Journal of Engineering, Mechanics and Modern Architecture
Vol. 4, No. 1, 2025 ISSN: 2181-4384

A REVIEW OF MACHINE LEARNING IN BANKING RISK MANAGEMENT AND POSSIBLE RESEARCH TOPICS

Annotation:

The 2008 global financial crisis brought to light the fundamental significance of bank risk management (GFC). The primary cause of the economic and financial disaster that ensued after the Great Financial Crisis was banks' utter disdain for risk management in the years preceding 2008. Bank culture and structure have changed as a result of the substantial regulatory measures that have since been put in place to address the flaws and deficiencies that were exposed in the financial services industry. The purpose of this article is to examine the degree to which machine learning has been studied in relation to risk management in the banking industry and to suggest possible directions for future research. It ranks bank-specific risks according to an analysis of bank reports and assesses The domains of risk management in banking where machine learning principles have been used.

Keywords: *Banks, Risk managing, Credit, Cards, Artificial Intelligence.*

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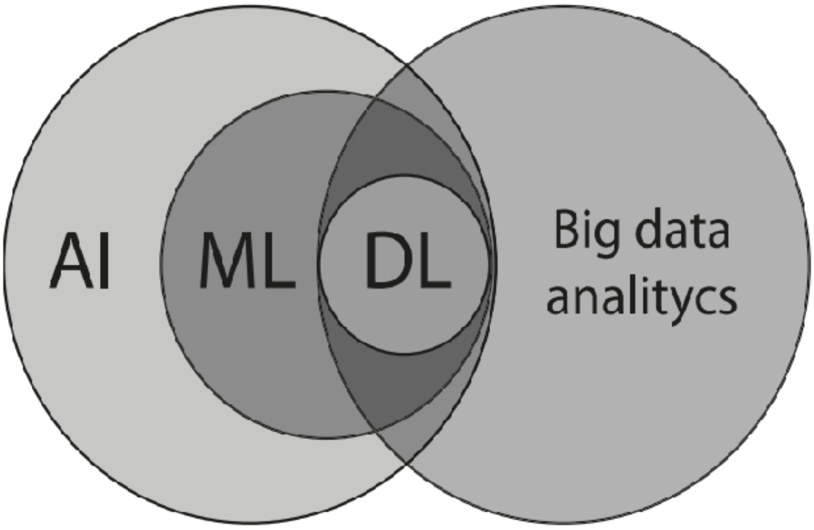
1. Introduction

To gauge the level of rivalry, central banks frequently employ concentration indices like the Herfindahl-Hirschman index and the concentration ratio. These indexes are usually computed by the National Bank of Serbia using the absolute value of assets. The values of the Rosenblatt index, entropy coefficient, Gini coefficient, and Lorenz curve graph from 2015 to 2019 are also included in this study. Significant regulatory reforms in the financial services sector resulted from the 2008 global financial crisis, which brought attention to the significance of bank risk management. The degree of machine learning research in banking risk management is examined in this article. It highlights unexplored topics or challenges, studies, examines, and assesses machine-learning techniques employed in this field, and offers suggestions for additional study. Instead than depending on the body of existing literature, the study offers a risk taxonomy that was created by surveying bank annual reports. Additionally, it evaluates the fields in which machine learning techniques have been studied, banking applications of AI and machine learning, and a developing trend in other economic sectors. Although banking risk management has grown significantly in the last few decades, more developments are urgently needed. Risk managers are essential in today's financial sector, and there are aspirations to improve banking risk management procedures by utilizing machine learning and artificial intelligence.

Figure 1: Connection and relation between artificial intelligence, machine learning, deep learning and big data analytics



The use of data learning, machine learning, and artificial intelligence in banking risk management is growing. These technologies have been widely used in credit risk for many years, and credit scoring frequently uses complex classification algorithms like Bayesian classifiers and logistic regression. These techniques are also essential for monitoring, stress testing, and predicting credit risk metrics like PD and LGD. The IFRS 9 projected credit losses impairment model is one area where AI and ML are being used in this industry.

