International Journal of Advance Industrial Engineering

E-ISSN 2320 –5539
Available at http://ijaie.com/

Research Article

Explainable Artificial Intelligence for Protecting the U.S. Financial System from Sanctions Evasion and Trade-Based Money Laundering

Pristly Turjo Mazumder*

Georgia State University

ABSTRACT

The integrity of the U.S. financial system is increasingly threatened by sophisticated sanctions evasion networks and trade-based money laundering schemes that exploit cross-border payment channels and global supply chains. While machine learning techniques have enhanced the detection capabilities of anti-money laundering and sanctions screening systems, their limited transparency poses significant challenges for regulatory compliance, supervisory review, and effective financial intelligence generation. This study proposes an explainable artificial intelligence framework for protecting the U.S. financial system by enabling detection models that not only identify illicit financial risk but also clearly articulate the underlying drivers of that risk. The research develops explainable AI-based anti-money laundering models tailored to U.S.-touch payment and trade finance environments, including cross-border wire transfers, correspondent banking flows, and ISO 20022-aligned messaging. The framework targets two priority threat domains identified in U.S. national-security guidance: sanctions evasion involving restricted jurisdictions and proxy counterparties, and trade-based money laundering linked to supply-chain manipulation, over-invoicing, and under-invoicing practices. Explainability mechanisms are integrated at the feature, counterparty, transaction routing, and documentation levels to generate investigator-readable narratives and examiner-ready audit trails.

Empirical results demonstrate that the incorporation of explainable artificial intelligence significantly reduces false-positive alert volumes and shortens investigation time compared to traditional opaque models, while improving the clarity and consistency of suspicious activity reporting. By enhancing transparency, accountability, and operational efficiency, the proposed approach strengthens regulatory trust and supports higher-quality financial intelligence outcomes. These findings underscore the role of explainable artificial intelligence as a critical enabler of effective anti-money laundering enforcement, sanctions compliance, and national-security protection within the U.S. financial system.

INTRODUCTION

The stability and credibility of the U.S. financial system are central to national security, economic resilience, and global financial governance. As the United States plays a pivotal role in international payments, trade finance, and correspondent banking, illicit actors increasingly exploit U.S.-touch transactions to move value across borders. Sanctions evasion networks, terrorist financing intermediaries, and trade-based money laundering schemes leverage the scale and complexity of global financial flows to obscure illicit activity, often embedding themselves within otherwise legitimate commerce and payment activity. These threats pose not only compliance risks for financial institutions but also strategic risks to U.S. foreign policy, sanctions enforcement, and financial intelligence operations.

In response, financial institutions have invested heavily in anti-money laundering and sanctions screening systems, many of which now rely on machine learning and advanced analytics to process large volumes of transactional and trade data. While these approaches have improved detection coverage and automation, they have also introduced new challenges. A significant proportion of contemporary AML systems operate as opaque or minimally interpretable models, generating alerts without sufficiently explaining why a transaction, counterparty, or trade relationship is deemed suspicious. This lack of transparency complicates internal investigations, weakens regulatory confidence, and increases the burden on compliance teams tasked with justifying decisions to supervisors and examiners.

The challenge is particularly acute in the context of sanctions evasion and trade-based money laundering. Sanctions evasion often involves layered payment routes, indirect counterparties, and jurisdictional arbitrage that cannot be reliably assessed through simple rule-based

*Author for Correspondence: pristly.turjo@gmail.com
DOI: https://doi.org/10.14741/ijaie/v.12.2.1

logic. Trade-based money laundering exploits pricing anomalies, document inconsistencies, and supply-chain manipulation, requiring contextual interpretation that extends beyond transaction amounts alone. In both cases, investigators and regulators must understand not only that risk exists, but how it manifests across counterparties, routes, documents, and economic rationale. Detection without explanation undermines the effectiveness of financial intelligence and limits the ability of institutions to produce high-quality suspicious activity reports.

Explainable artificial intelligence offers a promising pathway to address these limitations. By embedding interpretability into machine learning models, explainable AI enables systems to surface the features, relationships, and patterns that drive risk assessments. In a regulated financial environment, explainability is not merely a technical enhancement but an operational and supervisory requirement. Regulators, examiners, and law enforcement stakeholders require decision logic that can be reviewed, audited, and defended, particularly when models influence account restrictions, transaction interdictions, or SAR filings. Explainable AI therefore serves as a bridge between advanced analytics and the accountability expectations of the U.S. regulatory framework.

This research focuses on the design and evaluation of explainable AI-based AML models tailored specifically to the U.S. financial system. The study targets two U.S.-priority threat domains: sanctions evasion conducted through U.S.-touch payment flows, and trade-based money laundering embedded within cross-border supply chains. The proposed approach integrates explainability into detection models operating across wires, trade finance instruments, and cross-border payments, with explicit consideration of ISO 20022-aligned data structures and correspondent banking environments. The objective is to demonstrate how explainable AI can reduce false positives, accelerate investigations, and improve the clarity and evidentiary value of suspicious activity reporting.

By aligning technical design with regulatory usability, this study contributes to both academic research and practical policy implementation. It advances the literature on explainable artificial intelligence in financial crime detection while addressing real-world supervisory and national-security concerns. Ultimately, the paper argues that explainable AI is not only compatible with effective AML and sanctions enforcement, but essential to safeguarding the integrity of the U.S. financial system in an increasingly complex and adversarial global environment.

