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Financial revolution: a systemic analysis of artificial intelligence and machine learning in the banking sector

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ABSTRACT

This paper reviews the advances, challenges, and approaches of artificial intelligence (AI) and machine learning (ML) in the banking sector. The use of these technologies is accelerating in various industries, including banking. However, the literature on banking is scattered, making a global understanding difficult. This study reviewed the main approaches in terms of applications and algorithmic models, as well as the benefits and challenges associated with their implementation in banking, in addition to a bibliometric analysis of variables related to the distribution of publications and the most productive countries, as well as an analysis of the co-occurrence and dynamics of keywords. Following the preferred reporting items for systematic reviews and meta-analyses (PRISMA) framework, forty articles were selected for review. The results indicate that these technologies are used in the banking sector for customer segmentation, credit risk analysis, recommendation, and fraud detection. It should be noted that credit analysis and fraud detection are the most implemented areas, using algorithms such as random forests (RF), decision trees (DT), support vector machines (SVM), and logistic regression (LR), among others. In addition, their use brings significant benefits for decision-making and optimizing banking operations. However, the handling of substantial amounts of data with these technologies poses ethical challenges.

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1. INTRODUCTION

In the banking sector, artificial intelligence (AI) and machine learning (ML) are driving big change. AI can be described as a system's capacity to precisely comprehend outside data, derive knowledge from that data, and adaptively apply that knowledge to achieve goals and perform specific tasks [1]. In this sense, AI technologies have radically changed the field of information technology by developing intelligent devices and programs that operate and interact in a similar way to humans [2]. It is also one of the most prominent emerging technologies. Recently, we have witnessed the widespread application of AI in various fields [3]. However, intelligent systems that provide AI capabilities often rely on ML as the basis for their operation. This technique allows systems to learn from specific training data and automate the creation of analytical models that enable them to solve relevant tasks [4]. ML algorithms are a well-known technique for analyzing and predicting data, identifying patterns, and building AI models. Its accuracy has been demonstrated in a number of areas, including education, criminality, and health [5], and the banking industry is no different. Therefore, AI and ML techniques are increasingly used in the banking industry [6]. In this sense, companies are increasingly looking to use AI to gain benefits, driven by the availability of substantial amounts of data and by growing computing power. Nonetheless, they encounter challenges stemming from a limited grasp of how to generate value and fully leverage AI [7]. In this sense, knowledge of AI, especially ML, is essential to analyzing and developing intelligent and automated applications based on this data. Within this domain, various types of ML algorithms are present, encompassing supervised, unsupervised, semi-supervised, and reinforcement learning [8]. However, for more than a decade, there has been a lot of talk and exploration about using machine learning techniques. Although researchers have made progress in overcoming the above limitations, the search for an optimal model remains a challenge in various fields [9]. Nevertheless, these technologies are revolutionizing the way banks operate, interact with their customers, and make strategic decisions. AI and ML offer unprecedented potential to improve operational efficiency, enhance financial services, and deliver personalized customer experiences. But the widespread use of these technologies in the banking industry raises issues and questions that require an exhaustive review of the existing literature.

As AI and ML become more embedded in banking, there is a need to understand and critically assess the impact and reach of these technologies. There are numerous studies and research on AI and ML in banking, but the literature is fragmented and dispersed, making it difficult to gain a systemic and global view of the trends, challenges, and opportunities. In addition, the rapid evolution of AI and ML requires the constant updating of information and the identification of gaps and areas for future research. It is essential to address this issue to provide a solid and up-to-date basis for researchers, professionals, and decision-makers in the banking sector. Therefore, in this research, a systematic review of the literature (SRL) on AI and ML in the banking context is carried out. The systemic review will allow the integration, synthesis, and critical analysis of existing studies, identifying patterns, trends, and gaps in current knowledge. In addition, a comprehensive update of the literature will be carried out to include the most recent advances in AI and ML applied to the banking sector. This research will not only provide a comprehensive view of the current situation but will also serve as a guide for future research and aid in the formulation of well-informed decisions when ML and AI technologies are implemented in the banking industry.

The importance of this research is to tackle the requirement of a methodical and current understanding of the function of AI and ML in the banking sector. On the other hand, the main aim of this study is to carry out a literature review to provide a systematic and updated vision of the advances and to identify the main applications, algorithmic models, challenges, and opportunities of these technologies, among others. Likewise, through a critical analysis and an exhaustive synthesis of existing studies, it will seek to identify emerging trends, future research areas, and best practices for the successful adoption of these new technologies in the banking industry. By achieving these objectives, it is intended to contribute to the advancement of knowledge within this domain and establish a solid foundation for well-informed decision-making in AI and ML-powered banking. It is hoped that this review will enlighten other researchers interested in this area of study [10]. The structure of the document is divided as follows: section 2 details the process of the systematic literature review method. While the result and discussion are presented in section 3, section 4 presents the conclusion of the study.

