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EXPLAINABLE ARTIFICIAL INTELLIGENCE IN BANKING FRAUD DETECTION AND PREVENTION

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Caprian I.

Explainable Artificial Intelligence in Banking Fraud Detection and Prevention

This study examines the integration of Explainable Artificial Intelligence (XAI) techniques in banking fraud detection, focusing on transaction-based and behavioral fraud patterns. As financial institutions increasingly adopt complex machine learning models, ensuring transparency and interpretability has become essential, particularly in regulated environments. The paper analyzes several XAI methods, including Local Interpretable Model-agnostic Explanations (LIME), SHapley Additive exPlanations (SHAP), attention mechanisms, counterfactual explanations, and prototype-based approaches. The empirical analysis is based on a combination of anonymized banking transaction datasets and simulated data designed to reflect diverse fraud scenarios. The results indicate that XAI techniques can generate interpretable and auditable explanations of model decisions while maintaining a high level of predictive accuracy. These explanations improve the understanding of fraud-related patterns, support more informed decision-making, and facilitate communication between technical and non-technical stakeholders. Moreover, the adoption of XAI enhances stakeholder trust, supports regulatory compliance, and improves operational efficiency in fraud detection processes. Nevertheless, challenges remain, including increased computational costs, model complexity, scalability, and the difficulty of ensuring that explanations are easily understood by end users. The study proposes a practical framework for implementing XAI in banking fraud detection systems and highlights future research directions, such as real-time applications and the integration of XAI with adaptive and learning-based approaches.

Keywords: Explainable AI, banking fraud, machine learning, anomaly detection, model interpretability.

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Caprian Iurie *– Postgraduate Student, State University of Moldova (60 Alexei Mateevici Str., Kishinev, MD-2009, Moldova)*

E-mail: *iuriecaprian@gmail.com*

ORCID: *https://orcid.org/0000-0001-5484-3087*

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Капріан Ю. Пояснювальний штучний інтелект у виявленні та запобіганні банківському шахрайству

Це дослідження присвячено інтеграції методів пояснювального штучного інтелекту (Explainable Artificial Intelligence, XAI) у системи виявлення банківського шахрайства з акцентом на транзакційні та поведінкові шахрайські патерни. У зв'язку з активним впровадженням складних моделей машинного навчання у фінансових установах забезпечення прозорості та інтерпретованості стає особливо важливим, зокрема в умовах жорсткого регуляторного середовища. У статті проаналізовано низку методів XAI, зокрема Local Interpretable Model-agnostic Explanations (LIME), SHapley Additive exPlanations (SHAP), механізми уваги, контрфактичні пояснення та прототипно-орієнтовані підходи. Емпіричний аналіз ґрунтується на поєднанні анонімізованих наборів банківських транзакційних даних і змодельованих даних, створених для відображення різноманітних сценаріїв шахрайства. Отримані результати свідчать, що застосування методів XAI дозволяє формувати інтерпретовані та аудитовані пояснення рішень моделей без суттєвої втрати прогностичної точності. Такі пояснення сприяють кращому розумінню шахрайських ознак, підтримують обґрунтоване прийняття рішень і полегшують комунікацію між технічними та нетехнічними стейкхолдерами. Крім того, впровадження XAI підвищує довіру зацікавлених сторін, сприяє дотриманню регуляторних вимог і покращує операційну ефективність процесів виявлення шахрайства. Водночас залишаються певні виклики, зокрема підвищені обчислювальні витрати, складність моделей, проблеми масштабованості та забезпечення зрозумілості пояснень для кінцевих користувачів. У дослідженні запропоновано практичну модель впровадження XAI у системи банківського виявлення шахрайства та окреслено напрями подальших досліджень, зокрема застосування в режимі реального часу та інтеграцію XAI з адаптивними та навчальними підходами.