Risk Management at Banks

The process by which a bank determines, assesses, and takes action to reduce the likelihood that a negative outcome would result from its operational or investment choices is known as banking risk management.

The bank's management is taking on greater risk in an attempt to increase its owners' profits. Among the risks that banks face include Risks associated with interest rates, markets, credit, off-balance-sheet operations and technology, foreign exchange, and countries or sovereigns, liquidity risk, and bankruptcy risk. How well these risks are handled determines how well a bank performs. Furthermore, banks are the focus of regulatory attention because of these risks and their function in financial systems (Saunders et al. 2006). Because of the numerous dangers that can occur, the authorities mandate that banks maintain capital. Determining the banking industry's capital needs is essential to maintaining financial stability. Operational, market, and credit risks are just a few of the risk categories that have been addressed by the Basel rules since their development in 1998. Since credit risk is the biggest risk that banks face, they usually need the most capital. Trading activities are the source of market risk, whereas possible losses due to system malfunctions or outside circumstances are the source of operational risk. and are carried as a result of a bank's diverse activities. Since their creation in 1998, the Basel guidelines for calculating capital needs have undergone development and evolution. All of the major risk categories demand capital. The biggest risk that banks face and the one that often needs the most capital is credit risk. A bank's trading activities are the main source of market risk, On the other hand, operational risk is the potential for losses as a result of external events or internal system failures.

The majority of big banks compute economic capital in addition to regulatory capital, which is determined by the bank's models rather than by regulators' recommendations (Hull 2012). Credit, market, and operational risks are the primary hazards that banks encounter.

According to Jorion (2007), Risk associated with the market is the potential for losses "due to changes in the level or volatility of market pricesInterest rate risk is a component of market risk, stock market risk, foreign exchange risk, and commodity risk. Interest risk is the potential loss resulting from fluctuations in interest rates. Equity risk is the potential loss brought on by a decline in a stock's price. Foreign exchange risk is the chance that a bank's assets or liabilities will depreciate as a result of changes in the exchange rate. Commodity risk is the potential loss brought on by an adverse change in the price of the commodities owned. The foundation for market risk of the Basel Accord is comprised of a standardized approach and an internal models approach. The updated framework also changed the measure of risk under pressure to better capture tail risk (ES) by switching from Value-at-Risk (VaR) to Expected Shortfall (Basel Committee on Banking Supervision 2006).

Identification, measurement, and monitoring of different risk sources, including market, credit, and liquidity risk, are all part of effective risk management in banking. Determining the ideal degree of risk for the company to maximize shareholder value is the aim, not risk elimination.

2. ARTIFICIAL INTELLIGENCE

AI was first proposed in 1955 with the goal of creating computer systems that are intelligent like humans. It includes artificial general intelligence, superintelligence, and present AI. Even with advances in technology, it is still impossible to achieve general intelligence and superintelligence. Guidelines that forbid particular themes should be followed when creating content. The question of whether or not artificial general intelligence and super-intelligence will ever be created is still up for debate. At this point in its development, artificial intelligence (AI) can identify word sequences but cannot interpret such input in light of practical applications. Speech recognition, learning under uncertainty, decision-making, and visual perception are a few examples of activities that modern AI is capable of performing. Artificial Intelligence (AI) uses a variety of methods to simulate human behavior. These days, machine learning, deep learning, speech recognition, natural language processing, and visual recognition are some of the most pertinent in the financial services industry. Unsupervised and supervised learning are the two primary categories into which machine learning algorithms fall. Anything that contains sexual content and profanity, hate speech, violence, violent extremism, sensitive events, bullying, harassment, harmful items, or the promotion or abuse of alcohol, tobacco, or marijuana should not be created or shared.

A dataset, a model, and a cost function are the three fundamental parts of unsupervised learning. Without using labels, its main purpose is to help one comprehend the underlying structure of a dataset. All of the elements of unsupervised learning are included in supervised learning, with the primary distinction being that the data is labeled.

