

Explainable AI for Anti-money laundering in banking.

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Summary of research paper

Paper 1: Applications of Explainable Artificial Intelligence in Finance — A Review (2023)

This study provides a review of the applications of explainable artificial intelligence in the financial sector, particularly in banking. Examples include fraud detection, anti-money laundering, and how to manage and reduce risks. One of the challenges highlighted by the paper is the limited number of practical trials conducted and the complete reliance on synthetic data simulations. (Kumar et al., 2023)

Paper 2: Explainable Artificial Intelligence (XAI) in Finance: A Systematic Literature Review (2024)

This research paper reviews the uses of explainable artificial intelligence in the banking sector, focusing on model interpretation and regulatory compliance. It emphasizes the importance of employing certain techniques, such as SHAP and LIME, in machine learning applications within the financial domain. (Zhou et al., 2024)

Paper 3: Interpretable Machine Learning Models for Financial Fraud Detection (2023)

This research paper presented several models that could aim at detecting fraud or money laundering. The paper also mentioned mechanisms that could be relied upon, such as decision issuance, and it showed results with high accuracy, accompanied by explanations that made it easier for auditors and analysts to understand the program's mechanism.. (Han et al., 2023)

Paper 4: Comparative Analysis of Machine Learning Algorithms for Money Laundering Detection (2025)

This study addressed many studies and algorithms that fall under supervised learning, such algorithms include supervised learning itself. They use real transaction data to detect money laundering operations. Additionally, explainable learning techniques helped clarify the predictions of the models that were added to the system, and the result was the random forest. *(Nguyen et al., 2025)*

Paper 5: Artificial Intelligence for Anti-Money Laundering: A Review and Extension (2020)

This research paper presented and discussed some methods that contributed to and assisted in money laundering, but these methods are somewhat traditional. However, it highlighted supervised learning and deep learning. The difficulties and challenges faced were the inaccuracy and imbalance of information and the results of false positives. *(Han et al., 2020)*

Paper 6: Explainable AI in Financial Services: Transparency and Trust in Risk Management (2024)

The last paper, which is considered one of the most important ones I focused on, addressed many aspects, the most important of which was understanding the concept of the role of explainable artificial intelligence in risk management in the banking sector. When managing risks, the author meant combating money laundering and the impact of credit report. It also discussed how to enhance and gain customer trust by employing these technologies. Additionally, there was a focus on future plans and directions to allow the XAI system time to expand across many expects. *(Li et al., 2024)*

Critical Analysis

The papers I selected were rich in information presented by the authors, and they served as a central and key role in explaining the concept of explainable artificial intelligence. They also enhanced full transparency in applying this study at the level of effectiveness and regulatory compliance within banking sector institutions. Among the most important areas covered in the research papers were anti-money laundering, fraud detection, and credit reporting. In addition, techniques were applied that made it easier to test models, such as SHAP and LIME, and decision trees to illustrate how the model predicts decisions and how transactions were classified as suspicious.

Employing these techniques makes it easy for analysts to understand what those decisions are based on, as I mentioned earlier. Additionally, one of the important reasons for employing these techniques is the alignment between technical performance and regulatory requirements. However, there were studies that questioned the accuracy of the results due to the models used. According to research papers, especially Paper 6, performance and results were excellent using the Random Forest algorithm, which achieved impressive performance in interpretability and prediction based on the presented model. But I must admit that there are many drawbacks that overshadowed these experiments or studies, which can be described as weaknesses such as the limited real-world data due to data sensitivity and the need to maintain the privacy of its owners, which reduced the opportunity to generalize the results across all studies. However, even the idea of applying XAI is very limited in banks due to the internal regulations they abide by, and also because cost may be a significant reason for avoiding the use of this technology. For some studies, XAI may not be sufficient in banking environments or the financial sector in general.