2. RESEARCH METHOD

2.1. Search strategy

This SRL study followed the guidelines stipulated in the 2020 preferred reporting items for systematic reviews and meta-analyses (PRISMA) statement, which is widely recognized in the scientific community as the preferred standard for reporting systematic reviews and meta-analyses. These new reporting guidelines, which replace the 2009 statement, have considered advances in the methods used to search for, select, analyze, and synthesize studies [11]. In addition, a comprehensive analysis was performed according to the three main phases defined in the statement, which included a thorough review of the scientific literature and the application of strict criteria for the selection of relevant studies as shown in Figure 1. The data collected and synthesized from the selected studies allowed the research questions to be adequately addressed.

2.2. Research questions

The SRL is conducted to encompass and analyze existing research. This is accomplished by categorizing and reviewing existing papers. The first step in the review process is to define the research questions, which helps to accurately describe the coverage rate of existing papers [10]. Table 1 presents the research questions formulated to analyze the advances of AI and ML applied in the banking sector. Each of these questions is identified by the acronym RQ, which stands for “Research Question”.

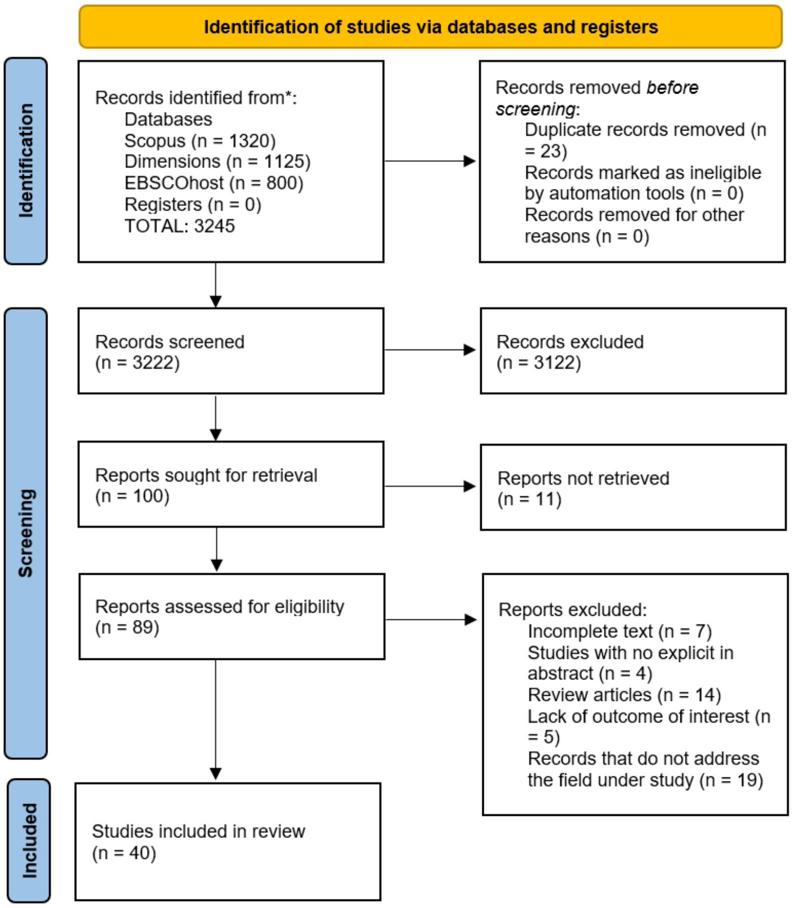

Figure 1. PRISMA 2020 flow diagram of the study

Table 1. Formulated research questions

Id	Research questions	Purpose
RQ1	What is the general trend of the annual publication and country with the greatest contribution in AI and ML in the banking sector?	The answer makes it possible to identify publication trends in the use of AI and ML in the banking sector, showing the growing interest over time. It also makes it possible to identify leading countries and disparities in research in this field.
RQ2	What are the most used keywords or terms related to AI and ML in the banking sector?	The answer makes it possible to identify the main themes and underlying structure in the existing literature on AI and ML in banking, providing a deep understanding of the evolution of key concepts. In addition, this analysis facilitates the identification of emerging areas of interest.
RQ3	What are the applications and algorithms of AI and ML in the banking sector proposed by different researchers?	The answer makes it possible to identify the AI and ML applications and algorithms applied by different researchers in the banking industry.
RQ4	What are the applications, algorithms evaluated and with the highest precision with the highest level of adoption in the banking sector?	The answer makes it possible to identify the level of adoption of the applications, the algorithms evaluated more frequently, and the algorithms with more precise results in each application in the banking sector.
RQ5	What are the most important advantages and challenges of AI and ML in the banking sector?	The answer to this question provides an overview of the advantages and challenges of the use of AI and ML in the banking sector.

