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Some Stylized Empirical Results on the Effect of Artificial Intelligence in Banking Sector

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Abstract: This paper is a survey of recent empirical work on the influence of artificial intelligence in banking industry. It is organized as a series of stylized results which mirror what is generally understood about the application of artificial intelligence and its impacts on the operation of banks. The review of the literature shows that (a) the application of artificial intelligence has significantly positive effect on the performance of banks, enhance risk management, (b) big data analytics support the decision-making process, (c) banks may face several challenges as they attempt to integrate artificial intelligence in their activities.

Keywords: Artificial intelligence, Bank, Survey, Machine learning, Big data

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1. Introduction

The wave of artificial intelligence(AI in short) is a common development trend around the world because of its ability to process millions of information automatically in a few minutes with high degree of accuracy. In the context of finance and banking industry, AI can be used in all core business areas of commercial banks such as detecting credit card frauds, stock exchange analysis, chatbots, virtual assistants, ATMs, etc. AI applications can significantly benefit commercial banks, but only if several challenges are addressed (Königstorfer & Thalmann, 2020)

In the literature, there is no consistent definition of AI, and the term AI is still a topic of discussion. McCarthy (2006), who coined the term in 1956, defined AI as "the science and engineering of making intelligent machines."The term AI is frequently used interchangeably with the terms ML even though the two terms are non interchangeable. Russel and Norvig (2013) defined AI as the study of an intelligent agent that performs actions, whereas they defined ML as a computer's ability "to adapt to new circumstances and to detect and extrapolate patterns." These authors stated that ML is a sub-area of AI.AI and ML needs big data to build its intelligence, both initially, subsequently and continuously. Cox and Ellsworth (1997)were among the first to use the term big data literally, referring to using larger volumes of scientific data for visualization. Big data is extremely crucial for AI development. Meanwhile, AI has been used to facilitate capturing and structuring big data as well as to analyze big data for key insights (O'Leary, 2013).

AI technology plays an important role in banking industry transformation, which has significant impact on the performance of banks. Several previous studies have described the relationship between the application of AI and the performance of banks in qualitative research and some have investigated it empirically (Alzaidi, 2018; Königstorfer & Thalmann, 2020; Kaya, 2019; Vedapradha & Ravi, 2018; Jewandah, 2018; Subudhi, 2019). These previous studies proved that the implementation of AI has a positive influence on the profitability and the technical efficiency of banks. The banking operational efficiency can be enhanced with the deployment of AI in risk management (Leo et al., 2019; Dzhaparov, 2020; Donepudi, 2017), in replacing workforce (Brynjolfsson & Mitchell, 2017; Lu et al., 2017), in assessing customers' credit scores (Li, 2020; Aniceto et al., 2020), in lending decision-making (Maha, 2020; Luong, 2019). However, not all prior studies found the positive effect of AI on the bank performance, the results of the study conducted by Frederica and Murwaningsari (2018) showed thatAI does not affect banking performance in their study area.

Through the comprehensive review of prior studies related to the research topic, it is important to notice that regarding to the measurement of AI variable, previous studies have not measured the level of AI application in banks, they only considered whether banks have applied AI or not. Most of previous studies have focused on the impact of AI applications on the bank performance, however, there are few studies on the determinant factor of the efficiency of the use of AI in banks. Besides that, many studies have investigated the contribution of the application of AI in banking sector in technologically advanced countries, there is few studies conducted in developing countries.

The aim of this paper is to review the increasing empirical studies on the relationship between AI and the bank performance, focusing on recent contributions that are expected to foster the implementation of AI in banking industry. The framework to tackle this task has been to pinpoint and discuss stylized results that have gathered consensus among empirical researchers. The article is organized as follows: Section 2 presents three stylized results, while Section 3presents several challenges of the implementation of AI and concludes the remarks.

