Jurnal Komunikasi Sains dan Teknologi
Vol. 3, No. 1, Juni 2024, pp. 270~278
ISSN: 2964 - 5077, DOI: 10.61098/jkst.v3i1.125

Review of Improving Banking Operational Efficiency through AI and ML: Strategy, Implementation and Impact

Idha Kristiana[1(✉)]
[1] Information System, Binus Online Learning, Bina Nusantara University, Jakarta, Indonesia
idha.kristiana@binus.ac.id

Article Info

Article history:

Received May 12 2024
Revised May 30 2024
Accepted June 03 2024

Keywords:

Operational Banking Efficiency
Artificial Intelligence
Machine Learning
Systematic Literature Review

ABSTRACT

Artificial Intelligence (AI) and Machine Learning (ML) are critical components in the financial industry's ongoing transformation of operational dynamics with the aim of improving efficiency. Utilizing a systematic literature review (SLR) approach, this article investigates the implementation and impact of AI and ML in banking. It focuses on the ways in which these technologies can optimize operational processes, the obstacles encountered by banks during their integration, and the potential future developments of these innovations in banking operations. The study evaluates the transformative potential of AI and ML in the banking industry, identifies the obstacles to their adoption, and addresses three research questions by examining the potential of AI and ML to enhance operational efficiency. Our research demonstrates that AI and ML substantially increase productivity by virtue of their sophisticated data processing and decision-making functionalities. Nevertheless, persistent integration obstacles include concerns regarding data security, substantial upfront investments, and deficiencies in expertise in AI and ML. In the future, AI and ML have the potential to significantly transform the finance industry. By proposing three novel use cases automating credit evaluation process, augmenting banking operations via Advanced Optical Character Recognition (OCR) solutions and optimizing data analysis efficiency the paper makes a scholarly contribution. The following recommendations provide banks with actionable insights on how to optimize operational efficiency through the utilization of AI and ML.

Corresponding Author:

Idha Kristiana
Information System, Binus Online Learning, Bina Nusantara University, Jakarta, Indonesia
Email: idha.kristiana@binus.ac.id

1. INTRODUCTION

Recent years have seen a tremendous shift in the banking sector due to the quick development of technologies like artificial intelligence (AI) and machine learning (ML). Optimizing operational efficiency is becoming more and more important as the financial sector keeps changing[1]. In a market that is changing quickly, banks are under pressure to save expenses, boost customer satisfaction, and strengthen their competitive advantage[2]. Given this, artificial intelligence (AI) and machine learning (ML) have become important facilitators of operational efficiency, with a plethora of apps that can automate work, expedite procedures, and yield data-driven insights[3]. However, successfully implementing AI and machine learning in banking operations is not without its challenges[4]. To benefit from these technologies, banks must navigate a complex landscape of technological, regulatory, and organizational barriers[5]. The purpose of this article is to provide a comprehensive review of AI and machine learning concepts, implementation, and influence on operational efficiency in the banking industry. This study explores the impact of Artificial Intelligence (AI) and Machine Learning (ML) on enhancing operational efficiency within the banking industry. It delves into three primary research questions to comprehensively understand the extent of AI and ML integration in banking operations. The first question investigates how AI and ML can boost operational efficiency in banks, focusing on the specific processes that these technologies optimize. The second question addresses the significant challenges that banks encounter when implementing these advanced technologies, including technological, regulatory, and organizational hurdles. Lastly, the article examines the future prospects of AI and ML in the banking sector, predicting how these technologies could continue to transform banking operations, drive innovation, and maintain competitive advantage in the financial landscape. This exploration aims to provide a thorough analysis of the transformative role of AI and ML in modern banking practices. Through a systematic literature review, we will analyze the current state of the art in AI and ML applications in banking, highlight the significant challenges that banks face when using these technologies, and investigate AI and ML's future potential to revolutionize banking operations[6]. This article aims to provide a detailed view of the role of AI and machine learning in improving operational efficiency in banking by synthesizing the existing body of information. The conclusions of this paper will be useful for banking professionals, policymakers, and researchers interested in the use of AI and ML in the financial industry.

2. BACKGROUND

2.1 Operational Efficiency in Banking

Operational efficiency is a vital component of a bank's overall strategy since it has a direct impact on profitability and customer happiness. Banks operate in a highly competitive environment, and even minor improvements in efficiency can have a substantial impact on profits[7]. Traditional ways of increasing operational efficiency, such as process reengineering and automation, have proven beneficial but have a limited reach and impact[8]. The introduction of AI and ML has created new potential for banks to improve operational efficiency through sophisticated analytics, automation, and decision support systems[9]. For example, AI-powered chatbots can be used to provide 24-hour customer service, minimizing the requirement for human interaction and increasing customer happiness [10]. Similarly, machine learning algorithms can be used to detect and prevent fraud, lowering the chance of financial loss and enhancing the overall security of banking operations[11].