2.3. Study selection and eligibility criteria

Generally speaking, all relevant article titles and abstracts were carefully reviewed before being chosen based on the inclusion and exclusion criteria. Every article should satisfy all inclusion requirements and none of the established exclusion criteria [12] as shown in Table 2. In this way, only articles from journals published in English were included, excluding conference proceedings, book chapters, conference reviews, editorials, and notes. The study period considered was from January 2018 to April 2023, to analyze the most recent impact of AI and ML in the digital transformation of the banking sector. In addition, only studies related to the banking sector were included, excluding those carried out in other contexts.

Table 2. Eligibility and selection criteria

Criteria	Inclusion	Exclusion
Document type	Article journal	Not article journal
Language	English	Non-English
Timeline	January 2018-April 2023	Before January 2018 and after April 2023
Access type	Open access	Not open access
Context	IA and ML in banking sector	Other than AI and ML in the banking sector

2.4. Systematic review process
2.4.1. Identification
In the first stage, a thorough keyword search is performed to identify relevant articles. Table 3 shows the search terms used in the three selected bibliographic databases: Scopus, Dimensions, and EBSCOhost. Initially, a total of 3,245 articles were retrieved in a preliminary search. The primary keys used for the search were "title, abstract, and keyword" in Scopus, "title and abstract" in Dimensions, and "subject terms, title, and abstract" in EBSCOhost.

Table 3. Keyword search query main

Search string
("Artificial intelligence" OR "machine learning") AND ("banking sector" OR "banking industry" OR "banking system" OR "bank")

2.4.2. Screening
This phase was the selection process. The process started with 3,245 articles retrieved in the first phase, and 23 duplicate articles were eliminated, as shown in Figure 1. Considering the study selection criteria and using the automated classification tools offered by the databases used, 3,122 articles were excluded. Because they were not the type of document required for the study, they were published outside the period considered and written in languages other than English. A total of 100 articles were recovered, of which 11 could not be recovered due to restricted access. This leaves 89 articles for the eligibility process. To determine eligibility, an exhaustive reading was carried out, excluding articles without explicit mention in the abstract as well as review articles, those with irrelevant results, and those that did not address the subject of the study or were not developed in a banking context.

2.4.3. Inclusion
In this last phase, the quality of the articles eligible for the study was assessed. In this sense, a checklist was used to assess reliability, which all remaining articles had to meet in order to be included in the review. Articles must have well-defined methodological procedures, well-defined objectives, and results supported by evidence. All articles were assessed and discussed by the researchers, who determined that forty articles met the requirements for inclusion in the review.

3. RESULTS AND DISCUSSION
This SRL aims to provide both researchers and the banking sector with information on the advances and challenges of AI and ML in order to enhance your understanding and perspective in this field of study. The results and discussion of the study are presented through the analysis of the collected data, which is structured according to the research questions (RQs) posed previously, namely, i) general annual and country publication trend on AI and ML in the banking sector (RQ1), ii) keywords or most used terms related to AI and ML in the banking sector (RQ2), iii) AI and ML applications and algorithms proposed in the banking sector by different researchers (RQ3), iv) the level of adoption of AI and ML algorithms and applications in the banking sector (RQ4), and v) advantages and challenges of implementing AI and ML in banking (RQ5).

3.1. General annual and country publication trend on AI and ML in the banking sector
The yearly output of articles relating to AI and ML in the banking industry has significantly increased, as shown in Figure 2(a). In the years 2018 and 2019, there was only one publication, indicating an initial level of interest in the topic under study. However, as of 2020 the quantity of publications has increased significantly, with eleven publications in each of the years between 2020 and 2022. This sustained increase shows a growing recognition of the importance of AI and ML in banking. In addition, the fact that there are already five publications as of April 2023 shows that interest and research in this area continue to

grow. Similarly, the steady growth in the number of publications also reflects the advancement of knowledge in the field and the need to share research and findings to further drive progress. This annual production trend indicates that AI and ML are becoming increasingly important in the banking system.