2. Stylized Results

2.1 Stylized Result 1: The implementation of artificial intelligence enhances risk management

In the 4.0 technology era, digital transformation is widely used by banks, and AI has been applied in banking operations. Products from AI have created favorable conditions for banks: human resource management, risk management, support management, revenue growth... Besides increasing sales, effective risk management helps banks improve operational efficiency. AI creates conditions for processing large arrays of unstructured data risk, more precise identification of potential problems in the future, full automation of manual processes in risk function, credit scoring automation, developing adequate market risk assessment models, ... GARP (2019) has conducted several surveys that certainly confirm that financial institutions are particularly interested in AI's ability to optimize risk functions. Before, Ginimachine (2018) has forecast that these new technology applications in risk management will save banks $31 billion by 2030. The research by Dzhaparov (2020) also showed that expectations from AI applications include improved risk management (40%), better data management (47%), and increased transparency (46%). Typical AI applications in bank risk management include blockchain, ML, robotic process automation (RPA), artificial neural networks, natural language processing (NLP), computer vision... These applications assist the bank in managing various risks: interest rate risk, market risk, credit risk, off-balance-sheet risk, technology, and operational risk, foreign exchange risk, country or sovereign risk, liquidity risk, liquidity risk, and insolvency risk (Leo et al., 2019).

Credit risk is the biggest risk for commercial banks. ML is a tool to help assess risk effectively through solving algorithms, speeding up the credit process, reducing the cost of data collection, management, and analysis, building a strong financial system (Ghodselahi and Amirmadhi, 2011; Milojević and Redzepagic, 2021; Dzhaparov; 2020). ML is proven to be more effective in credit scoring, credit monitoring, internal credit rating, credit process when compared to traditional methods. The building tenets of AI and ML are learning from past data (Donepudi, 2017). The methods of using credit risk assessment such as Support Vector Machine (SVM), Decision Tree (DT), Neural networks (NNs) are widely used in credit risk management (Leo et al., 2019). DT is a model of the data that encodes the distribution of the class label in terms of the predictor attributes; it is a directed, acyclic graph in a form of a tree. A DT can be used to predict the values of the target or class attribute based on the predictor attributes (Ghodselahi and Amirmadhi, 2011). The studies by Kabari and Nwachukwu (2013) using DT combined with NNs with an accuracy of more than 88% can adequately decide if customers applying for the loan should be granted or not. Or the study by Roy and Urolagin (2019) proposed using a 2-step process, DT and SVM, to accurately determine the level of customer responsibility to effectively credit risk assess. NNs are defined as massively parallel processors, which tend to preserve the experimental knowledge and enable their further use. They simulate the human brain with the intent to collect empirical evidence during the learning process, and inter-neural connections (synapses) are used to store the knowledge. An important feature of NNs, in addition to the ability of learning, is the ability to generalize the learned knowledge. In the economic field, Ghodselahi and Amirmadhi (2011) showed that NNs are used in priority problems where the variables are in non-linear relationships and SVM can be used in credit scoring applications to improve the overall accuracy from a fraction of a percent to several percent. Research conducted by Lai et al. (2006) and Van Gestel et al. (2003) uses the LSSVM model (least square SVM) to measure credit risk assessment. The results show that, compared with traditional techniques linear discriminant analysis, log it analysis artificial neural, SVM helps banks better assess credit risk. In addition, the bank minimizes credit risk through asymmetric information handling. According to Mhlanga (2019), AI can help to solve the problem of information asymmetry is through signaling and the use of big data and deep learning. ML platform can momentarily draw information from various sources include public data, images from satellites, registered from companies, and data from social media like SMS and messenger services and interaction data at the same time (Dzhaparov, 2020). Therefore, AI and ML assist lenders to do serious credit risk analysis, to assess the behavior of the customer, and subsequently by the verification of the ability of the clients to repay the loans. In the study of Königstorfer and Thalmann (2020), AI increases the number and varieties of data types considered for credit risk assessment. This enhanced capability to make accurate predictions using more diverse data is also based on a variety of new algorithms.

In operational risk, AI technology measures and assesses risk and it can also help in opting for an appropriate risk mitigation strategy and finding instruments that can facilitate shifting or trading risk (Aziz and Dowling, 2018). The AI technology used prevents external losses such as credit card fraud. Banks build fraud detection systems in place. The systems are oriented towards increasing the detection rate while minimizing the false positive rate. Models are based on samples of estimated counterfeit and legitimate transactions in supervised detection methods while in unsupervised detection methods outliers or unusual transactions are identified as potential cases of fraud. Both seek to predict the probability of fraud in a given transaction (Leo et al., 2017). In addition, the bank expanded into new areas related to document analysis performing repetitive processes, as well as detection of money laundering that requires analysis of large datasets (Aziz and Dowling, 2018). Thus, great hopes are set upon blockchain technology to reduce the risk of using the banking system for money laundering and terrorism financing. Cyber security is also a matter of concern for banks. Blockchain technology helps prevent and remediate cyber-attacks. Block chain's decentralized and distributed structure help to avoid attacks and it can restore data and processes; the consensus mechanism that is fundamental to the blockchain requires to overcome information theft; blockchain technology makes use of various forms of encryption in various points, thus providing multi-layer protection against cyber security threats; blockchain network transparency also provides protection against virtual attacks and block chains are often hosted on cloud platforms that have solid cyber security controls (Dzhaparov, 2020).