2.2 The Role of AI and ML in Banking

AI and machine learning are increasingly being used in banking applications such as customer service, risk management, and compliance[12]. AI-powered chatbots provide 24-hour customer service, while machine learning algorithms detect and prevent fraud. AI-powered technologies are also being utilized to optimize branch operations, simplify loan processing, and improve client segmentation. AI and machine learning have enormous potential benefits in banking, such as improved customer experience, lower costs, and better risk management[13]. For example, AI can be used to assess consumer behavior and preferences, allowing banks to provide personalized services and increase customer loyalty[14]. ML may be used to examine massive datasets and detect patterns and trends, allowing banks to make better decisions and lower their risk of financial loss[15].

2.3 Challenges in Implementing AI and ML

Despite the potential benefits of AI and machine learning, banks confront considerable obstacles when integrating these technologies[16]. These obstacles include data quality and availability, regulatory compliance, and the requirement for large investments in infrastructure and training[17][18]. Furthermore, a lack of experienced staff and the requirement for culture change inside the business are significant impediments to the implementation of AI and machine learning[18]. Successful application of AI and ML in banking necessitates a thorough understanding of the technology as well as the ability to navigate the complex regulatory landscape. For example, banks must guarantee that their AI and ML systems meet regulatory standards such as data protection and security[18]. They must also spend in training and development programs to guarantee that their staff are equipped to work with AI and ML systems.

3. METHOD

This study uses systematic literature review (SLR) to methodically analyze and synthesize literature on using AI and ML to improve banking operational efficiency. Based on Kitchenham [19], this chapter describes a systematic and transparent strategy to synthesize AI and ML strategies in banking operations literature. This study uses SLR concepts to identify research gaps, suggest implementation options, and assess the effects of AI and ML integration in banking. SLR approach ensures reproducibility and reduces bias, improving synthesis findings' reliability and validity.

3.1. Identification of Research Questions

This study examines how AI and ML affect banking operational efficiency and the many problems they face. The study seeks to comprehend AI and ML's role in altering banking operations beyond a simplistic narrative by embracing these difficulties' complexity. Thus, the authors developed three Research Questions (RQs) in Table 1 to lead this study.

Table 1. Research Question

Research Question	Purpose
RQ1: How can AI and ML enhance operational efficiency in the banking industry?	To investigate the potential of Artificial Intelligence (AI) and Machine Learning (ML) technologies in optimizing operational processes within the banking sector, aiming to identify specific applications and strategies for efficiency improvement.
RQ2: What are the main challenges faced by banks in implementing AI and ML?	To identify and analyze the primary obstacles encountered by banking institutions when integrating AI and ML solutions into their operations, with a focus on understanding factors such as data privacy concerns, regulatory compliance, and organizational barriers.
RQ3: What are the prospects of AI and ML in transforming banking operations?	To explore the anticipated long-term impact and trajectory of AI and ML technologies on the banking industry, aiming to forecast emerging trends, advancements, and potential paradigm shifts in banking practices, thus informing strategic planning and decision-making processes.

3.2. Data Collection

Data was collected from Science Direct, IEEE Xplore, Springer Link, and ACM Digital Library, four leading academic literature databases. These resources were chosen for their extensive peer-reviewed papers and research-related literature. The writers used each database's sophisticated search functions to search systematically. The authors selected "AI and ML in banking" as the main target term to match the Research Questions after preliminary trial searches across all five databases. Table 2 shows this systematic literature review (SLR)'s final search query to find relevant studies in the selected databases.

Table 2. Selected Databases

Databases	Results
Science Direct	15
IEEE Xplore	14
ACM Digital Library	5
Springer Link	6

3.3. Review Protocol

A search across 4 databases found 318107 studies. Figure 1 depicts the selection procedure. The authors initially filtered the findings to include only English studies published from 2019 to find the most current and relevant research. They found 141231 studies. After retrieving full-text publications, the authors set inclusion and exclusion criteria for title and abstract screening. Authors completed this screening concurrently to ensure reproducibility and reduce selection bias.

Several key factors determine study inclusion. The research questions must be answered first. 2. To assure data relevance and timeliness, post it from 2019 to the present. Third, the study must incorporate banking-related AI/ML terms. Finally, the study should examine banking operations and AI/ML utilization. By contrast, exclusion criteria improve selection. Eliminating non-English items standardizes language and accessibility. Since non-banking AI and ML studies do not help the research issue, they are removed. Non-academic or non-peer-reviewed materials are omitted for study credibility.