On the other hand, Figure 2(b) shows the analysis carried out with the Bibliometrix package and the graph generated with Microsoft Excel. This analysis highlights the importance of AI and ML in the banking sector and that research in this area has been particularly prominent in several countries. Among the top 10 contributing countries in terms of published papers on the topic, India leads with more than 25 contributions. This indicates that the academic and scientific community in India is highly engaged in researching and developing new applications of AI and ML to improve efficiency and innovation in the banking sector. China comes in second with ten papers published, underscoring its focus on applying these emerging technologies in banking. These results demonstrate the growing importance of AI and ML in the banking industry and highlight the leadership of India and China in generating and advancing knowledge in this field.

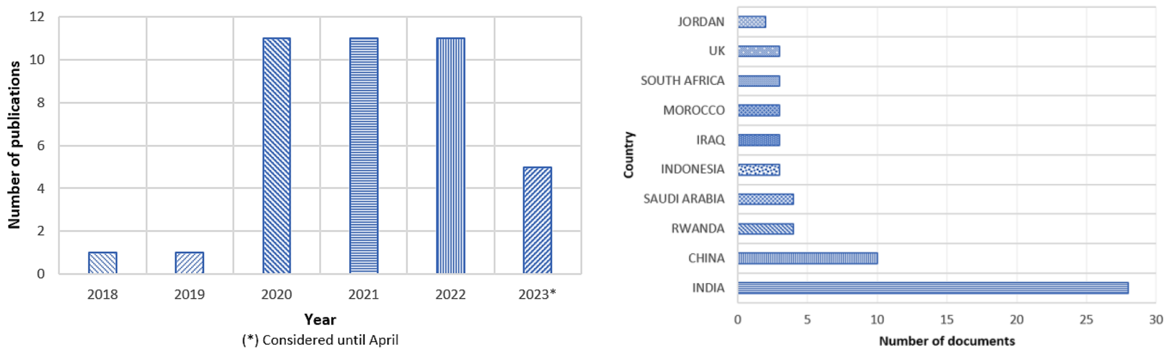

Figure 2. Scientific production in (a) annual production trend of publications included in the study and (b) top 10 productive countries

3.2. Keywords or most used terms related to AI and ML in the banking sector

Figure 3(a) shows the analysis of the co-occurrence network with VOSviewer software and reveals the keywords that stand out about the impact of AI and ML. The most prominent terms are ML and AI, indicating their central relevance to the topic under study. In addition, the presence of specific terms related to the banking sector is observed, such as credit risk, fraud detection, credit cards, and customer loyalty. Concepts related to algorithms and learning techniques are also identified, such as random forests (RFs), decision trees (DTs), and support vector machines (SVMs).

Meanwhile, Figure 3(b) shows the analysis of the terms most used by the authors between 2018 and April 2023, where it is evident that the progress of AI and ML in the transformation of the banking sector has been the subject of increased attention in recent years. Among the 10 most used terms in research on this topic, a slight increase in the use of the terms AI and ML was observed in 2020 and 2021, and their use continued to increase in 2022. This indicates that researchers and practitioners are increasingly recognizing the importance of these technologies in banking and are exploring new applications and approaches. The analysis also shows that the terms credit risk, fraud detection, churn prediction, and DT. have gained relevance in the context of AI and ML. Although their use was slightly pronounced in 2020 and 2021, a significant increase in their use was observed in 2022. This suggests that researchers are paying more attention to the application of these technologies to address challenges related to credit risk management and fraud detection in banking using different ML algorithms such as DTs and RFs. Similarly, until April 2023, the terms continue to show an increase in their use, which indicates that research in this area continues to be active and that the academic and scientific communities are interested in delving into these topics. These results highlight the importance of these technologies in banking and reflect the need to develop innovative approaches and efficient tools to improve decision-making in the sector.