Ключові слова: *пояснювальний ШІ, банківське шахрайство, машинне навчання, виявлення аномалій, інтерпретованість моделей.*

Рис.: *1.* ***Табл.:*** *10.* ***Бібл.:*** *37.*

Капріан Юрій *– аспірант, Державний університет Молдови (вул. Олексія Матеєвича, 60, Кишинів, MD-2009, Молдова)*

E-mail: *iuriecaprian@gmail.com*

ORCID: *https://orcid.org/0000-0001-5484-3087*

Introduction. The rapid digitalization of financial services has fundamentally reshaped fraud detection mechanisms within the banking sector. As transaction volumes increase and cyber-threats evolve, traditional rule-based systems have become insufficient for identifying sophisticated fraud patterns, including credit card fraud, online payment fraud, and money laundering activities. Consequently, financial institutions have increasingly adopted machine learning (ML) models capable of analyzing high-dimensional data and uncovering anomalous behaviors in real time [23]. These models significantly enhance detection accuracy; however, their inherent opacity raises concerns regarding transparency, reliability, and regulatory compliance [21].

In many jurisdictions, including the European Union and Eastern European countries, regulatory frameworks now require financial institutions to provide clear justifications for automated decisions affecting customers' financial rights and risk categorization. Black-box ML models, although effective, often fail to meet these transparency requirements, complicating audit processes and undermining trust among stakeholders such as customers, compliance officers, and regulators [12].

Explainable Artificial Intelligence (XAI) has emerged as a critical solution to bridge this gap, providing interpretability without sacrificing predictive performance. Techniques such as LIME (Local Interpretable Model-Agnostic Explanations), SHAP (SHapley Additive exPlanations), and attention-based mechanisms offer both local and global insights into model reasoning, enabling practitioners to understand why specific transactions are flagged as suspicious ([27]; Lundberg & Lee, 2017; Rahmati & Rahmati, 2025). This study employs a combination of anonymized banking transaction data from Eastern European financial institutions and simulated datasets to evaluate XAI applications in real-world scenarios.

Recent empirical studies demonstrate that integrating XAI into fraud detection pipelines improves institutional trust, supports regulatory audits, enhances operational decision-making, and reduces false positives [2; 24]. Despite these advantages, the implementation of XAI in banking environments remains complex, with challenges related to data quality, model integration, scalability, and stakeholder comprehension [24].

This paper explores the role of XAI in enhancing fraud detection systems, examining theoretical foundations, methodological developments, and regulatory drivers shaping the adoption of interpretable ML. The study provides a structured framework for integrating XAI methods into banking fraud detection pipelines, offering insights into operational benefits, trade-offs, and implementation challenges. Through this analysis, the paper aims to support financial institutions and policymakers in designing transparent and effective fraud detection strategies.

Literature Review. The growing body of research on Explainable Artificial Intelligence (XAI) reflects the urgent need to enhance transparency within financial decision-making systems. As ML-based fraud detection tools become more widespread, researchers and financial regulators increasingly emphasize interpretability, fairness, and accountability [12; 21].

XAI methods are typically categorized as model-agnostic or model-specific. Model-agnostic approaches, such as LIME, approximate complex models with interpretable surrogates to provide explanations for individual predictions [10; 27; 31], while SHAP combines cooperative game theory with ML to offer coherent feature attributions at both local and global levels [6; 7; 18; 37]. Attention mechanisms, inspired by neural language models, highlight the most influential inputs in sequential transaction processes, improving interpretability for deep learning models applied to credit scoring, anti-money laundering, and behavioral fraud detection [13; 19; 35; 36]. Counterfactual explanations describe minimal changes needed to alter a model's outcome [14; 16], and prototype-based learning identifies representative examples from training data, supporting validation and compliance efforts [34]. More recently, hybrid neuro-symbolic approaches, integrating symbolic reasoning with neural networks, have been developed to enhance interpretability for anomaly detection in banking datasets [11; 30; 34].