After the title and abstract screening, 76 papers remained. The authors then set quality criteria to evaluate possible primary studies. After thoroughly reviewing the 40 articles' introductions, discussions, conclusions, headings, tables, and figures, 40 primary studies remained. The final number of main studies selected for this SLR highlights the lack of research on AI and ML and banking operational efficiency.

3.4. Data Extraction and Synthesis

It begins with a thorough review of titles and abstracts before examining topic findings and screening procedure in full-text articles that meet the study objectives. The importance of data collection is emphasized, with a standardized form used to extract authorship details, publication years, research objectives, methodologies, main findings, and concluding remarks from the selected articles. After that, systematic narrative synthesis was used to analyze the gathered data. This activity involved compiling and analyzing study results to find patterns, variances, and themes. Therefore, by offering a comprehensive overview of the academic ecosystem surrounding AI and ML in finance,

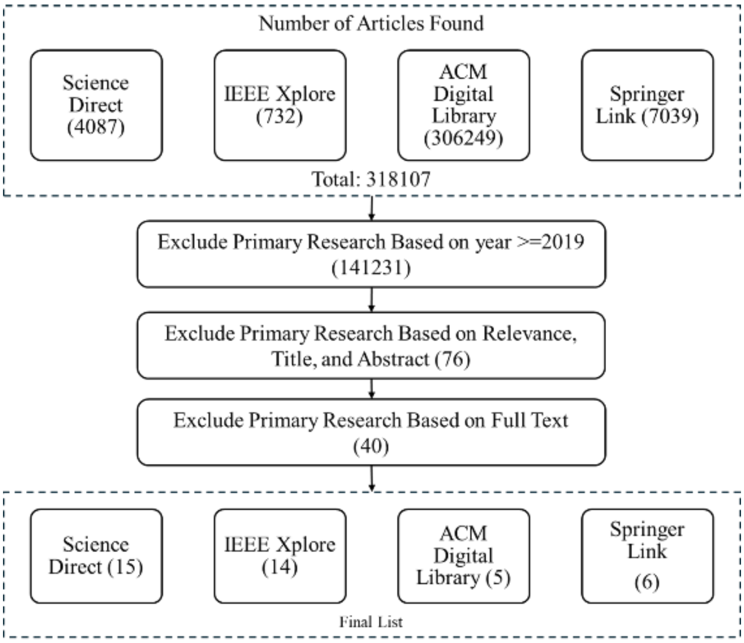

Figure 1. Literature Review Results

4. RESULTS AND DISCUSSION

This section discusses our thorough literature review of AI and ML's benefits to banking operations, their implementation obstacles, and their future possibilities. These findings show the current state of AI and ML in banking and their transformational potential.

4.1. Enhancement Of Operational Efficiency in The Banking Industry Through AI And ML

During the pursuit of improving operational efficiency in the banking sector via AI and ML, several significant discoveries have surfaced. The implementation of AI-powered automated customer service has substantially diminished the necessity for human involvement in customer engagements, consequently enhancing operational effectiveness and customer contentment[20]. Virtual assistants and chatbots powered by artificial intelligence can simultaneously process a high volume of inquiries, which is a significant enhancement over conventional customer service methods[10]. Machine learning algorithms have transformed fraud prevention and detection by analyzing patterns and identifying anomalies with greater efficiency than human operatives[21]. The implementation of these systems has dramatically decreased monetary losses and bolstered the protection of banking operations[22]. In a similar vein, the implementation of AI models has enhanced credit risk assessment by generating more precise forecasts based on intricate datasets; this has ultimately led to a reduction in credit default risk and empowered financial institutions to oversee their lending portfolios more efficiently[23]. Significant progress has been made in operational process automation, an additional crucial domain, through the integration of AI and ML. In addition to reducing expenses, the automation of routine processes and tasks has increased the velocity and precision of operations, freeing up human laborers to concentrate on more strategic endeavors[24]. Notwithstanding this progress, there remain deficiencies that present prospects for further investigation. Further integrating AI into customer service could enable the provision of more intricate and individualized interactions. The dynamic nature of financial fraud necessitates ongoing enhancements in machine learning models for the purpose of detecting and thwarting novel fraudulent strategies[25]. Moreover, credit risk models might derive advantages from improved artificial intelligence algorithms that incorporate a more extensive spectrum of socio-economic variables. Figure 2 shows the frequency of topics addressed in a systematic literature review (SLR) related to the application of Artificial Intelligence (AI) and Machine Learning (ML) in banking operations.

