usage, thereby escalating stability in the market. On a positive note, back-testing was recognised as an area that can benefit from AI and ML techniques. Back-testing, as earlier highlighted, is a very useful technique for banks and their supervisors in their evaluation of risk models. AI could therefore improve understanding of risk in the market, which could, in turn, improve the stability of markets.

[22] https://www.fca.org.uk/publication/corporate/fca-research-agenda.pdf

The FSB also argues that while AI and ML techniques are beneficial to financial system stability through the reduction of costs, increase in efficiency and increase in profitability for banks, all banks, and financial institutions must establish sound corporate governance structures and risk management standards that take cognizance of the impact of these techniques on institutions' balance sheets are understood. In the absence of a sound governance framework, the application of AI and ML could lead to a rise in operational risk and other risks to banks. Furthermore, given these advantages to consumers of financial services, there must exist proper corporate governance structures and risk management standards to protect the privacy and data of both consumers and investors of the system.

In addition, concerns were raised when the services provided by some third-party providers to banks and other financial institutions were similar as well as based on the same data and algorithms. As these third-party providers grow, the scalability of their solutions may, in the future, lead to the appearance of new systemically important players that may be outside the regulatory perimeter. In this case, FSB (2017) noted that "third-party dependencies and interconnections could have systemic effects if such a large firm were to face a major disruption or insolvency." That could lead to instability in the financial system.

Furthermore, the FSB (2017) report points to the possibility of improved supervisory efficiency and better systemic risk analysis in the financial system for regulators and supervisors with the use of AI and ML. However, the outcome of the use of AI for financial risk management and bank supervision is likely to be reduced volatility but fatter tails, which implies reduced day-to-day risk but higher financial system instability and hence more systemic risk (Danielsson, 2017).

Danielsson (2017) assert that both micro-prudential supervision and risk management are well-suited for AI because compliance is based on clearly identified rules and transaction that gives rise to huge quantities of structured data. AI systems are also designed to mimic human behaviour, using well-defined objectives that produce observed outcomes. However, Danielsson (2017) further emphasized that financial stability, whose focus is on systemic risk, is different from micro-prudential supervision and risk management. That is because financial stability considers the risk of the whole system and is, therefore, more complex, which can make its modelling much more difficult. Continuous usage and extensive adoption of AI for supervision and risk management may therefore increase systemic risk. That is because the complexity of the financial system makes it endogenous. AI can’t be an efficient substitute for macro-prudential authority, even if it can be for micro-prudential authority.

6.4 Conclusions and Recommendations

This paper provided an overview of FinTech in general and Artificial Intelligence in particular as used by banks for their operations as well as by bank supervisors for supervision and risk management. It is widely stated that data is the new ‘Oxygen’ and AI is the new ‘electricity’ of financial services. FinTech and AI-based technological innovations are happening at a fast pace. Both regulators and players are learning how AI tools can be used in the banking sector for compliance, risk management, and supervision, amongst other tasks.

The burgeoning application for AI in the banking world calls for close scrutiny of this field and a deep understanding of its use as well as consequences in banking. Supervisors and banks from developed jurisdictions like the USA and others like China are leading the way in these efforts.

The main concerns of using AI techniques by banks and their supervisors is because of its difficulty in explaining the technology, especially to senior decision-makers, algorithmic transparency because they are designed as a "black box" lacking an articulated reason for a particular decision, and difficulty to spot bias or issues that could lead to unfair treatment of some of customers and possibility of legal or systemic risk if widely used. Also, advances in AI and FinTech are occurring fast, and all regulators will struggle to keep up with these advances.

The following are some recommendations proffered to bank supervisors and deposit insurers on the usage and regulation of AI-based solutions:

i. Given the complexity of AI-based applications, banking system supervisors should collaborate with FinTechs so that the staff of the supervisory agencies can be exposed to a very different way of thinking and working in a more agile and experimental manner. AI/ML applications should be properly managed so that they can assist institutions in understanding their consumers and operations better.
ii. Banking sector supervisors should offer guidance that ensures the appropriate implementation of AI/ML models in banks. Bank supervisors should carefully review and possibly apply their own existing laws, regulations, and supervisory approaches for AI usage by banks. If such laws and policies or guidelines are not found to be relevant or are outdated, relevant laws from AI-leading jurisdictions like the US should be carefully reviewed and their appropriateness evaluated and possibly applied for supervisory uses.
iii. Banks and other financial institutions should be made to institute ethical guidelines and frameworks for the use of AI so as to build trust and instill confidence, especially on data protection and security issues.
iv. It is very important to identify and apply greater examination, evaluation, and oversight of AI tools used by banks that could have a material impact on depositors, consumers, compliance, or safety and soundness of insured or supervised banks.
v. Bank supervisors should develop expertise in AI and its associated technologies.

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