In anti-money laundering, AI helps prevent anti-money laundering by analyzing internal, publicly available and transactional data within customers' wider network (Vedapradha and Ravi, 2018). Based on a large network, the bank is able to detect money laundering through statistical methods and using machine-learning techniques (Leo et al., 2019). Besides, the Financial Stability Board (2017) and Milojević and Redzepagic (2021) show that machine learning is also one of the applications to help overcome the problems of fraud prevention and anti-money laundering. AI and ML could be used for anticipating and detecting fraud, suspicious transactions, default, and the risk of cyber-attacks, which could result in improved risk management (Milojević and Redzepagic, 2021). Anti-Money Laundering (AML) refers to a set of procedures, laws, or regulations designed to stop the practice of generating income through illegal means. Most banks use AI-based systems, which are more robust and intelligent to the AML pattern (Donepudi; 2017). In addition, a C5.0 algorithm was applied to predict risk levels based on the different customer potential risk factors to create the set of rules for cluster allocation (Leo et al.,2019).

To assess liquidity risk, the bank uses ANN and assesses the probability of risk occurrence using Bayesian Networks (Leo et al., 2019). ML was applied to new liquidity risk analyses leading to improved management ability to deal with liquidity risk issues (Milojević and Redzepagic, 2021). New tools, techniques and reporting can be established, and these can be expected to significantly contribute to the Internal Liquidity Adequacy Assessment Process (ILAAP) and Asset Liability Management (ALM) improvement.

AI technology helps manage market risk more accurately. ML is particularly suited to stress testing market models to determine inadvertent or emerging risk in trading behavior (Aziz and Dowling, 2018). Zhang et al. (2017) proposed a combined model of the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model and the Extreme Learning Machine (ELM) can be used to calculate Value-at-Risk (VaR). Research shows that ML models perform better in volatility forecasting and VaR calculation in terms of efficiency and accuracy. It can be used as an essential tool for risk management. AI helps to gauge the impact of trade on the market. Day (2017) argues that ML can help quant's get to grips with the elephant-splash problem in a couple of ways. On one hand, it can complement conventional market impact models. Firms can use artificial intelligence to squeeze more information from sparse historical data, machine learning can be used to create trading robots that teach themselves how to react to market changes.

2.2 Stylized Result 2: The implementation of artificial intelligence/machine learning with big data analytics help bank to assess customers' credit scores more accurately and to generate higher-quality lending decisions

One of the outstanding applications of AI and big data is to help people make faster and more accurate decisions. Banks have begun to use these technologies in their lending decision-making process by providing the necessary data for machine learning. The main applications include: (1) AI and big data make it easier for banks to collect diverse information from customers; (2) ML helps banks assess customers' credit scores and (3) approve loans more quickly. AI has positive effects on customer-oriented applications such as chatbots, customer insights, and credit ratings (Kaya, 2019).

AI applications based on big data help banks understand customers better. Through solutions such as AI Chatbots and big data, banks can exploit the "vestige" left by customers in the digital world to "diagnose" customer interests and characteristics. The AI/ML, with its associated database of historic loan performance records, enhances the organizational knowledge base contributes to better decision-making (Luong, 2019). Normally, to determine the credit safety of customers, most banks rely on data that directly shows the financial ability of customers, including employment contracts, salary statements, credit history is recorded on public or private credit bureaus. However, this information is still limited. Those who have never borrowed, never opened a card will have no credit history or some customers do not have an employment contract, salary statements accurately reflect actual income... Even for those who have borrowed, after many years the customer's financial situation has also changed, the information recorded on the system is no longer relevant. AI-based credit scoring machine learning models combine a customer's credit history and the potential data of big data. ML uses a large source of information mined from AI to improve better credit decisions, including behavioral data, online shopping habits, telecommunications, payment of bills, even health data... Specifically, even though a customer doesn't have any bank loans, they still have many other things to pay monthly. Timely payment can partly determine a customer's creditworthiness. For example, customers who pay postpaid mobile phone bills on time, the ability to spend online, shop online... also create new measures of credit scoring. As a consequence, taking advantage of the vast amount of information also requires advanced analytical techniques that humans cannot process in a short time. Daniel (2019) introduced a few case studies on the effectiveness of AI applications in the banking sector. JPMorgan Chase's Coin N platform was launched with the main function of "analyzing legal documents and extracting key data points and terms". The evaluation of 12,000 trade credit agreements has been shortened from 360,000 hours when manually evaluating before, to seconds after using AI technology. Commonwealth Bank of Australia has launched its in-house Ceba to over a million customers. Ceba can successfully differentiate 500,000 different ways customers may request for different banking activities.