Connections

The connection I observed in the six research papers I selected was that they all agreed on enhancing relationships and complete transparency, and they all emphasized the interpretability of AI systems in the banking sector. All the papers agreed that fraud can be detected, that money laundering can also be combated, and that suspicious transactions can be identified. They indicated that artificial intelligence is not merely a study or hypothesis; all the papers confirmed its applicability, and it has also become a necessity for gaining trust, ensuring transparency, and complying with regulatory requirements in the banking sector.

The papers also agreed on the use of interpretation techniques such as LIME and SHAP, and on the other hand, it was also agreed to use decision trees. The common aspect in these tools is bridging the gaps and voids that may occur in the presented models, and they also make it easier for decision-makers to understand the reasons behind the data and why transactions are classified as suspicious. Another problem mentioned and agreed upon is the false alerts in the AML system, which requires accurate models with precise information to train the model. Additionally, the application of these techniques is limited in the banking sector. That is, AI has not yet been fully adopted in the banking field due to trust and internal regulations that banks are subject to.

Critical Analysis

This is a critical analysis regarding the research papers I selected for this project. There are many strengths and weaknesses associated with using explainable artificial intelligence in the banking sector. It appears that XAI has contributed significantly and somewhat noticeably to improving the transparency of results and models and also helped reduce or combat money laundering. However, on the other hand, some studies have directly shown that integrating XAI introduces complexity and clear challenges in the banking sector.

Conflicts Between Findings

Although all studies agree that using XAI improves transparency and reduces and detects fraud, there are some differences, which can be called contradictions, the most important of which are:

The impact of interpretability on performance: The first and third papers confirmed that integrating XAI does not negatively affect model accuracy, but rather enhances it and confines users to regulatory and legal compliance. Meanwhile, the sixth paper highlighted and addressed the issue that interpretability can contribute to a reduction in performance in certain models that can be classified as complex, such as the use of deep neural networks, where it becomes difficult to accurately interpret each feature.

Differences in preferred interpretation techniques: Decision trees were the primary reliance for some studies, and SHAP was also used in some models of studies to provide clear, accurate, and understandable explanations for analysts. Meanwhile, some studies focused primarily on analyzing the most important features or using LIME. The reason for the difference is the nature of the data fed into the model and the purpose of applying the model.

Balancing performance and regulation: The focus varied among the selected papers, and there are different priorities depending on accuracy and effectiveness in preventing money laundering, fraud, and suspicious transactions. Some papers primarily focused on transparency and regulatory compliance.

Synthesis Matrix for literature review

Study	Authors	Year	Research Design	Key Findings / Results	Methodology	Limitation
<i>Applications of Explainable Artificial Intelligence in Finance</i>	Kumar et al.	2023	Review	XAI reduce fraud/helping AML detection, build trust, improve transparency.	A review of the literature and case studies	the model depends on synthetic data and simulations
<i>Explainable Artificial Intelligence (XAI) in Finance</i>	Zhou et al.	2024	Systematic Literature Review	aim of discrepancies between both interpretability and accuracy	A thorough analysis of XAI's use in banking	scant empirical support
<i>Interpretable Machine Learning Models for Financial Fraud Detection</i>	Han et al.	2023	Empirical study	increase the level of detection accuracy for the AML and financial fraud; easy to analysis and understand the results	SHAP + Decision Trees + feature significance	Limited realistic datasets were could used for testing
Comparative Analysis of Machine Learning Algorithms for Money Laundering Detection	Nguyen et al.	2025	Comparative ML study	interpretability and accuracy (Random Forest + SHAP).	XGBoost, Random Forest, and Gradient Boosting with XAI	restricted dataset to particular bank transactions. (privacy)
Artificial Intelligence for Anti-Money Laundering: A Review and Extension	Han et al.	2020	Review	Examines ML, DL, for AML. notice a high rate of false positives outcome	Review of the literature	Unbalanced datasets leading to high rate of false positives
Explainable AI in Financial Services: Transparency and Trust in Risk Management	Li et al.	2024	Conceptual study	How XAI can encourages compliance and trust	Conceptual structure	scalable deployment is necessary.

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