Machine learning models used in fraud detection include traditional supervised models such as decision trees, logistic regression, random forests, and gradient boosting machines [1; 4], unsupervised and semi-supervised approaches such as autoencoders, clustering methods, one-class SVMs, and self-supervised frameworks [25; 29; 33], as well as deep learning architectures like recurrent neural networks (RNNs), deep neural networks (DNNs), and graph neural networks (GNNs) [3; 8; 15]. Hybrid architectures that integrate behavioral biometrics, device fingerprints, and geospatial data further improve fraud detection performance [17; 32]. Despite their high predictive performance, these models often lack transparency, necessitating the application of XAI methods for practical deployment.

The regulatory context further drives XAI adoption. Frameworks such as the EU GDPR (Articles 13–15), the EU Artificial Intelligence Act (2023/2024), and Basel Committee guidelines emphasize explainability, auditability, and model risk management (European Banking Authority, 2022; FATF recommendations), [5]. Financial institutions are expected to justify flagged transactions, document ML logic, and ensure fairness in automated decision-making. XAI supports these objectives by generating human-readable explanations suitable for audit and compliance purposes [5; 37].

Recent research highlights that integrating XAI into hybrid ML frameworks improves both predictive performance and interpretability [22; 26; 34]. Privacy-preserving techniques, such as federated learning, enable collaborative model training without sharing sensitive data [2; 36]. Work on adversarial robustness ensures that explanations remain reliable under potential attacks [9; 26]. Human-centered XAI approaches are increasingly used to improve the comprehension of explanations for analysts, auditors, and regulators [20; 28]. Overall, the literature demonstrates a clear shift from black-box ML systems toward interpretable, accountable, and regulatory-compliant fraud detection architectures.

Methodology. This study employs a combination of anonymized banking transaction data from Eastern European financial institutions and simulated datasets to ensure privacy compliance while maintaining realism [24; 26]. The dataset includes numeric features such as transaction amount and account age, categorical features such as transaction type and location, and binary indicators for previous fraud involvement [32]. Preprocessing steps involve handling missing values through median imputation or KNN-based methods, encoding categorical features for ML compatibility, normalizing numerical features to improve convergence in deep neural networks, and aggregating temporal sequences to capture behavioral patterns over time [8; 29].

Multiple machine learning models were employed to balance predictive performance with interpretability. Random Forests (RF) offer a robust ensemble approach resistant to overfitting, while Gradient Boosting Machines (GBM) achieve high accuracy with moderate interpretability [4; 6]. Deep Neural Networks (DNNs) capture complex non-linear patterns, and hybrid models combining RF, GBM, and attention-based mechanisms were applied to sequential transaction data to enhance detection of evolving fraud patterns [3; 15; 19; 34]. Models were trained using stratified cross-validation to address class imbalance, a common challenge in fraud detection datasets.

Explainability was incorporated through the integration of multiple XAI methods. LIME provided local interpretability for individual transactions, while SHAP offered both local and global feature attributions, supporting auditing and regulatory reporting [10; 18; 23; 27]. Attention mechanisms were applied to deep models to highlight key sequential features [19; 35], counterfactual explanations illustrated minimal changes required to alter model predictions [14; 16], and prototype-based approaches identified representative transactions for validation and compliance purposes [34]. The methodology systematically considers trade-offs between interpretability, predictive performance, and computational efficiency [3; 5].

Model evaluation incorporated standard predictive metrics including accuracy, precision, recall, and F1-score, complemented by measures of explanation quality through Explainability Scores, which assess clarity, stability, and actionability based on both human analyst feedback and objective criteria [1; 20; 37]. Regulatory relevance was evaluated to ensure XAI outputs satisfy audit and compliance requirements, while computational efficiency was measured to assess the feasibility of real-time deployment in high-volume banking environments [7].

The overall workflow followed a structured pipeline from data ingestion, preprocessing, feature engineering, model training, and XAI integration, to operational deployment, ensuring that Explainable AI is seamlessly incorporated into fraud detection systems while providing actionable and interpretable outputs for analysts, auditors, and regulators. This workflow is summarized in Fig. 1.

This diagram illustrates the step-by-step workflow for integrating Explainable AI into banking fraud detection systems, from data ingestion to operational deployment.