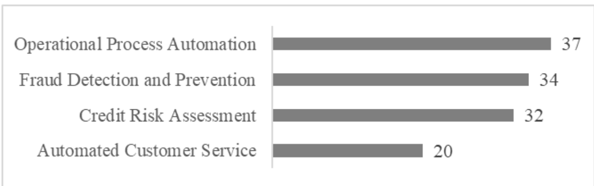

Figure 2. Application AI/ML in Banking Operation

4.2. Main Challenges Faced by Banks in Implementing AI And ML

The scholarly literature emphasizes the critical significance of safeguarding data privacy and security when the financial industry implements AI and ML technologies[26]. Guarding sensitive information against unauthorized access or breaches presents banks with formidable obstacles, given the magnitude of consumer data at stake. Existing research suggests that the integration of AI and ML solutions has brought data privacy and security concerns to the forefront, requires comprehensive protocols and measures to effectively mitigate risks[27]. Financial industry aiming to incorporate AI and ML technologies into their operations face a formidable obstacle in navigating the complex regulatory environment[28]. Compliance standards must be rigorously adhered to satisfy the stringent regulatory requirements that regulate data usage, consumer protection, and financial transactions[29]. Research emphasizes the intricate nature of compliance frameworks and judges' preoccupation with regulatory issues to guarantee the smooth integration of AI and ML solutions while maintaining legal and ethical principles[30]. Technical obstacles are encountered when attempting to modernize the operations of legacy banking systems and integrate AI and ML solutions[31]. Frequently, workflow disruptions and operational inefficiencies result from incompatibility concerns between newly implemented AI-powered technologies and pre-existing infrastructure. The significance of meticulous preparation and strategic execution approaches in minimizing disruptions and optimizing the integration procedure for AI and ML solutions in banking ecosystems is widely emphasized in research[24]. Implementation efforts in the banking industry are significantly hampered by the dearth of qualified personnel qualified in the development and management of AI and ML systems. A workforce possessing advanced technical skills and domain knowledge is imperative for the design, deployment, and maintenance of AI-driven solutions, which require specialized expertise[18]. The complex nature of the transformational voyage is highlighted by the obstacles identified during the implementation of AI and ML technologies in the banking industry.

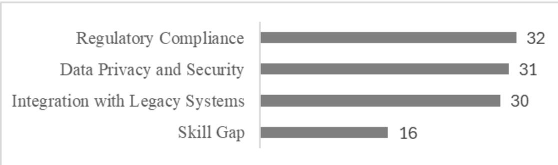

Figure 3. Challenges in Implementing AI/ML in Banking

Figure 3 shows frequency at which topics discussed in a systematic literature review (SLR) pertaining to fully harness the capabilities of artificial intelligence (AI) and machine learning (ML) in the financial industry, it is critical to address data privacy and security concerns, bridge the skill gap, navigate regulatory complexities, and overcome integration challenges. Banks can establish a foundation for sustained prosperity in an ever more digitalized environment by considering these obstacles proactively and implementing a comprehensive strategy for integrating technology. In the context of data security and regulatory compliance, further investigation is required to formulate all-encompassing approaches that effectively tackle these obstacles[16]. Furthermore, there is a need for research on efficacious training initiatives that can enhance the competencies of financial sector personnel in AI and ML.

4.3. Prospects of AI And ML In Transforming Banking Operations

Exploring the potential impact of AI and ML on banking operations unveils auspicious prospects for industry-wide progress and innovation. The utilization of AI and ML in the banking industry has the capacity to significantly transform consumer experiences through the provision of hyper-personalized financial advice and individualized products[32]. By integrating AI and ML technologies, financial industry can enhance the precision of their decision-making processes in diverse sectors such as lending, investments, and risk management. By utilizing sophisticated analytics and predictive modeling, financial institutions can enhance decision-making procedures, reduce vulnerabilities, and take advantage of developing prospects, thus fostering increased productivity and earnings[33]. AI and ML are indispensable components in bolstering the robustness of banking operations through their ability to forecast and alleviate operational risks. Through the implementation of machine learning algorithms and predictive analytics, financial institutions can proactively identify and mitigate potential risks and vulnerabilities[34]. Innovation is stimulated in the development of financial products and services by AI and ML. By utilizing technologies such as automated investment platforms and dynamic pricing models, banks are empowered to develop inventive solutions that effectively address the changing demands and preferences of their customers[35]. Banks can achieve product differentiation, capture market share, and maintain a competitive advantage in an ever more dynamic and competitive environment by leveraging the capabilities of AI and ML. The topical frequency of a systematic literature review (SLR) pertaining to the prospects of AI and ML in transforming banking operations is illustrated in Figure 4.