Credit scoring is a technique using statistical analysis data and activities to evaluate the credit risk against customers. Financial data in general and credit data in particular usually contain irrelevant and redundant features. The redundancy and the deficiency in data can reduce the classification accuracy and lead to the incorrect decision (Liu and Motoda, 2012; Guyon and Elisseeff; 2003). Some studies build and test AI/ML application models in credit scoring with high accuracy and speed. Tang et al. (2019) reported a higher incidence of accuracy from the machine learning models, in measuring the credit risk of the energy industry in China. Similar results were found in studies by Buehler et al. (2019) and Ban et al. (2018) for various financial applications as well. Ha and Nguyen (2016) constructed a credit scoring model based on deep learning and feature selection to evaluate the applicant's credit score from the applicant's input features. This study was analyzed using Australian credit datasets and German credit ones. Research comparing the accuracy of a new credit scoring model and previous analytical methods (Linear SVM, CART, k-NN, Naïve Bayes, MLP). The results of the public data showed that the proposed method results in a higher prediction rate than a baseline method for some certain datasets and also shows comparable and sometimes better performance than the feature selection methods widely used in credit scoring. Removing redundant features saves a lot of time in analysis, which takes several tens of minutes to analyze when using the new method while other methods must run several hours.

However, Dastile (2020) points out that ML is unlikely to lead to higher credit prediction accuracy. Several potential ML-related techniques are commonly used in research to determine credit scoring accuracy through algorithmic technology, such as Support Vector Machines (SVM, which makes a line that seeks to maximize the distance between the instances from different groups), Decision Trees (DT, that classify instances by ordering them into sub-trees, from the root to some leaf), Bagging (or Bootstrap aggregating, takes n bootstraps from the full sample and builds a classifier that gives a vote for each sample and uses a majority vote for classifying each instance), Ada Boost (adaptative boosting is similar to bagging, just include a weight in each vote based on its quality), and Random Forest (RF, that classifies by majority decision of votes given by a multitude of decision trees), Vieira et al. (2019). Aniceto et al. (2020) analyzed the adequacy of borrower's classification models using machine learning techniques by comparing predictive accuracy of SVM, DT, Bagging, Ada Boost, and RF with a benchmark based on a Logistic Regression model. A database from a large Brazilian financial institution of 124,624 consumer loans with a tenor of 24 months and the repayments should be made on a monthly basis has been used. Delays of 2 months to repay the loan imply default since this is the criterion used by the financial institution to classify customers. The study finds significant reliability of the ML models because the results show that the ML is better than the traditional model based on logistic regression. While ML algorithms have an average accuracy of 63%, Logistic Regression depicts competitive outcomes. According to the results, RF and Ada boost perform better when compared to other models while SVM models show poor performance using both linear and nonlinear kernels. At the same time, Li (2020) also pointed out that Random Forest and CART have the highest predictive efficiency and should be employed, for a better and more informed risk assessment.

AI and big data generate higher-quality lending decisions. Maha (2020) researched the influence of AI and Big data on loan decisions with data from thirteen banks located in Saudi Arabia. The study used the Cronbach Alpha coefficient to determine the stability, and regression analysis to test the impact of independent variables. The results indicate loan decisions are significantly influenced by AI and Big data, more than 50%. Moreover, AI has a statistically positive impact on the quality of loan decision-making. There was also a positive association between experience, educational qualification, and using big data and AI. Currently, the application of AI in approving loan decisions is not popular in Saudi Arabia's banks. Loan decisions are discretionary and mostly the loan director is responsible, banks may use artificial technology to enhance the loan analytical techniques. At the same time, the author also recommends that bank managers pay attention to the factors of employees' work experience and education level to achieve high efficiency when applying innovations related to big data and AI.