3.3. AI and ML applications and algorithms proposed in the banking sector by different researchers

In the last decade, advancements in AI and ML technology have turned into essential instruments, offering a broad spectrum of uses within the banking sector. In customer segmentation [13]–[15], applied different models of ML algorithms such as K-means. Likewise, to model and predict potential clients who intend to obtain loans, Zhang [16] applied the backpropagation neural network (BPNN), the RF, and the

SVM. Among these models, the RF algorithm displayed the highest level of accuracy, with an average prediction accuracy of 94%. Similarly, Koufi *et al.* [17] have developed an algorithmic model for predicting potential customers (PCPA). The focus is on predicting full-bank users who might be candidates for mortgage loans. This predictability gives the marketing department an advantage in targeting potential customers efficiently and quickly, especially at a low cost. The findings indicate that gradient boosting outperforms other approaches such as DTs, logistic regression, and SVM. On the other hand, Safarkhani and Moro [18] developed a highly accurate classifier to forecast the customers who will enroll in a long-term deposit program provided by a bank, aiding in the identification of potential clients. In tests on real data from a bank, the DT achieved a prediction accuracy of 94.39%, outperforming other models.

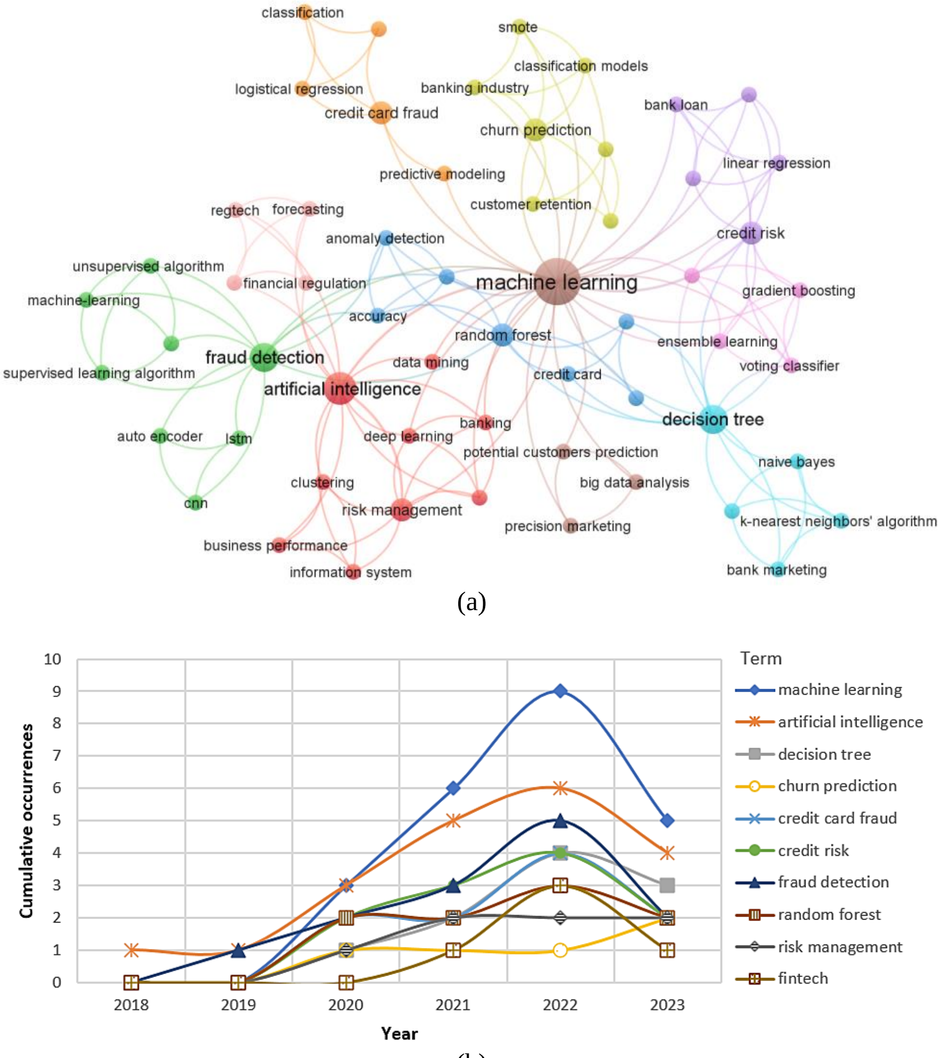

Figure 3. Analysis of terms in (a) co-occurrence author's keywords map and (b) keyword dynamics