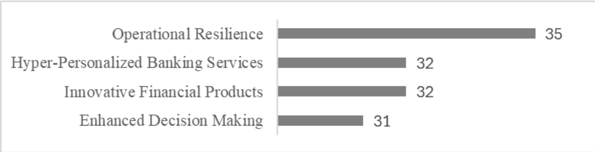

Figure 4. Prospects of AI/ML in Transforming Banking Operations

Several suggestions for improving banking operations through the implementation of cutting-edge technologies have been derived from the systematic literature review. To begin with, the implementation of sophisticated Optical Character Recognition (OCR) solutions can substantially enhance the efficiency of banking operations as shown in Figure 5. These solutions effectively log manual data input errors and streamline the processing of documents[36]. Furthermore, by implementing AI and machine learning to automate the credit evaluation process, expedited and more precise credit assessments can be achieved, thereby reducing personnel burden and default risk as shown in Figure 6. AI-driven analytics has the potential to significantly improve the efficiency of data analysis in the finance industry[36]. By processing vast quantities of data, these systems can reveal insights with greater speed and precision than conventional approaches as shown in Figure 7. In addition to improving customer satisfaction and regulatory compliance, these developments optimize operational efficiency.

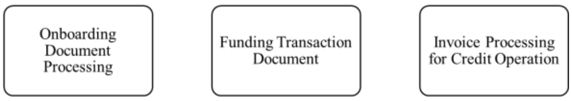

Figure 5. Efficient of Banking Operation with Advanced OCR Solution

In three critical domains, sophisticated Optical Character Recognition (OCR) solutions have the potential to substantially augment the efficacy of banking operations. To begin with, "Onboarding Document Processing" streamlines customer onboarding by reducing the need for manual data input and expediting the process by automating the extraction and processing of information from client documents during the account opening phase via OCR. Furthermore, OCR technology facilitates the precise and timely extraction of financial information from transaction documents during "Funding Transaction Document" processing, thereby enhancing the efficiency and dependability of transaction processing. In conclusion, "Invoice Processing for Credit Operation" demonstrates the potential of optical character recognition (OCR) in automating the retrieval of data from credit-related invoices. This would significantly reduce the time between invoice receipt and payment processing, thereby expediting credit management workflows. In general, the implementation of OCR in these domains not only optimizes processes that heavily rely on documents but also diminishes errors and operational expenditures, thereby enhancing the operational efficacy of the banking industry.

Particularly in credit proposal preparation, the incorporation of AI and machine learning into banking operations has substantially transformed procedures that were formerly labor-intensive and time intensive. Historically, the generation of credit proposals has been a protracted undertaking, necessitating a thorough examination of borrower background information, financial statements, and documents to evaluate creditworthiness. The manual vetting procedure may require a significant investment of time, frequently exceeding several weeks or even months. The emergence of AI and ML technologies has significantly transformed the environment in which credit proposals are formulated. Large volumes of data, including complex financial histories and documentation, can be analyzed by AI systems with an unrivaled degree of accuracy and velocity. By reducing human error, this capability not only speeds up generating credit proposals but also improves their precision. This process is further streamlined through the implementation of Optical Character Recognition (OCR) models[37], which enable the automatic extraction and decoding of text from scanned images and documents, thereby accelerating data entry and reducing errors. Furthermore, extensive industry analysis is conducted using Large Language Models (LLMs), which crunch through vast quantities of unstructured data including financial reports and market trends to offer nuanced insights into the economic landscape of prospective borrowers[38]. These analyses enhance banks' comprehension of industry-specific opportunities and hazards, thereby fortifying the credit evaluation process. Figure 3 illustrates the automation of the credit evaluation process using AI and ML technologies. This depiction emphasizes the integration of advanced computational methods to streamline and enhance the accuracy of credit assessments in banking operations.

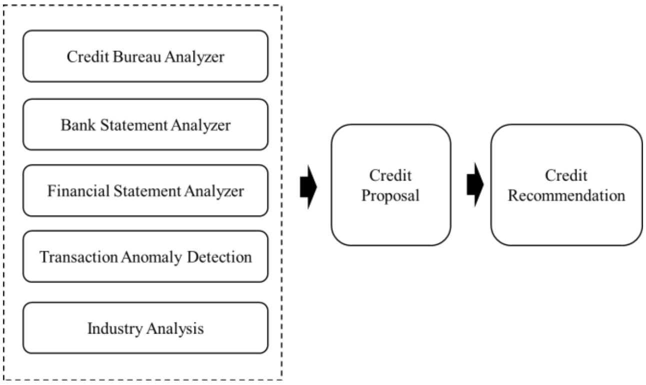

Figure 6. Automation Credit Evaluation Process using AI/ML

This change not only speeds up making decisions but also enables financial institutions to manage an increased quantity of credit applications with greater efficiency. By decreasing the time required to process credit proposals, financial institutions can enhance the quality of their services, thereby increasing client satisfaction and gaining a competitive advantage in the marketplace. This paradigm shift exemplifies the way AI and ML are optimizing banking procedures, resulting in financial services that are more dynamic and responsive.