The main purpose of supervised learning is to help in classification, and it can accurately quantify accuracy. A subfield of artificial intelligence called machine learning has found successful applications in a variety of fields, such as aerospace engineering and medicine.

Artificial neural networks are the foundation of deep learning, a subset of machine learning. An interconnected collection of neurons that can affect how each network or neuron behaves is called a neural network. A neural network is essentially a group of nodes that are separated into three distinct functions: the input layer, the hidden layer, which uses an algorithm to decide the model, and the output layer. Deep learning uses computational techniques that work well for learning data representation and model prediction. The latter enables the machine to generate complex hypotheses based on comparatively basic concepts.

3. Suggestions for machine learning and artificial intelligence

With the right approach and implementation strategies, this section addresses the potential and suggestions for a successful integration of AI and ML in banking risk management. The recommendations are specific to developed and developing economies, as well as small, mid-sized, and large international banks. Applications of AI and ML can aid all banks, and research is being done to assist them in this process. Even while some sizable, well-established institutions may have already used these technologies, there is always space for development and the achievement of new objectives.

4. Operational Risk

With an emphasis on fraud detection and the identification of questionable transactions, machine learning is used in operational areas to mitigate risk by identifying and averting issues. In addition to a survey of software options for automating detection and monitoring, a logistic regression prototype was created. The precise algorithms employed in these solutions are not covered in detail in the publication.

As attacker tactics change, this study emphasizes the importance of machine learning-based intelligent systems in spam security. Advanced machine learning algorithms are used by Proof Point's MLX technology to identify spam and guard against its associated costs, including financial loss, malware attacks, interrupted communications, and lost productivity. Although it is not the objective of this study, the technology demonstrates the application of machine learning to cybersecurity risk management The mentality and readiness to take risks assist a bank's goal of increasing shareholder value. The GFC was caused in part by the careless incentive schemes used by bank personnel, indicating a problem with the risk culture. Bonuses and pay for bank employees were determined by sales and profit goals, which had nothing to do with the caliber of the loans they made. Prior to 2008, successful banks were more likely to take on greater risks, according to studies conducted after the Great Financial Crisis. Before the Great Financial Crisis (GFC), some people cheated to exceed expectations, which caused the bank to lose 4.9 billion. This instance illustrated the shortcomings of inadequate control systems and a weak risk culture. When combined, they would be disastrous for the bank.

5. Credit scoring, analysis and monitoring

Phase 1: For this section, a bank might assess a number of ML and AI methods, including as Lasso logistic regression, Bayes classifier, nearest neighbor, classification trees, logistic regression, discriminant analysis, DL (artificial neural networks, SVM), and so forth. Phase 2: The bank can start using AI and ML in credit analysis and rating procedures if phase 1 findings are favorable (as shown by the many studies included in this paper).

It can be applied gradually, starting as a parallel solution, extra tool, or anything similar. The bank should be aware that the procedure will require a lot of data if it chooses to use DL, the most advanced part of ML. Big data analytics will play a significant part in this situation, thus the bank should have all the necessary people and technical resources ready for the job.

6. Additional risk management applications of machine learning and artificial intelligence

Other dangers are subject to similar findings and suggestions for general risk management, especially credit risk management. For instance, machine learning (ML) is used in market risk management for a number of purposes, including curves of interest rates, foreign exchange risk estimation, and volatility prediction. Furthermore, the majority of the steps, procedures, and suggestions described for credit risk management also apply to market risk management. These basically consist of suggestions for internal model creation, simulations, ICAAP, recovery plans, capital adequacy calculations and/or RWA, and stress testing, In the fields of stress testing, simulations, recovery, and contingency planning, in particular, the application of AI and machine learning to liquidity risk management is accelerating. The use of Bayesian networks and artificial neural networks for managing liquidity risk has been investigated recently. The Procedure for Assessing Internal Liquidity Adequacy (ILAAP) and Asset Liability Management (ALM) are expected to be greatly improved by the creation of new analysis, tools, processes, and reporting using AI and ML. This will ultimately improve crisis management, particularly in the face of obstacles like the COVID-19 pandemic's impact on liquidity.