On the other hand, Sahu *et al.* [19] apply AI and ML models to bank fraud detection, particularly aimed at identifying deceitful credit card transactions. Based on the experimental findings of the different supervised models, naive bayes and SVM are 97% accurate, and logistic regression is 99% accurate in detecting credit card fraud. Likewise, Almuteer *et al.* [20] combine the convolutional neural network (CNN), auto-encoder (AE), and long short-term memory (LSTM) models for improved performance and detection of credit card fraud. Converting into four models that can be used: CNN, AE, LSTM, and AE&LSTM. After training the models, with an overall precision of 0.99, the AE model shows the highest precision, closely followed by the CNN and LSTM models, both with a precision of 0.85. In contrast, the AE&LSTM model has the lowest precision, coming in at 0.32. Similarly, Vengatesan *et al.* [21] used automated classification techniques such as logistic regression and the k-nearest neighbor (KNN) algorithm to predict fraudulent banking activities. After training, the accuracy value of the KNN algorithm, which is 0.95, gives the best results. Likewise, other authors have implemented both similar and distinct models, including SVM, logistic regression, RF, DT, KNN, artificial neural network (ANN), support vector classifier (SVC), extreme gradient boosting (XGBoost), extra tree (ET), ET-AdaBost, random forest-AdaBost (RF-AdaBost), decision tree-AdaBoost (DT-AdaBost), among others [22]–[28], as well as an unsupervised model like isolation forest [29]. On the other hand, Sasikala *et al.* [30] apply a state-of-the-art ML method to identify fraud in credit card transactions. They utilize the SVM hyperparameter optimization method, which includes a grid-based cross-validation search and utilizes kernel replication theory with various functions like linear, Gaussian, and polynomial to separate the hyperplane. This approach enhances the model's accuracy.

Similarly, Hayder *et al.* [31] use AI and ML models for recommendation engines. In addition, they highlight the importance of bank advertising as an effective way to target customers. They propose a predictive model that uses ML algorithms, incorporating four classifiers: KNN, DT, naive Bayesian, and SVM. The DT performed the best, achieving an accuracy of 91%, while the SVM classifier followed closely with an accuracy of 89%.

Likewise, in study [32], they studied the accuracy of the algorithms called RF and linear regression to approve bank loans and minimize credit risk. It is observed that the average precision rate of the RF algorithm has experienced an improvement of up to 70.5% compared to linear regression, which has an average precision of around 69.5%. Similarly, in the study [33], they applied ML using the KNN model to fill in the missing information about the unknown credit status in user training. On the other hand, Chen [34] points out that the increase in customer credit risk, aggravated by the pandemic, has increased the probability of defaults, which has generated the need to investigate and identify high-risk customers in banking. Therefore, they propose ML models for prediction. The experimental results demonstrate that both the improved logistic regression and the ANN model exhibit a clear advantage in predicting credit risk, depending on the data evaluated. Other authors also develop and compare different models for credit risk assessment: SVM, DTs, AdaBoost, RF, logistic regression, ANN, and XGBoost. Of these, the different models with greater predictive accuracy are obtained by each author: AdaBoost and RF [35], DT [36]–[40]. On the other hand, Putri *et al.* [41] propose to analyze credit risk using SMV. In testing the SVM algorithm, radial basis functions (RBF), linear, polynomial, and sigmoid were used. Among the four models, the SVM with a polynomial kernel stands out as the best, as it has the highest accuracy of 0.9508.

3.4. The level of adoption of AI and ML algorithms and applications in the banking sector

After analyzing and identifying the AI and ML applications and algorithms proposed by researchers in the studies examined, the level of adoption of these applications in banking operations is determined. In addition, the most evaluated algorithmic models were identified. Likewise, to compare the algorithmic models that present greater precision, the most valued and categorized models have been selected. In this way, the study offers a comprehensive analysis to give researchers a deeper understanding of how this technology is progressing in the banking sector.

3.4.1. Adoption level of AI and ML applications in the banking sector

Figure 4 shows the level of adoption of the most important applications that are generating significant contributions to the banking field. Fraud detection is an application where AI and ML are widely implemented, indicating that it is a priority area to prevent fraudulent activities using these technologies. Similarly, credit risk analysis is another of the applications where technologies such as AI and ML are widely implemented, indicating that most banks use these technologies to assess the solvency and risk of customers in their credit decisions. On the other hand, customer segmentation is the application with the lowest implementation of AI and ML, which indicates that in this area, few banks use these technologies to better classify and understand their customers. As for the recommendation engine, AI and ML have a low implementation rate, which could mean that their implementation is not yet so common in banking services. Overall, these findings indicate a varied uptake of AI and ML within the banking industry, with varying degrees of deployment in different areas.