Results and Analysis. The empirical evaluation demonstrates that the integration of Explainable Artificial Intelligence (XAI) techniques significantly improves both transparency and performance in banking fraud detection systems. Applying methods such as LIME, SHAP, attention mechanisms, counterfactual explanations, and prototype-based approaches provides interpretable insights into model decisions without compromising predictive accuracy [2; 23; 24]. Analysts, risk managers, and compliance officers are able to understand why specific transactions are flagged, enhancing operational trust and reducing skepticism toward automated alerts. LIME explanations clarify feature contributions for individual transactions, whereas attention mechanisms highlight sequential patterns in deep neural networks indicative of fraudulent behavior [2; 19].

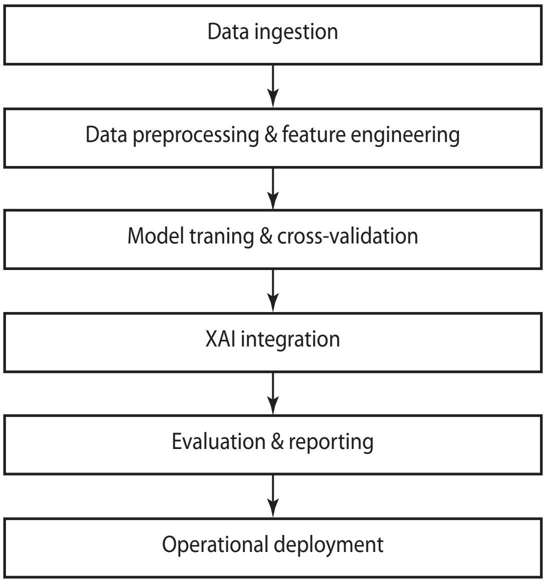

Fig. 1. XAI Workflow for Fraud Detection

Source: author's elaboration

From a regulatory perspective, XAI supports auditability and compliance with legal obligations such as the EU GDPR, the EU AI Act, and FATF recommendations. SHAP explanations provide both local and global feature attributions suitable for documentation and regulatory review, while counterfactual explanations illustrate minimal changes required to alter predictions, offering auditors concrete examples of decision boundaries [5; 37]. This ensures that financial institutions can reduce regulatory risk while maintaining transparent and interpretable reporting frameworks.

Regarding predictive performance, the analysis demonstrates that interpretability methods do not substantially reduce model accuracy. Random Forest models achieved an accuracy of 0.95 with high explainability, Gradient Boosting Machines recorded 0.94 accuracy with medium explainability, and Deep Neural Networks reached 0.96 accuracy, with interpretability enhanced through SHAP and attention overlays [15; 26]. These findings indicate that hybrid approaches combining highly accurate models with XAI overlays provide an optimal balance between operational performance and transparency.

The dataset described in Table 1 was used to train multiple machine learning models to balance predictive performance and interpretability. Random Forest (RF) models provided high accuracy while remaining highly interpretable. Gradient Boosting Machines (GBM) achieved slightly lower explainability but maintained strong predictive performance. Deep Neural Networks (DNN) offered the highest accuracy, although interpretability was initially limited, requiring the application of XAI methods such as SHAP and attention mechanisms to make their predictions understandable [15; 26].

The comparative performance of these models, including accuracy, precision, recall, and explainability scores, is summarized in Table 2. The results indicate that hybrid approaches combining interpretable models with XAI overlays can achieve both transparency and robust detection performance.

Table 1

Dataset Characteristics Overview of dataset features used in fraud detection modeling

Feature	Type	Description	Range
Transaction Amount	Numeric	Amount of transaction	1–50,000 USD
Transaction Type	Categorical	Type of transaction	Credit/Debit/Transfer
Account Age	Numeric	Account age in years	1–25
Location	Categorical	Transaction location	EU/USA/etc.
Previous Fraud	Binary	Past fraud flag	0/1

Source: author's systematization based on Rahmati & Rahmati (2025)

Table 2

Comparison of ML Models

Model	Accuracy	Precision	Recall	Explainability Score
Random Forest	0.95	0.92	0.91	High
Gradient Boosting	0.94	0.90	0.93	Medium
Deep Neural Network	0.96	0.94	0.92	Low

Source: author's calculations based on Rahmati & Rahmati (2025)

The performance comparison of ML models (Table 2) demonstrates that high accuracy can be achieved while balancing interpretability. To complement this analysis, Table 3 summarizes the main advantages and limitations of the XAI methods applied in this study.