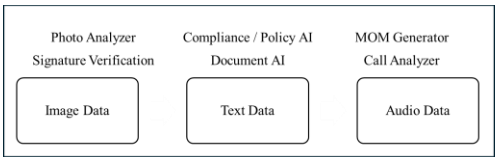

Figure 7. Efficient of Data Analysis through AI

Figure 7 depicts an advanced data analysis procedure powered by artificial intelligence, which effectively converts image data into text data, and then further into auditory data. Convolutional neural networks (CNNs) perform an initial analysis of image data to identify objects, discern patterns, and produce textual descriptions[39]. Subsequently, natural language processing (NLP) models, including transformers, process the given text. These models can execute various tasks including entity extraction, sentiment analysis, and summarization[40]. Finally, audio data is generated from the refined text data using text-to-speech (TTS) technologies. Text-to-speech (TTS) systems powered by artificial intelligence generate speech that appears natural in a variety of languages and accents, thereby rendering the information audible[41]. The effective incorporation of AI technologies into various data formats facilitates the development of advanced applications, minimizes human fallibility, and processes data at magnitudes and velocity that are unattainable through human labor. As a result, the utility and effectiveness of data analysis are significantly improved.

5. CONCLUSION

This research highlights the profound capacity that Artificial Intelligence (AI) and Machine Learning (ML) must improve the financial industry's operational efficiency. By conducting an exhaustive review of the literature, we have addressed crucial issues pertaining to the advantages, difficulties, and future potential of AI and ML implementations in the banking sector. AI and ML substantially contribute to operational improvements through the optimization of data processing and the refinement of decision-making processes, as confirmed by our analysis. Nevertheless, the implementation of these technologies is not devoid of obstacles. Banks encounter challenges including substantial upfront investments, apprehensions regarding data security, and a scarcity of proficient AI and ML experts. The future of banking operations utilizing AI and ML appears bright despite these obstacles. The three suggested use cases optimized data analysis, automated credit evaluation procedures, and improved banking operations via Advanced Optical Character Recognition (OCR) solutions—illustrate the pragmatic implementations and advantages that AI and ML can provide to financial institutions. In addition to optimizing operational processes, these advancements also augment customer satisfaction and operational clarity. In the forthcoming period, financial institutions that invest strategically in and deploy AI and ML are expected to attain a competitive advantage through enhanced operational efficiency and resilience amidst the ever-changing financial environment.

ACKNOWLEDGEMENTS

Author thanks ... . In most cases, sponsor and financial support acknowledgments.

REFERENCES

[1] Y. Chen, E. Kumara, V. S.-A. of O. Research, and undefined 2021, “Invesitigation of finance industry on risk awareness model and digital economic growth,” *Springer*, vol. 326, p. 15, Jul. 2023, doi: 10.1007/s10479-021-04287-7.

[2] A. R.-P. J. of A. of Egypt and undefined 2021, “Impact of E-Banking on Customer Satisfaction,” *archives.palarch.nl*, vol. 18, no. 8, p. 4220.

[3] A. George, A. G.-P. U. I. Innovation, and undefined 2023, “A review of ChatGPT AI’s impact on several business sectors,” *puiij.com*, 2020.

[4] A. Ashta, H. H.-S. Change, and undefined 2021, “Artificial intelligence and fintech: An overview of opportunities and risks for banking, investments, and microfinance,” *Wiley Online Libr.*, vol. 30, no. 3, pp. 211–222, May 2021, doi: 10.1002/jsc.2404.

[5] O. Bukola Adeoye *et al.*, “Fintech, Taxation, and Regulatory Compiliance: Navigating The New Financial Landscape,” *Financ. Account. Res. J.*, vol. 6, no. 3, pp. 320–330, Mar. 2024, doi: 10.51594/FARJ.V6I3.858.

[6] P. Brereton, B. Kitchenham, D. Budgen, and M. Turner, “Lessons from applying the systematic literature review process within the software engineering domain,” *J. Syst. Softw.*, 2007.

[7] T. T.-J. of A. Finance, E. and Business, and undefined 2020, “The impact of balanced scorecard on performance: The case of Vietnamese commercial banks,” *oak.go.kr*.

[8] A. Harika, M. Sunil Kumar, V. Anantha Natarajan, and S. Kallam, “Business Process Reengineering: Issues and Challenges,” pp. 363–382, 2021, doi: 10.1007/978-981-15-6707-0_35.