Coordination of humans and AI/ML is required in the lending decision-making process. Modern technologies help improve efficiency when making loan decisions but they have not completely replaced the role of humans. The use of AI/ML in organizational decision-making involves three components: the people, the technology, and the organizational practices. ML is essentially learning how to work by people and work based on the unique characteristics of each organization. Recent research has shown that the application of AI has not yet yielded outstanding results, due to the lack of foundational practices that can facilitate the full integration of AI/ML in business operations throughout the firms' various units, Webb (2018). Change of Mind (Marks et al., 2018) is a more granular measure of AI/ML usage, as it considers the changes in both decisions and confidence levels and thus more closely reflects the belief in the joint work between the human experts and the AI/ ML. Luong et al. (2019) conducted a study on the application of advanced algorithms in evaluating loan applications with the research question: How do technology and organizational practices affect firms' performance when they deploy AI/ML for complex decision-making? This study followed the major guidelines of experimental economics methodology and design a controlled lab experiment with participants were 152 students in the Baruch College. Then, linear regression analysis was used to test hypotheses about the relationship between AI/ML, incentive structures, and making loan decisions. Each participant will evaluate 100 loan applications in the following order: (1) self-assess the loan applications; (2) view the evaluation results of AI/ML and consider adjusting the lending decision; (3) view the results of how each loan actually performs. Revised Decisions are the decisions that are modified per AI/ML predictions and thus represent a willingness to listen to the AI/ML. The result shows that in order for firms to reap benefits from algorithmic decision-making, it is crucial that both proper IT resources and organizational processes be concurrently implemented. Only when the two exist together can firms narrow the theoretical gap between their highest possible potential capacity and their realized capacity. Moreover, research shows that not having to apply intelligent algorithms to jobs always brings higher efficiency and saves more resources. Technologies lacking in reliability cannot help human decision-makers translate organizational knowledge into effective decisions. The authors also point out the importance of the technical skills of the bank staff directly making the decisions. They are still critical for organizational decision-making in that with expertise and skills they can differentiate between high quality and low-quality algorithmic advice. In the case of having to use a low-quality algorithm, experts should be more likely to be able to override the bad algorithmic advice than non-expert decision-makers.

2.3. Stylized Result 3: The implementation of artificial intelligence positively affects the performance of bank

AI has provided newer opportunities across all industries. Banking professionals has shifted in attitude towards technological tools and now they aim to work hand in hand with the technological developments in order to boost the performance of banks. A set of studies concerning the relationship between the implementation of AI and the performance of bank found that banks which have integrated AI applications into daily operations could increase profitability as well as technical efficiency. The contribution of AI into bank performance can be explained in two ways: (1) AI implementation could reduce the demand for less-skilled labor, improve labor productivity, thereby enhancing the operational efficiency; (2) The application of AI could enhance profitability by refining the decision-making process, providing better customer experience, offering innovative products and services to customers, thus generating higher revenue.

It is widely accepted that increasing operational efficiency is very crucial in improving performance. The banking operational efficiency can be enhanced with application of innovative technologies in banks to achieve efficiency (Lagarde, 2018). In fact, the banking operational efficiency can be improved with the implementation of AI in replacing human labor and workforce. Lu et al. (2017) proved that one of the considerable effects of information technology (IT)-enabled automation on staffing decisions is the substitution of technology for labor. Labor demand might fall for tasks that are close substitutes for capabilities of AI. Each time an AI system crosses the threshold where it becomes more cost-effective than humans on a task, profit-maximizing managers will seek to substitute machines for people. This can have impacts throughout the economy, shifting labor demand, increasing productivity, reducing prices, and reshaping industries(Brynjolfsson & Mitchell, 2017). Kaya (2019) draw similar conclusions that by reducing the human work of repetitive nature, AI program could reduce the demand for less-skilled labor, thereby reducing employee compensation and improve the productivity and the efficiency of remaining bank staff.