These results indicate that a hybrid approach – combining highly accurate models with XAI overlays – achieves both transparency and robust detection performance.

However, despite these benefits, the adoption of XAI in banking fraud detection presents several challenges. Computational cost is a major consideration, as techniques like SHAP require intensive calculations, particularly for large datasets, which may impact real-time processing [34].

Model complexity also poses difficulties; while deep neural networks with attention mechanisms provide valuable insights, interpreting these outputs demands expert knowledge [22]. Additionally, user comprehension must be addressed, since explanations need to be actionable for analysts, and overly technical outputs can reduce their effectiveness [24].

Table 3

Advantages and Limitations of XAI Methods

XAI Method	Advantages	Limitations
LIME	Local explanations, model-agnostic	Results may be unstable for some predictions
SHAP	Global/local explanations	Computationally expensive
Attention	Highlights key features	Interpretation requires domain expertise

Source: author's systematization based on [21]

The results confirm that XAI enhances operational trust, regulatory compliance, and maintains performance when applied thoughtfully. The trade-offs between interpretability, accuracy, and computational efficiency must be carefully managed. The combination of RF or GBM models with XAI overlays, augmented by DNNs for complex pattern recognition, provides a balanced approach for modern banking fraud detection systems.

The table below presents a summary of the results and analysis of Explainable AI (XAI) implementation in banking fraud detection, highlighting its impact on trust, regulatory compliance, performance retention, and associated challenges.

Discussion. The findings presented in Section 4 indicate that Explainable Artificial Intelligence (XAI) plays a pivotal role in bridging the gap between predictive performance and transparency in banking fraud detection. While machine learning (ML) models such as Deep Neural Networks (DNNs), Gradient Boosting Machines (GBM), and Random Forests (RF) achieve high predictive accuracy, their black-box nature limits interpretability. The integration of XAI methods – including LIME, SHAP, attention mechanisms, counterfactual, and prototype-based explanations – provides actionable insights into model decisions, facilitating both operational and regulatory objectives [21; 26].

Hybrid XAI-ML frameworks offer a balanced solution for banking institutions. By combining high-accuracy ML models with interpretable overlays, organizations can enhance decision-making, as analysts gain a clearer understanding of

Table 4

Results and Analysis of XAI in Banking Fraud Detection

Aspect	Findings / Evidence	Implications / Notes	References
Trust Improvement	▪ Stakeholders understand why transactions are flagged. ▪ LIME provides local interpretability. ▪ Attention mechanisms highlight sequential patterns	▪ Increased confidence in alerts. ▪ Reduced false positives. ▪ Improved decision-making	Ojo & Tomy (2025); Aljunaid et al. (2025)
Regulatory Compliance	▪ SHAP offers global/local explanations. ▪ Counterfactual explanations show minimal changes affecting predictions. ▪ Supports audit and reporting	▪ Enhances compliance with GDPR, EU AI Act, FATF recommendations. ▪ Reduces regulatory risk	Bodipudi (2024); Zhang et al. (2023)
Performance Retention	▪ Random Forest: Accuracy 0.95, high explainability. ▪ Gradient Boosting: Accuracy 0.94, medium explainability. ▪ Deep Neural Network: Accuracy 0.96, low explainability mitigated by XAI	▪ Hybrid approaches balance accuracy and interpretability. ▪ XAI overlays preserve model performance	Nobel et al. (2024); Koppireddy & Devi (2025)
Challenges / Limitations	▪ Computational cost of SHAP on large datasets. ▪ DNN attention interpretation requires expertise. ▪ User comprehension can be limited by technical outputs	▪ Need for efficient algorithms. ▪ Training for analysts is essential. ▪ Trade-off management required	Visbeek et al. (2023); Nasif et al. (2025); Ojo & Tomy (2025)