[9] F. Königstorfer, S. T.-J. of behavioral and experimental, and undefined 2020, “Applications of Artificial Intelligence in commercial banks–A research agenda for behavioral finance,” *Elsevier*.

[10] I. Lee and Y. J. Shin, “Machine learning for enterprises: Applications, algorithm selection, and challenges,” *Bus. Horiz.*, vol. 63, no. 2, pp. 157–170, 2020, doi: https://doi.org/10.1016/j.bushor.2019.10.005.

[11] S. K. Hashemi, S. L. Mirtaheri, and S. Greco, “Fraud Detection in Banking Data by Machine Learning Techniques,” *IEEE Access*, vol. 11, no. January, pp. 3034–3043, 2023, doi: 10.1109/ACCESS.2022.3232287.

[12] V. Mahalakshmi, N. Kulkarni, … K. K.-M. T., and undefined 2022, “The role of implementing artificial intelligence and machine learning technologies in the financial services industry for creating competitive intelligence,” *Elsevier*.

[13] M. Satheesh, S. N.-I. Management, and undefined 2021, “Applications of artificial intelligence on customer experience and service quality of the banking sector,” *americanscholarspress.us*, vol. 6.

[14] S. Carbo-Valverde, P. Cuadros-Solas, and F. Rodríguez-Fernández, *A machine learning approach to the digitalization of bank customers: Evidence from random and causal forests*, vol. 15, no. 10 October. 2020. doi: 10.1371/journal.pone.0240362.

[15] P. Carmona, A. Dwekat, and Z. Mardawi, “No more black boxes! Explaining the predictions of a machine learning XGBoost classifier algorithm in business failure,” *Res. Int. Bus. Financ.*, vol. 61, p. 101649, 2022, doi: https://doi.org/10.1016/j.ribaf.2022.101649.

[16] M. Rahman, T. H. Ming, T. A. Baigh, and M. Sarker, “Adoption of artificial intelligence in banking services: an empirical analysis,” *Int. J. Emerg. Mark.*, vol. 18, no. 10, pp. 4270–4300, Nov. 2023, doi: 10.1108/IJOEM-06-2020-0724/FULL/HTML.

[17] M. Thowfeek, … S. S.-S. S., and undefined 2020, “Drivers of artificial intelligence in banking service sectors,” *researchgate.net*, vol. 6.

[18] I. Kristiana, A. Ramadhan, A. Trisetyarso, E. Abdurachman, and M. Zarlis, “Capability Development to Generate Business Value Through Customer-centric Analytics in the Banking Industry: A Systematic Review,” *J. Syst. Manag. Sci.*, vol. 13, no. 2, pp. 64–82, 2023, doi: 10.33168/JSMS.2023.0205.

[19] B. Kitchenham, “Kitchenham , B .: Guidelines for performing Systematic Literature Reviews in software engineering . EBSE Technical Report EBSE-2007-01 Guidelines for performing Systematic Literature Reviews in Software Engineering,” *Icse*, no. January 2007, 2021.

[20] K. B. Ooi *et al.*, “The Potential of Generative Artificial Intelligence Across Disciplines: Perspectives and Future Directions,” *J. Comput. Inf. Syst.*, vol. 00, no. 00, pp. 1–32, 2023, doi: 10.1080/08874417.2023.2261010.

[21] A. Corallo, A. M. Crespino, M. Lazoi, and M. Lezzi, “Model-based Big Data Analytics-as-a-Service framework in smart manufacturing: A case study,” *Robot. Comput. Integr. Manuf.*, vol. 76, p. 102331, 2022, doi: https://doi.org/10.1016/j.rcim.2022.102331.

[22] E. Zdravevski, P. Lameski, C. Apanowicz, and D. Ślęzak, “From Big Data to business analytics: The case study of churn prediction,” *Appl. Soft Comput. J.*, vol. 90, 2020, doi: 10.1016/j.asoc.2020.106164.

[23] Y. Cao and J. Zhai, “A survey of AI in finance,” *J. Chinese Econ. Bus. Stud.*, vol. 20, no. 2, pp. 125–137, 2022, doi: 10.1080/14765284.2022.2077632.

[24] D. Pramod, “Robotic process automation for industry: adoption status, benefits, challenges and research agenda,” *Benchmarking An Int. J.*, vol. 29, no. 5, pp. 1562–1586, Jan. 2022, doi: 10.1108/BIJ-01-2021-0033.