3.4.2. Model of algorithms evaluated in the different applications

Figure 5 shows the algorithms evaluated and used in different AI and ML applications by the different authors in the studies analyzed. In customer segmentation, K-Means, SVM, RF, and DTs stand out as the most evaluated to group customers into different segments based on similar characteristics. This can assist businesses in gaining a deeper insight into their clientele and adapting their marketing approaches more effectively. In fraud detection, a variety of the most frequently evaluated algorithms are observed, such as RF, logistic regression, SVM, KNN, and DTs, all of which can help identify and prevent fraudulent activity in various situations. On the other hand, for the recommendation engine, the most common algorithms are

KNN, SVM, and DTs, which are evaluated to provide personalized suggestions. Similarly, for credit risk analysis, DTs, RF, SVM, and logistic regression are the most frequently evaluated algorithms for assessing the risk associated with credit applicants. These results provide an overview of the most frequently evaluated and dominant algorithms in each area. Furthermore, these could serve as valuable initial references for forthcoming projects or investigations concerning AI and ML within this field of study. Nevertheless, it is crucial to emphasize that the selection of an algorithm is contingent upon the particular issue, the data at hand, and the goals of the application.

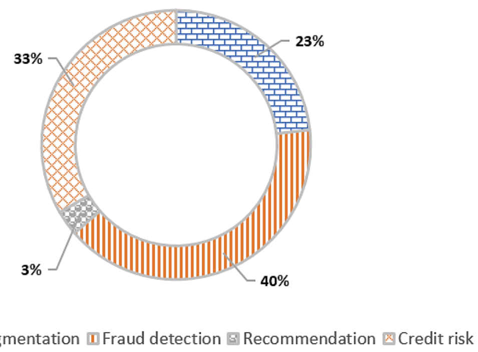

Figure 4. The level of adoption of AI and ML in banking in different areas

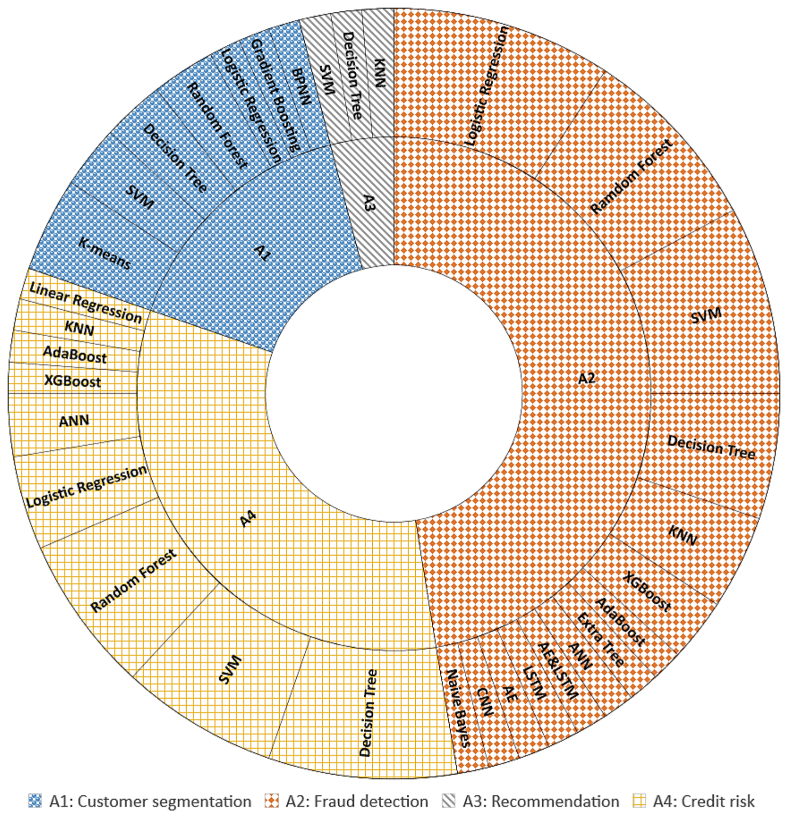

Figure 5. Algorithms model evaluated in the different applications

3.4.3. Model of the algorithms with the highest level of precision

Table 4 shows a comparison of algorithms that have shown high accuracy or an area under the curve (AUC) greater than 80% or 0.80 in various application areas evaluated by various researchers. It is evident that there is no default algorithm for specific applications; rather, the choice of algorithm depends on data handling and contextual factors. In other words, the higher accuracy of one algorithm does not make it inherently superior to another, as it is effectiveness depends on the data it analyzes. The accuracy of each algorithm depends on several factors, such as the size of the data set, the way the data is divided for training and testing, and the variables under consideration, among others. All these details are available in the respective papers.