Mor and Gupta (2021) applied the stochastic frontier (Cobb–Douglas function) to estimate the technical efficiency and technical inefficiency of 47 Indian commercial banks. These authors found that AI applications such as chatbots, virtual assistants, ATMs could reduce technical inefficiency and improve the performance of these examined banks. The implementation of AI could take over repetitive tasks from bankers, provide 24/7 access and supplement the bank employee's work. The influence of AI on the technical efficiency of these banks has reduced technical inefficiency to 11%, primarily due to internal factors or decision making. Therefore, the study suggests that Indian commercial banks should enhance the deployment of AI for boosting performance and reducing the technical inefficiency instead of increasing the number of staffs in the banking industry. Empirical research conducted by Abusalma (2021) also support for the hypothesis that the deployment of AI systems and smart agents raise the efficiency and effectiveness of employees. The author employed the descriptive and analytical approach and developed a questionnaire to measure the impact of AI on job performance of 319 managers working in Jordanian commercial banks in Amman. The results showed that there is a statistically significant influence of AI on job performance through genetic algorithm and intelligent systems. It is true that by applying AI technologies, bank managers are able to build detailed monitoring, training and development plans for each employee performance based on background processes that rely on big data or data analytics related to employee practices in real time (Alhashmi et al., 2019).

Alzaidi (2018) explored the adaption of AI in banking sector of Middle East region which is known for its mixed pace acceptance of various technological tools in the local banking industry. The author collected data from surveying 200 bank employees of the selected banks across the region and employed descriptive and explanatory research method to clarify the areas of implementation of AI and its impact on the performance of banking sector. The research results indicated that AI adaptation in banking sector in Middle East region is far from reaching to complete maturity level within the industry but use of AI in banking industry had become trendsetter. The use of AI can boost efficiency of overall system by increasing ease of service, increasing predictability capabilities of system, and reducing manual errors and discrepancies. Therefore, when applying AI in day-to-day operations, the performance of local banks in Middle East region can be significantly boosted. Using similar framework, Aljaber (2020) identified the impact of AI on the efficiency of accounting systems in 16 Jordanian banks. The author stressed that AI has considerably positive impact on the efficiency of accounting systems in Jordanian banks. The author also gave recommendations that Jordanian banks need to increase the use of AI to raise the bank's efficiency, and that the management of banks should assist expert systems in acquiring knowledge from the knowledge bases stored in the systems in many areas that support the capabilities of the higher management.

Besides shifting labor demand, improving labor productivity and efficiency, the second contribution of AI into bank performance is through higher revenue generation. The application of AI could boost profitability by refining the decision-making process, providing better customer experience, offering innovative products and services to customers. Setiawan and Cavaliere (2021) revealed that the productivity of bank fluctuates when the bank cannot integrate AI programs into banking system effectively and reliably. These authors stated that banks in the United Stated which have successfully deployed AI programs have greater financial performance. Indeed, AI proved to be a better decision-making tool for credit scoring, marketing of products & services, risk management, and many other operational areas. By using AI, commercial banks can reduce losses in lending, increase security in processing payments, automate compliance-related work, and improve customer targeting (Königstorfer & Thalmann, 2020). AI is expected to generate US$1.2 trillion of additional value for the financial industry by 2035 (Stefaneal & Goyal, 2019). In the case of Swedish bank industry, Bergström et al. (2018) also observed that AI help to substitute the local brick and mortar offices in customer services in banking sector.

With the application of AI tools, banks could develop innovative products and offer tailor-made products which are better suited to customer preferences. Kaya (2019) found a linear relation between AI patent applications and return on assets (ROA) in the banking sector in ten European countries from 2010 to 2015, with a correlation of 80%. More specifically, AI patents positively impact ROA at statistically significant levels and explain 7% of the variation in bank profitability. This study also concluded that banks are more profitable in countries where the level of AI patent activity is higher. In the same line, Vedapradha and Ravi (2018) argued that banks adopting AI are able to provide better client service experiences. Banks automate processes, migrate their infrastructure and applications to the cloud to create a seamless customer journey. Since AI can improve efficiency, accuracy, can operate 24 hours, detect fraud, help comply with regulations, offer innovative services, provide a better customer experience, reduce costs and increase revenue, banks increasingly utilize AI tools. Indian banking industry has experienced similar trend.