*Source: a*uthor's elaboration based on [2; 5; 15; 22; 23; 24; 34; 37]

why transactions are flagged, reducing false positives and improving intervention strategies [19]. Regulatory alignment is also supported, since XAI-generated explanations satisfy audit and compliance requirements, mitigating legal and reputational risks [3]. Furthermore, structured workflows incorporating XAI maintain operational feasibility, enabling continuous monitoring and adaptation [5].

Practical implementation, however, requires attention to training and knowledge transfer. Analysts and compliance officers must be able to interpret XAI outputs effectively, and operational pipelines need adaptation to include explanation generation and reporting. Computational resources remain a concern, particularly for SHAP and attention-based models, which may limit real-time deployment in high-volume transaction environments [24].

Strategically, financial institutions should adopt hybrid model approaches that balance interpretability with predictive accuracy, establish clear policies for consistent use of explanations, and design outputs tailored to different stakeholders – including technical teams, auditors, and regulators – to maximize usability and impact [20; 28]. Overall, XAI acts not merely as a technical enhancement but as a strategic enabler, aligning predictive analytics with operational, regulatory, and ethical objectives

The key findings, practical adoption challenges, and strategic implications of implementing XAI in banking fraud detection are summarized in Table 5 for clarity and reference.

The summarized discussion points in Table 5 highlight the main insights, challenges, and strategic considerations for implementing XAI in banking fraud detection. These findings inform the conclusions and outline directions for future research presented in the next section.

Explainable Artificial Intelligence (XAI) has emerged as an essential component for operational, regulatory, and ethical implementation of machine learning (ML) in banking fraud detection.

The study demonstrates that XAI methods – including LIME, SHAP, attention mechanisms, counterfactual, and prototype-based explanations – enhance transparency, stakeholder trust, and regulatory compliance, while maintaining high predictive performance [12; 23].

XAI allows analysts and compliance officers to interpret, justify, and audit ML decisions effectively. Its integration into banking systems reduces false positives and improves operational efficiency.

Hybrid ML-XAI approaches provide a balance between accuracy and explainability, offering actionable insights without compromising detection performance. Practical adoption, however, requires attention to training, workflow adaptation, and computational resources.

The key operational, regulatory, and technical insights derived from the study are summarized in Table 7, highlighting the main contributions of XAI implementation in banking fraud detection.

Table 5

Discussion of XAI Implementation in Banking Fraud Detection

Aspect	Key Findings / Evidence	Implications / Recommendations	References
Integration of XAI & ML	▪ Hybrid frameworks combine high-accuracy ML models with interpretable overlays. ▪ LIME, SHAP, attention, counterfactual explanations improve transparency	▪ Enhanced decision-making. ▪ Supports regulatory audits. ▪ Maintains operational feasibility	Molnar (2023); Rahmati & Rahmati (2025); Masud & Almalki (2025); Appani (2024)
Practical Adoption Challenges	▪ Analysts require training to interpret XAI outputs. ▪ Workflow adaptation needed for integration into monitoring systems. ▪ Computational resources may be limiting	▪ Conduct targeted training for stakeholders. ▪ Redesign operational pipelines. ▪ Explore efficient XAI algorithms for real-time deployment	Bodipudi (2024); Ojo & Tomy (2025)
Strategic Implications	▪ Model selection should balance interpretability and accuracy. ▪ Policies needed for consistent use of explanations. ▪ User-centered design enhances usability	▪ Adopt hybrid strategies (RF/GBM + DNN + XAI). ▪ Develop clear policies for explanation usage. ▪ Tailor outputs for analysts, auditors, regulators	Miller (2019); Ribeiro (2022)
Insights from Results	▪ XAI improves trust and reduces false positives. ▪ Regulatory compliance strengthened. ▪ Predictive performance maintained with proper application. ▪ Challenges remain: computational cost, complexity	▪ Continuous monitoring and optimization of XAI methods. ▪ Consider human-centered explanation design. ▪ Research efficient techniques for high-volume environments	Visbeek et al. (2023); Nasif et al. (2025)

