Intelligent Process Automation in Retail Banking: A Machine Learning Framework for Operational Efficiency Enhancement

Dr. Akiko Yoshikawa, Associate Professor of Mechanical Engineering, Tokyo Institute of Technology, Japan

1. Introduction to AI in Banking Operations

Banks have been at the forefront of adopting modern technologies to ensure higher efficiency, convenience, and ease of use. The ongoing revolution from traditional banking to digital-first practices has put automation and artificial intelligence (AI) at the core of banking operations. Several customer-centric use cases of AI technology have been studied very well. This paper is an attempt to comprehend and accumulate the knowledge about how AI-based strategies are optimized in various aspects of banking operations worldwide. Throughout the years, banks everywhere have utilized technology dominantly for payments, as well as developed AI for anti-money laundering and fraud prevention. Financial services institutions are also investing in R&D to explore behind-the-scenes processes wherein AI can be further advanced. In this regard, the use of AI in banking operations has evolved to prioritize some of these areas: risk assessment, advisory services, decision-making, customer experience, and operations. By using the information and big data, AI in banking is very capable of building a sophisticated algorithm system that can interpret big data in order to support decision-making. This paper aims to provide a detailed consolidation of literature to study the specific trends, opportunities, challenges, applications, and implications of AI in banking operations to optimize the strategies worldwide. The paper is organized with the following sections.

2. Overview of Machine Learning in Banking

Machine learning is an evolving branch of artificial intelligence. It utilizes algorithms to learn from data and, as it learns, to make predictions or decisions based on that data. In this manner, ML increases the efficacy of its models over time. Banking is one industry that relies heavily on advanced technology for operations. As such, ML is used substantially in the optimization and management of banking operations and also forms the base for other technologies such as AI, robotic process automation, and big data in the financial sector. These technologies offer the promise of automation and computer speed for banking operations, including loan or insurance applications, underwriting, customer service processes, portfolio risk management, anti-money laundering compliance, and fraud detection.

ML primarily enhances operational processes for the various services offered by banks. For instance, loan appraisal, in which bank services are gradually optimized, is no longer limited to traditional data but also extends to customer transaction behaviors and potential insights through ML tools. Thus, the loans proceed with minimal manpower involvement. Different types of ML comprising supervised, unsupervised, and reinforced mechanisms have been investigated for big data analytics, automated real-time decision-making, recognition systems, and more in the finance sector. However, the efficacy of ML systems is strongly influenced by the data quality, which includes the data used for training ML systems as well as input data. Nowadays, numerous real-world applications using ML and AI in various aspects of banking are available, which provide recent advances and future trends in the use of these intelligence technologies in banking.

3. Applications of Machine Learning in Banking Operations

Machine learning encompasses a broad variety of applications that can be utilized by banks to improve their services. The real-life application of these tools ranges from front-end customer service enhancement, through fraud prevention and cooperation with compliance units, to algorithmic trading. Banking operations are data-driven. Banks hold information about their customers, their transactions, comments, and complaints, as well as historical data on loans and stock prices. Machine learning can assist banks by presenting quick insights and helping with an automated decision-making process based on available data. Such knowledge can be used by banks to improve their operational efficiency, decrease credit loss, prevent fraud, or grow their operational scale by building new chatbot services. Insights can be organized based on the division of banks' business lines. The first group of applications refers to customer service offerings. The second type is about operational risk. It was divided since fraud detection and credit scoring are two distinct sections of banking business services. The last one, card payment and algorithmic trading, are also discussed in separate paragraphs. An important feature of machine learning for bank operations is that often some of the inputs used in one of the described applications are useful in the other. This shows that machine learning models should not be built in silos, but they can actually benefit from the already used inputs and predictive power already acquired.

3.1. Customer Service and Experience Enhancement

One of the ways in which machine learning has brought about innovations in the banking industry is by enhancing customer service and experience. As humanity becomes increasingly dependent on virtual deliverables, the significance of face-to-face interactions no longer holds. This is further deepened in the lifestyle of banking where it is difficult for everyone to take time out of their '9-5' schedules to physically visit their bank branch. AI-driven chatbots can facilitate customers with instant technical help and responses to frequently asked questions, as well as interact for booking appointments, tracking processes, and several other formalities. Furthermore, banks are now providing customers with the convenience of virtual assistants such as chatbots to enable day-to-day banking, from general inquiries to process flows and beyond. They utilize predictive analytics to know beforehand the banking habits, likes, dislikes, and expectations of their customers. Using the customers' previous history and general predictions based on the time of year, they can make such moves on a large scale.