7. Customer credit solution application service blueprint

This study investigates the impact of artificial intelligence (AI) on the banking customer's journey, with a focus on credit applications and granting decisions. A Customer Credit Solution Application-Service Blueprint (CCSA) is proposed based on data and expertise, highlighting the role of AI in customer accessibility and acquisition. The framework is validated through consultation with industry professionals and provides insights into future research directions and potential growth in the field.

8. Visit bank's website & apply for a credit solution

Banking institutions are utilizing robo-advisors to convert website traffic into credit solution applicants. The use of robo-advisors helps customers select the best credit solution based on their eligibility and banking needs. Trivedi (2019) emphasizes the importance of information, system, and service quality for a seamless customer experience, with personalization playing a key role. Machine learning is employed to analyze data and enhance customer experience, while trust remains crucial in customer interactions with banking institutions.

9. Acquire customer

This study explores the process of customer acquisition, credit decision, and post-decision in the realm of financial inclusion. Approaches such as targeted ads, machine learning techniques, and data mining models are utilized to improve customer acquisition and credit risk assessment. The ultimate goal is to balance organizational risk, maximize profit, and increase financial empowerment for customers.

10. Receive a decision

The integration of AI in the banking sector presents challenges and opportunities, such as privacy concerns, organizational resistance, and the impact of the COVID-19 pandemic. Despite these challenges, investing in AI technologies is crucial for reducing future risks and enhancing customer experience.

11. Customer contact call center

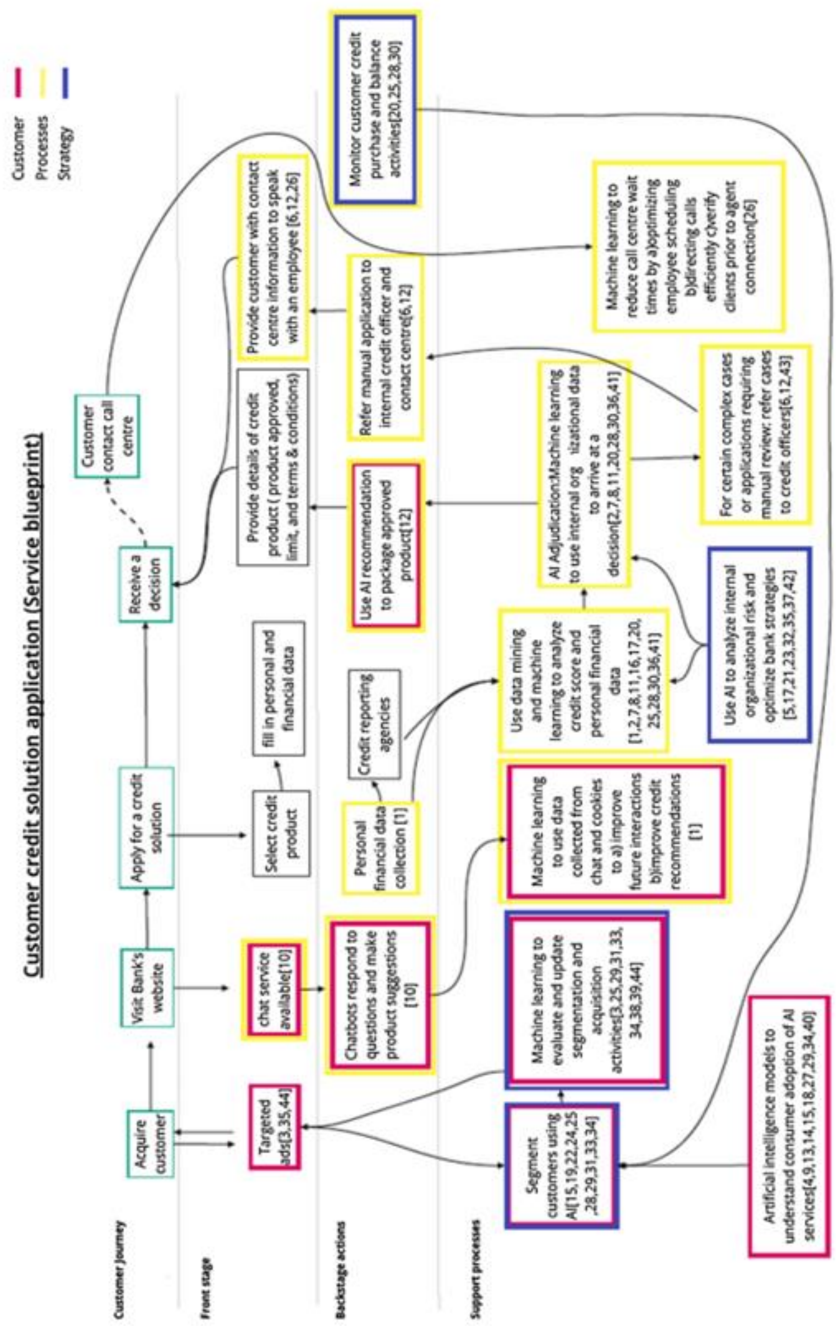
This study outlines the relationship between humans and AI in financial institutions. Customers prefer humans for high-complexity tasks, emphasizing the importance of integrating human employees for cases that require manual review. While AI offers benefits, relationship banking remains crucial for competitive advantage. Optimizing banking channels through AI can improve appointment scheduling and service time.