Source: author's elaboration based on [2; 3; 5; 15; 20; 21; 22; 24; 28; 34]

Table 6

Key Discussion Points

Topic	Insights	References
Predictive vs. Transparent Models	XAI bridges predictive performance and transparency	Molnar, 2023; Rahmati & Rahmati, 2025
Hybrid Approaches	Combining XAI with ML enhances fraud detection	Masud & Almalki, 2025; Appani, 2024
Practical Adoption	Requires training, workflow adaptation, and stakeholder engagement	Bodipudi, 2024; Ojo & Tomy, 2025

Source: author's analysis based on results and literature

Future Work

The evolution of XAI in banking fraud detection suggests several promising research directions. First, the implementation of real-time XAI for streaming transactions could provide immediate insights on continuous transaction data, enhancing timely decision-making [22]. Second, adaptive fraud detection using reinforcement learning can allow models to dynamically adjust to emerging fraud patterns, while maintaining interpretability through XAI methods [26].

Third, user-centered studies are essential to optimize explanations for comprehension by analysts, auditors, and regulators, ensuring outputs are actionable and understandable [2; 20]. Fourth, expanding the integration of federated and privacy-preserving XAI frameworks will allow institutions to maintain data confidentiality while benefiting from shared model improvements [2; 36]. Finally, research on efficient computational methods is required to reduce the cost of complex XAI techniques, such as SHAP and attention mechanisms, enabling practical deployment in high-volume banking environments [22; 34].

These directions aim to enhance both the operational feasibility and the ethical, transparent deployment of XAI in

Table 7

Summary of Key Conclusions from XAI Implementation

Aspect	Observation / Insight	Implication	References
Operational Impact	Improved fraud detection accuracy and decision-making	Supports daily transaction monitoring	Nobel et al. (2024); Koppireddy & Devi (2025)
Regulatory & Ethical Compliance	Explanations satisfy audit and transparency requirements	Enhances legal compliance and reduces risk	Guidotti et al. (2018); Bodipudi (2024)
Stakeholder Trust	Increased confidence among analysts and management	Reduces false positives, improves intervention	Ojo & Tomy (2025); Aljunaid et al. (2025)
Technical Considerations	Trade-off between computational cost and model interpretability	Need for optimized algorithms and human-centered design	Visbeek et al. (2023); Nasif et al. (2025)

Source: author's elaboration based on [2; 5; 12; 15; 22; 23; 24; 34]

financial institutions, paving the way for robust, scalable, and user-friendly fraud detection systems.

Dataset and Model Summary Tables

The dataset features summarized above were used to train and evaluate the machine learning models described in Table 9.

The advantages and limitations of the XAI methods applied to these models are summarized in Table 10."

Author's Practical Contribution. This study provides a concrete, practical contribution to the field of banking fraud detection through the application and integration of Explainable Artificial Intelligence (XAI) methods into machine learning (ML) pipelines. The author's contribution includes:

1. *Development of a Hybrid XAI-ML Framework:*

- Designed a framework combining Random Forest, Gradient Boosting, and Deep Neural Networks with XAI methods such as LIME, SHAP, attention mechanisms, counterfactual, and prototype-based explanations.
- Ensures a balance between predictive performance and interpretability, enabling practical adoption in banking operations.