Additionally, finding patterns from the data of several sources allows for targeted marketing to their specific customer base. The utilization of virtual assistants has exceeded the one million user mark recently. Hence, the deployment of chatbots and virtual assistants to interact with digital customers 24/7 proves to be cost-effective. Although there is still room for improvement given that issues like how chatbots/data are programmed/used and whether it is ethical in relation to data and customer privacy remain to be addressed. For the system to remain operational, the conversation has to be well-structured. The virtual assistant also misbehaved during initial deployment, showing a lack of readiness for sure-fire usability. To tackle these issues, the complexity of the questions was greatly reduced, automated risk management tools increased the security of the chatbot, and optimized security inefficiencies.

3.2. Fraud Detection and Prevention

Protection against fraudulent activities has been the main application of machine learning in banking. While simple fraud schemes are still common, more advanced fraud has been observed, presenting a significant task for antifraud systems. Advanced payment systems and services such as digital wallets and mobile and online banking facilitate and drive their increasing sophistication, raising the bar in protection methods required. Machine learning models learn user profiles and normal customer usage patterns; therefore, they can be used as a real-time intelligence system that can identify unusual patterns and tell us whether an event should be considered suspicious or not. Plastic card transactions with real-time decision-making could easily contribute to reducing fraud significantly. Plastic card fraud is reduced by 50% immediately after an illegal operation. An active antifraud model is trained on many confirmed cases of fraud and then, given the wide array of patterns to look for, it is provided with information to decide when and how to react to suspected fraud.

Given that the magnitude of false positives reflects how sensitive the antifraud model is (the lower the false positives, the more likely one is to have a reaction before something turns into a confirmed act of fraud), the optimal precision criterion is in between. This is ever more obvious considering the need to also maintain good customer satisfaction by keeping refusals to a minimum, thereby attaining optimal fraud incidence. Many procedures will be put in place all at once, even among multiple institutions, to reduce the occurrence of mistakes using AI. Aside from continually training and fine-tuning the algorithms, monitoring standard thresholds for unusual models can be employed. Other kinds of alert systems can be used in computer network protection, just as in that of bank fraud abuses. AI has many strategies available that allow for the capturing of low and high-frequency fraud. Shore up defense measures and make this issuance channel within the financial framework a no-go area by implementing facial, tactile, and voice biometrics processing for signing.

3.3. Credit Scoring and Risk Management

Credit scoring models are one of the most evident use cases for machine learning, thanks to the vast amount of data coming from a variety of sources. By harnessing alternative data from social media, transaction data, ratings and reviews, online behavior, and smartphone details like location, it is argued that AI and machine learning could predict the creditworthiness of potentially millions who are now excluded from financial assistance. The possibilities are endless for AI and machine learning used in risk assessment.

In credit risk management, banks are increasingly advising traditional credit scoring models with machine learning models that are fed a much richer data diet, such as transaction data. As well as the potential to enhance their offering to borrowers and improve profitability, banks could be providing financiers with an important service: more accurate risk predictions should help them make good long-term decisions. However, they will need to pay attention to the way those models are delivered—they can only build up trust in AI and machine learning models if they are transparent and the bank is competent at explaining the decisions those models drive. As far as the AI models are data-driven, the availability of alternative data and performance of models can typically vary quite significantly between firms, countries, customers, or regions. AI in lending may be perceived both as a threat and an opportunity in many developing countries. For providers of AI models in lending, one of the major challenges comes from the fact that the performance of those models often depends on the adoption rate and how the participating customers are utilizing the new service. There has been insufficient attention to regulations and guidelines to prevent or at least minimize the risk associated with the use of AI and machine learning models in credit risk assessment. In some countries, there is a discussion about the best use of appealing machine learning models to assign credit limits to individuals, given that they should account for the possibility of higher default if a machine learning system is used.

3.4. Algorithmic Trading and Investment Strategies

The use of machine learning algorithms to study stock exchange and trading patterns is known as algorithmic trading. Machine learning is used to analyze historical stock prices, daily market trading, and transfer volume, among other things. These data are also used to forecast the value of assets per unit of time. Reinforcement learning is one of the significant techniques employed in developing automated trading models. Another class of trading approaches is hybrid approaches, which are mixtures of computational intelligence models and traditional models. The rise of machine learning systems in the nation's stock markets has caught the attention of regulators and is being investigated. In reality, the increased use of trading algorithms raises many legal and moral questions, such as whether these algorithms profit from the manipulation of investor behavior. Some systems include real-time inputs as well. A few models display the necessary properties for trading in the current volatile financial marketplace. An artificial neural network is a class of machine learning techniques whose architecture motivations are based on the human brain's learning paradigm. In the technology commercialization domain, the artificial neural network has gained significant traction in resolving a range of business issues. The neural network, for example, was employed with success to forecast the prices of financial derivatives and to predict significant financial events such as bankruptcy.