12. General discussion

Recent research has highlighted the growing use of AI in improving customer service, particularly in the banking sector. The adoption of robo-advisors and other AI tools has shown potential in automating processes, enhancing customer satisfaction, and driving profitability. Researchers are now exploring the use of AI in strategic insights and business strategies, as well as addressing challenges and risks associated with AI implementation. Practical case studies and the investigation of AI-driven models in financial products are recommended for further research. Key theories such as TAM and diffusion of innovation are being studied, with a call for exploring new variables and methods to understand customers' relationship with AI better. The customer-centric utilization of AI is leading to new dimensions that impact customer experience, emphasizing the importance of understanding AI's impact on customers for improving customer service.

13. Future research directions

The literature (44 publications) on AI and banking from 2005 to 2020 was thoroughly examined in this study, which also offered suggestions for further research in the area. Among the suggestions include investigating the elements that influence the adoption of AI by organizations, examining the organizational obstacles related to the adoption of AI, and going beyond the current AI models in credit scoring. The results are intended to assist those working in the banking business and decision-makers in developing strategic choices that will optimize the benefits of AI technologies.



14. Result

The management of risk is crucial for the success of banks and for the stability of the financial system. AI has the potential to transform the working environment and add significant business value in banking. However, it is important to note that AI is not a panacea and the human element remains crucial in risk management. Issues such as data security, regulation, and ethics need to be addressed before AI can become a central component of a bank's infrastructure. The ongoing question of AI and ethics also merits further research in the field of risk management.

Artificial Intelligence (AI) has the potential to revolutionize various aspects of everyday life, with significant investments and implementations seen in the US and China. In Europe, there is a mixed landscape regarding AI adoption, prompting policymakers to introduce measures to increase AI activity. While AI could fundamentally change financial services, its implementation in banking has been limited due to regulatory concerns. However, as competition in banking intensifies, rapid adoption of AI technologies may be crucial for banks to remain competitive and enhance profitability. AI and ML are increasingly influencing banking risk management, offering potential support in mitigating worldwide financial and economic difficulties, such as those resulting from the COVID-19 pandemic. This study addresses issues including model risk, data availability and security, and the requirement for qualified personnel while outlining suggestions and ideas for the effective AI and ML applications in risk management. By emphasizing the importance of a comprehensive risk management strategy, this research provides a roadmap for phased AI and ML application to improve risk management, reduce costs, streamline processes, and enhance client services..

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