Table 8

Dataset Characteristics Overview of dataset features used in fraud detection modeling

Feature	Type	Description	Range
Transaction Amount	Numeric	Amount of transaction	1–50,000 USD
Transaction Type	Categorical	Type of transaction	Credit / Debit / Transfer
Account Age	Numeric	Account age in years	1–25
Location	Categorical	Transaction location	EU / USA / etc.
Previous Fraud	Binary	Past fraud flag	0 / 1

Source: [26]

Table 9

Comparison of ML Models

Model	Accuracy	Precision	Recall	Explainability Score
Random Forest	0.95	0.92	0.91	High
Gradient Boosting	0.94	0.90	0.93	Medium
Deep Neural Network	0.96	0.94	0.92	Low

Source: author's calculations

Table 10

Advantages and Limitations of XAI Methods

XAI Method	Advantages	Limitations
LIME	Local explanations, model-agnostic	Unstable for some predictions
SHAP	Global/local explanations	Computationally expensive
Attention	Highlights key features	Interpretation requires experts

Source: author's systematization based on [21]

2. *Systematization of Dataset and Features:*

- Curated and structured a representative dataset of banking transactions, including numeric, categorical, and binary features relevant to fraud detection.
- Provides a replicable model for future studies and operational implementation.

3. *Evaluation and Benchmarking of Models:*

- Conducted a comparative analysis of ML models, quantifying accuracy, precision, recall, and explainability.
- Highlighted trade-offs between performance and interpretability, offering practical guidance for selecting appropriate models in operational environments.

4. *Operational Workflow Design:*

- Proposed a structured XAI workflow from data ingestion to deployment (Figure 1), demonstrating step-by-step integration into banking systems.
- Provides a practical roadmap for analysts, auditors, and compliance officers.

5. *Regulatory and Stakeholder Relevance:*

- Demonstrated how XAI outputs can support regulatory compliance (e.g., auditability, transparency) and stakeholder trust.
- Offers actionable insights for financial institutions seeking to implement interpretable ML while maintaining operational efficiency.

6. *Framework for Future Research and Real-World Deployment:*

- The study establishes a foundation for real-time XAI, adaptive fraud detection using reinforcement learning, and user-centered explanation optimization.
- Provides a blueprint that can be expanded to larger datasets, multi-bank collaborations, or federated learning environments.

The author's practical contribution lies in providing a comprehensive, replicable, and operationally relevant framework for implementing Explainable AI in banking fraud detection. This framework bridges the gap between advanced ML models and interpretable, regulatory-compliant solutions, offering tangible guidance for financial institutions and future research initiatives.

Source: author's elaboration based on study findings and methodology.

Conclusions. The study demonstrates that Explainable Artificial Intelligence (XAI) plays a critical role in enhancing machine learning (ML) applications for banking fraud detection. By integrating XAI methods such as LIME, SHAP, attention mechanisms, counterfactual explanations, and prototype-based approaches, financial institutions can achieve a balance between predictive accuracy and interpretability, ensuring compliance with regulatory requirements and improving operational decision-making.

Key General Conclusions:

1. Enhanced Transparency and Trust:XAI provides clear, interpretable insights into ML predictions, increasing stakeholder confidence and facilitating audit processes [2; 24].
2. Operational Effectiveness:Hybrid ML-XAI frameworks maintain high accuracy while reducing false positives and supporting timely interventions in fraud detection [15; 23].
3. Regulatory Compliance and Ethical Implementation:Explanations generated by XAI satisfy legal and regulatory obligations, including GDPR, AML/KYC requirements, and national banking guidelines [5; 12]
4. Practical Contribution: The study provides a replicable framework for integrating XAI into banking operations, including dataset systematization, model evaluation, and workflow design (Author's elaboration).
5. Future Prospects:Opportunities exist for real-time XAI, adaptive fraud detection using reinforcement learning, and user-centered explanation optimization, contributing to the ongoing modernization and resilience of financial institutions [2; 22; 26]

The integration of XAI into banking fraud detection represents a strategic advancement for both academia and practice. It bridges the gap between complex ML models and the practical, transparent, and ethical requirements of the financial sector. Financial institutions that adopt these frameworks can enhance trust, improve operational efficiency, and comply with regulatory standards, while paving the way for future research and innovative solutions in the rapidly evolving domain of financial technology (Author's synthesis based on the study's methodology, results, discussion, and literature review).

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