[25] Y. Shen, C. Guo, H. Li, J. Chen, Y. Guo, and X. Qiu, “Financial Feature Embedding with Knowledge Representation Learning for Financial Statement Fraud Detection,” *Procedia Comput. Sci.*, vol. 187, pp. 420–425, 2021, doi: 10.1016/j.procs.2021.04.110.

[26] J. Lee, “Access to finance for artificial intelligence regulation in the financial services industry,” *Eur. Bus. Organ. Law Rev.*, 2020, doi: 10.1007/s40804-020-00200-0.

[27] P. Parameswarappa, “Importance of Information Governance &Implementation in Banking Industry,” *Available SSRN 4190576*, 2022, [Online]. Available: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4190576

[28] J. Lee and A. Darbellay, *Data Governance in AI, FinTech and LegalTech: Law and Regulation in the Financial Sector*. books.google.com, 2022. [Online]. Available: https://books.google.com/books?hl=en&lr=&id=9eRvEAAAQBAJ&oi=fnd&pg=PR1&dq=%22data+governance%22+framework+and+regulatory+compliance+and+advanced+analytics+and+banking+sector&ots=sK-Sjmy-BL&sig=uTxwiFD01IYDSaYfUapm4j2NhJg

[29] M. Rhahla, S. Allegue, and T. Abdellatif, “Guidelines for GDPR compliance in Big Data systems,” *J. Inf. Secur. Appl.*, vol. 61, p. 102896, 2021, doi: https://doi.org/10.1016/j.jisa.2021.102896.

[30] H. Sadok, F. Sakka, and M. E. H. El Maknouzi, “Artificial intelligence and bank credit analysis: A review,” *Cogent Econ. Financ.*, vol. 10, no. 1, 2022, doi: 10.1080/23322039.2021.2023262.

[31] E. Indriasari, H. Prabowo, F. L. Gaol, and B. Purwandari, “Intelligent Digital Banking Technology and Architecture: A Systematic Literature Review,” *Int. J. Interact. Mob. Technol.*, vol. 16, no. 19, pp. 98–117, 2022, doi: 10.3991/ijim.v16i19.30993.

[32] I. W. R. Wijaya and Mudjahidin, “Development of conceptual model to increase customer interest using recommendation system in e-commerce,” *Procedia Comput. Sci.*, vol. 197, no. 2021, pp. 727–733, 2021, doi: 10.1016/j.procs.2021.12.194.

[33] A. S. Edu, "Positioning big data analytics capabilities towards financial service agility," *Aslib J. Inf. Manag.*, vol. 74, no. 4, pp. 569–588, Jan. 2022, doi: 10.1108/AJIM-08-2021-0240.

[34] D. Broby, "The use of predictive analytics in finance," *J. Financ. Data Sci.*, vol. 8, pp. 145–161, 2022, doi: 10.1016/j.jfds.2022.05.003.

[35] H. Hampton and A. Foley, "A review of current analytical methods, modelling tools and development frameworks applicable for future retail electricity market design," *Energy*, vol. 260, p. 124861, 2022, doi: https://doi.org/10.1016/j.energy.2022.124861.

[36] M. M. Mariani and S. Fosso Wamba, "Exploring how consumer goods companies innovate in the digital age: The role of big data analytics companies," *J. Bus. Res.*, vol. 121, pp. 338–352, 2020, doi: https://doi.org/10.1016/j.jbusres.2020.09.012.

[37] Q. Shambour, "A deep learning based algorithm for multi-criteria recommender systems," *Knowledge-Based Syst.*, vol. 211, p. 106545, 2021, doi: 10.1016/j.knosys.2020.106545.

[38] M. S. Khan and H. Umer, "ChatGPT in finance: Applications, challenges, and solutions," *Heliyon*, vol. 10, no. 2, p. e24890, 2024, doi: 10.1016/j.heliyon.2024.e24890.

[39] L. Nosrati, A. M. Bidgoli, and H. H. S. Javadi, "Identifying People's Faces in Smart Banking Systems Using Artificial Neural Networks," *Int. J. Comput. Intell. Syst.*, vol. 17, no. 1, 2024, doi: 10.1007/s44196-023-00383-7.

[40] A. Mehrotra, "Artificial Intelligence in Financial Services - Need to Blend Automation with Human Touch," *2019 Int. Conf. Autom. Comput. Technol. Manag. ICACTM 2019*, pp. 342–347, 2019, doi: 10.1109/ICACTM.2019.8776741.

[41] A. Gandhi, K. Adhvaryu, S. Poria, E. Cambria, and A. Hussain, "Multimodal Sentiment Analysis: A Systematic review of History, Datasets, Multimodal Fusion Methods, Applications, Challenges and Future Directions," *Inf. Fusion*, 2022, doi: https://doi.org/10.1016/j.inffus.2022.09.025.