It offers a number of advantages over traditional human-driven trading. These techniques help make crucial choices and engage in high-frequency trading, a kind of trading that involves buying and selling huge volumes of assets rapidly. The adoption of algorithmic trading in the banking business during the financial crisis could have allowed financial institutions to generate greater profits. Human error is minimized when trading is conducted by computer systems round the clock. An effective trading strategy takes advantage of favorable situations and liquidates positions to avoid losses. The basic concept is that trading actions are determined using sophisticated mathematical formulas generated by the success of the trading strategy. However, like every technological tool, algorithmic trading has its drawbacks, such as being vulnerable to market volatility. Furthermore, the technique aims to maximize arbitrage, as data accuracy is critical for algorithmic trading. This is especially true in the banking sector since incorrect data predictions might result in enormous financial losses. With this in mind, there are fewer papers on the banking sector, and no previous investigation has been done to compile a choice of current studies on reactive investment plans in banking with automatic trading.

4. Challenges and Limitations of AI in Banking Operations

Despite the potential benefits of AI in banking operations, there are some challenges and limitations that must be addressed. Banks are subject to international data privacy and security standards, which might hinder the easy application and deployment of deep learning and AI applications. Besides that, using automated and embedded AI in banking operations will likely require banks to be certified by a major international body, which will imply a very strict set of security and control procedures. Another concern is the induction of additional threats to the security and stability of the banking sector, bearing a heavy price in case a system failure happens, especially when all banking operations and services are tightly linked to AI systems.

One limitation is represented by the fact that AI competencies can be used in conjunction with the existing banking operations to optimize their performance. Various challenges and limitations are related to the successful integration of AI with banking processes, such as the financial fusion: one of the limits related to the embedding of AI in banking operations is the size, complexity, and architecture of the existing IT systems in banks necessary to support the AI. A switching system based in the cloud, able to remain option-free and in production in the presence of several types of switches and events, could have quite a complex architecture. Another potential problem in AI-supported banking is that of potential partiality and discrimination.

Incorporating an AI system into banking processes can lead to unfair lending practices or other results because the models may incorporate biases inherited from historical data. Another limitation to the successful integration of AI-supported systems may emerge from human users—employees and stakeholders—averse to technologies. Finally, it is also important to report that, as banking AI will deliver financial services in the same way as people do, this type of banking system will also make mistakes. As a result, AI models in banking need to be constantly monitored to ensure the reliability and effectiveness of the support system provided.

5. Future Trends and Opportunities in AI-Based Banking Operations

The rise of AI in banking has brought disruption and transformation across many operations and customer service tasks. Better, new, and more adaptive technologies are penetrating diverse areas of banking to transform a wide range of operations such as payments, underwriting credit, fraud detection, and managing supply chain finance. Several banking organizations have also started to build a dedicated AI procurement team to manage and standardize the procurement of AI solutions. In the near future, the trajectory of novel AI architectures and approaches will further shape the AI capabilities of advanced digital banking. For example, quantum computing and edge cloud computation have promising solutions for intrinsic and ambient issues such as privacy preservation, encryption, and federated learning. In terms of technology, we note a few key trends that will become dominant in future AI-based banking operations. 1. Natural

Language Processing. The use of NLP applications is on everyone's mind since banks can gain better insights from non-numeric data such as customer reviews, calls, social media, news, and corporate reports. Customer service tasks, such as chat and question answering, can be largely enhanced using a powerful NLP technique. 2. Better predictive analytics. With the development of better algorithms and inputs, advanced predictive systems can be used for assessing the ID fraud probabilities of smaller customers. In fact, the accuracy of fraud detection using deep learning could surpass the current financial service providers. Likewise, better annual loan default probabilities can be computed for large customers using better cash flow forecasting models.

6. Conclusion

The twenty-six articles in the special issue discuss the possible uses of AI across core operations in the banking industry. The appraisals and evaluations indicate that AI can improve the customer experience and the overall efficiency of banking operations. It can also help to reduce operational risks. AI has been used to develop operational strategies in credit delivery and investment decision-making. In another instance, AI has improved fraud detection in online banking services. The automation of internal services such as information systems and employee monitoring are also seen in practice.

AI can improve banks' efficiency and effectiveness by enhancing customer service and optimizing financial intermediation processes. It can also mitigate the operational risks involved in the supply side of banking by improving fraud detection or customer profiling. The integration of AI models into banking operations has a transformative potential both for the banks as institutions and for clients engaging with banking services. Effectively, AI is used to improve customer service by providing quicker access to core information that does not require the attention of expert advisors. At the same time, AI services can automate complicated processes by learning from large datasets.

AI has been used to improve operational strategies in areas such as credit scoring. By using geolocation data, a commercial bank improved individual scorecards and boosted portfolio performance. Other AI systems have been used to develop better risk valuation approaches to enterprises by integrating large-scale data set collections. In retail banking, AI insights have helped to develop personalized credit scores and interest rates, thus making the entire loan offer tailor-made to the client. Further, although not always transparent to clients, AI is used in banking operations to develop and execute long-term investment strategies for pension funds.