Table 4. Comparison of algorithms in various application areas

Source	Application	Algorithm model	Accuracy	AUC
[16]	Customer segmentation	RF	94%	-
[18]	Customer segmentation	Arbol de decisions	94.39%	-
[13]	Customer segmentation	RF	97%	-
[19]	Fraud detection	LR	99%	-
		SVM	97%	-
		Naïve Bayes	97%	-
[20]	Fraud detection	AE	0.99	-
		CNN	0.85	-
		LSTM	0.85	-
[21]	Fraud detection	KNN	0.95	-
		LR	0.95	-
[22]	Fraud detection	DT	-	0.938
		LR	-	0.946
		SVC	-	0.936
		KNN	-	0.927
		Naïve Bayes	-	0.908
		RF	-	0.911
[29]	Fraud detection	Isolated forest	95.76%	-
[23]	Fraud detection	LR	94.9%	-
		DT	91.9%	-
		RF	92.9%	-
		KNN	93.9%	-
[24]	Fraud detection	KNN	99.95%	-
[26]	Fraud detection	RF	0.9890	0.9886
		DT	0.9522	0.9982
		XGBoost	0.9853	0.9996
[27]	Fraud detection	RF-AdaBost	99.95%	1
		DT-AdaBoost	99.67%	1
		ET-AdaBoost	99.98%	1
		XGB-AdaBoost	99.98%	1
[31]	Recommendation	DT	91%	-
		SVM	89%	-
[37]	Credit risk	DT	80%	-
[34]	Credit risk	LR	80%	-
[41]	Credit risk	SVM Polynomial	0.9508	0.9419

3.5. Advantages and challenges of implementing AI and ML in banking

Manjaly *et al.* [42] highlight the immense potential of AI within the banking field, emphasizing that AI-driven advanced data analysis has the capacity to combat transaction fraud and enhance adherence to banking regulatory standards. By implementing AI technologies, it is possible to reduce costs and increase productivity in the banking industry. Likewise, it has great advantages in improving the risk management practices of the information system and improving banking business performance [43]. It also improves credit risk management [38], [40], [44], [45]. In credit risk analysis, it would be beneficial not only for banking institutions but also for the customer, since it would allow them to be more informed about the risk of not meeting their payments [46], and it also minimizes credit card fraud [45], [47]. It also improves customer segmentation and increases automated teller machine performance [45]. In addition, the application of AI and ML in banking can provide customers with personalized, effective, and cost-effective services [48] Similarly, automating processes with the implementation of AI benefits banking institutions by improving their profitability and performance, reducing the need for human intervention, and increasing the efficiency of business processes [49].

However, there are various challenges associated with the application of AI that could undermine the trust of users or customers in the banking system [48]. Another challenge for AI in banking is that it is hampered by potential malicious control of large data sets, where hackers can input false information to influence AI decisions [50]. On the other hand, Ahmed [51] points out that the use of AI has revealed numerous ethical problems, such as the incorrect evaluation of credit history, the exchange of false information, and unauthorized operations. Therefore, creating a friendly and ethical AI system is challenging.

3.6. Limitation of the study

An important limitation of this study is its narrow data sources. The research team only utilized three preeminent databases: Dimensions, Scopus, and EBSCOhost. While these platforms offer extensive coverage of the scientific literature, it remains possible that pertinent research in lesser-known databases was not included in the review. This limitation may have excluded valuable studies, which could have enhanced comprehension of the subject matter. Nevertheless, the authors utilized rigorous inclusion criteria and applied the PRISMA methodology to ensure the quality and coherence of the studies included in the analysis.

4. CONCLUSION

The study concludes that AI and ML technologies have a significant advance in banking. The review of forty articles selected with the PRISMA 2020 method from databases such as Scopus, Dimensions, and EBSCOhost revealed that AI and ML are mainly applied in customer segmentation, credit risk analysis, fraud detection, and recommendation engines that contribute to the transformation of the sector, using algorithmic models such as DTs, RFs, SVM, logistic regression, and linear regression. Specifically, the study found that credit risk analysis and fraud detection are the areas where these technologies are most frequently used in banking. The study's observations suggest that AI and ML can be valuable tools for credit risk analysis and management, as well as for credit card fraud prevention and detection. They can also be used to segment potential banking customers and generate personalized recommendations for services offered by the industry. In addition to these benefits, ethical challenges associated with handling large amounts of data are also mentioned. This suggests that while AI and ML offer numerous benefits, it is important to address concerns related to privacy, security, and ethics in the processing and use of customer data while taking full advantage of these technologies. This work has opened several questions that require further research on the subject under study. Further work is needed to explore each of the applications that these technologies present in the banking field.

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