Jewandah (2018) mentioned that the need to use AI is a growing and the Indian banking sector is gradually shifting itself towards adopting AI. AI provides banks new opportunities by automating the frontline, by engaging with customers in a more automated and intelligent way. Hence, the development of AI field will increase productivity at a reduced cost for banks.AI in banking applications is not just limited to frontline service, it also benefits the back and middle offices of investment banking and all other financial services. Subudhi (2019) stated that AI in banks is bringing in more efficiency to their back-offices and even reducing fraud and security risks. The use of AI can reduce back-office costs, replace manually intensive reconciliations with automated ones, and potentially reduce costs and increase speed.

Several previous studies have described the positive impact of AI on the performance of banks in qualitative research and some have proven it empirically. However, there is a body of empirical literature that points out that the use of AI does not dramatically affect banking performance. Frederica and Murwaningsari (2018) analyzed the effect of AI and operational risk management on banking performance by implementing regulations as a moderating variable. This study gathered data through a survey of170 bank employee respondents who had implemented banking digitization. By employing multiple linear analysis methods, the researchers found that while operational risk management positively impacts the performance of banks, the use of AI does not affect banking performance in the study area. These authors also stressed that currently the sampled banks are also in the early stages of investing in and integrating AI, consequently, in the short term there is no clear impact of AI on banking performance. Additionally, the empirical finding proved that the implementation of regulations helps to strengthen the influence of AI on banking performance, but not for the impact of operational risk management on banking performance. This paper provided several managerial implications that banks need to analyze the role of using AI and active risk management in improving performance. In addition, the deployment of AI should be continuously monitored, and banks should pay attention to the adequacy of infrastructure, talented human resources, and adequate risk management.

3. Concluding Remarks and Challenges of the Implementation of Artificial Intelligence

AI technology in the banking sector is widely invested and applied as it brings many benefits to banks. This paper is a survey of recent empirical work on the influence of AI in banking sector. It is organized as a series of stylized results which mirror what is generally understood about the application of AI and its impacts on the operation of banks. The review of the literature shows that the application of AI has significantly positive effect on the performance of bank by enhancing risk management, improving labor productivity and efficiency, reducing the demand for less-skilled workforce, providing better customer experience, offering innovative products which meet the customer needs, accurately assessing customers' credit scores, supporting the decision-making process. However, few studies point out that when banks are in the early stages of investing in and integrating AI, there may be no clear effect of AI on banking performance in the short term.

Although the application of AI in the banking sector brings many benefits in day-to-day operations, it also poses several challenges. The first issue is related to human resources. To successfully deploy AI into digital transformation, banks have to develop good strategies in information collection, data standardization, infrastructure construction as well as ensure qualified human resources to operate this process. The study conducted by Ukpong et al. (2019) highlighted another challenge of the AI revolution is the changing job skills and job demands that it will place on workers. Kalyanakrishnan et al. (2018) also argued that banks must keep their employees updated with new technologies and processes that may be in place with use of AI in various areas of banking. The second challenge is about information security. Developing AI tools requires a large volume of data and extensive resources, which may lead to privacy issues and may increase the risk of some financial institutions using certain data without their being fully aware of this issue (Fernández, 2019). Hence, when using big data in AI applications, banks must comply with the law and regulations on the right to collect, access and use personal data. The "black box" algorithm used in the AI operating model will also bring great challenges in information transparency. The use of complex algorithms could result in a lack of transparency to consumers (Financial Stability Board, 2017). Nguyen (2020) explains that the transparency of AI systems is affected because: (1) it is difficult to decipher how the system reaches its conclusions and (2) it is difficult to verify why the system made the recommendation. Moreover, the use of information from data sources also needs to be carefully considered because data from unknown sources in cyberspace is not necessarily reliable and suitable when included in the complexity analysis model of the financial industry (Nguyen, 2019). In addition, legal challenges also affect the success of AI applications in the banking sector. The legal system related to digital technology has not been completed, creating a big data synchronization barrier. Legal regulations on data protection, privacy, and consumer interests make it difficult to share or collect customer data. Of course, the different legal systems also pose challenges in the exchange of data information between countries. Managers need to build a long-term AI technology application strategy with a specific phased roadmap. Some notes for effective application of AI during operation are to ensure the linkage of information systems, information infrastructure, professional resources, identify potential businesses, identify risks encountered, financial security and information security infrastructure. In order to promote the advantages and overcome the limitations when using this technology, it is necessary to evaluate specifically with each bank case to give an overview, as a basis for building a more effective development strategy.

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