Literature Review

Conventional AML and Sanctions Monitoring Frameworks

Traditional anti-money laundering and sanctions compliance systems have historically relied on rule-based approaches, threshold triggers, and deterministic scenarios derived from regulatory guidance and known typologies. These systems emphasize transparency and auditability, as decision logic is explicitly defined and easily reviewed by compliance officers and regulators. However, the rigidity of rule-based frameworks limits their effectiveness in detecting complex and evolving illicit finance schemes, particularly those involving layered transactions, indirect counterparties, and cross-border trade structures. As transaction volumes and payment velocities have increased, conventional systems have also generated high false-positive rates, creating substantial operational burdens for financial institutions and reducing the overall quality of financial intelligence outputs.

Sanctions screening frameworks face similar constraints. Name-matching algorithms, static risk scores, and jurisdiction-based filters are effective for straightforward cases but struggle with proxy actors, front companies, and jurisdictional arbitrage. In the context of trade-based money laundering, traditional approaches often fail to capture pricing manipulation, document inconsistencies, and supply-chain distortions that require contextual and relational analysis. These limitations have driven growing interest in data-driven and machine learning-based detection techniques.

Machine Learning in Financial Crime Detection

The application of machine learning to financial crime detection has expanded rapidly over the past decade. Supervised learning models, including logistic regression, decision trees, random forests, and gradient boosting techniques, have been widely adopted for transaction monitoring and customer risk scoring. Unsupervised and semi-supervised approaches, such as clustering and anomaly detection, have been used to identify novel or previously unseen illicit behaviors. More recently, deep learning architectures have been explored to capture non-linear relationships and high-dimensional interactions within large transactional datasets.

Empirical studies consistently show that machine learning models outperform rule-based systems in terms of detection accuracy and coverage. However, this performance advantage often comes at the cost of interpretability. Complex ensemble and deep learning models tend to function as black boxes, offering limited insight into why specific transactions are flagged. In regulated financial environments, this opacity undermines trust in model outputs, complicates validation efforts, and raises concerns during supervisory examinations. As a result, the adoption of advanced machine learning techniques in AML and sanctions compliance has been uneven, with institutions balancing detection performance against explainability and governance requirements.

Cxplainable Artificial Intelligence in Regulated Domains

Explainable artificial intelligence has emerged as a response to the transparency challenges posed by complex machine learning models. XAI techniques aim to make model decisions understandable to human users by providing feature importance measures, local explanations, rule approximations, or visual representations of decision logic. In high-stakes domains such as healthcare, credit risk, and legal decision-making, explainability is increasingly viewed as essential for accountability, fairness, and trust.

Within financial services, XAI has been applied most extensively to credit scoring and fraud detection, where regulatory expectations for model explainability are well established. Research demonstrates that explainable models can improve user confidence, facilitate error detection, and support compliance with governance standards. However, the application of XAI to AML and sanctions enforcement remains comparatively underdeveloped. Many studies focus on technical explainability metrics without addressing the practical needs of investigators, examiners, and auditors who must rely on model outputs to support enforcement actions and regulatory filings.

Trade-Based Money Laundering and Supply-Chain Analytics

Trade-based money laundering represents one of the most complex and least transparent forms of illicit finance. It exploits legitimate trade transactions to disguise the movement of value through mechanisms such as over-invoicing, under-invoicing, false invoicing, and misrepresentation of goods. Academic and policy-oriented literature highlights the difficulty of detecting TBML due to fragmented data, inconsistent documentation standards, and limited visibility across global supply chains.

Recent research has explored the use of data analytics and network-based methods to identify TBML risk indicators, including price deviations from market benchmarks, abnormal trade routes, and unusual counterparty relationships. While these approaches offer promise, they often lack integration with payment data and do not provide explanations that are readily usable by compliance investigators. The absence of explainability limits their operational adoption, particularly in environments where decisions must be justified to regulators and law enforcement agencies.

Research Gaps and Contribution of This Study

The existing literature reveals several critical gaps at the intersection of AML, sanctions enforcement, and explainable artificial intelligence. First, there is limited research that jointly addresses sanctions evasion and trade-based money laundering within a unified analytical framework, despite their frequent overlap in real-world cases. Second, while machine learning models demonstrate strong detection capabilities, their lack of transparency restricts their regulatory acceptability and investigative usefulness. Third, current XAI research rarely considers the specific operational and supervisory contexts of the U.S. financial system, including payment rails, correspondent banking structures, and reporting obligations.

This study addresses these gaps by proposing and evaluating an explainable AI framework explicitly designed for AML and sanctions enforcement in the U.S. financial system. By integrating explainability into detection models across payment and trade finance domains, the research advances both theoretical understanding and practical implementation of regulator-ready financial crime analytics.

METHODOLOGY

Research Design and Analytical Approach

This study adopts a quantitative, model-driven research design combined with applied regulatory analysis to evaluate the effectiveness of explainable artificial intelligence in detecting sanctions evasion and trade-based money laundering within the U.S. financial system. The methodology is structured to reflect real-world anti-money laundering operations, with emphasis on regulatory usability, auditability, and investigative relevance rather than purely predictive accuracy. The research framework integrates machine learning-based risk detection with explainability mechanisms that translate model outputs into actionable insights for compliance investigators and supervisory authorities.

The analytical approach follows four sequential stages: data integration across U.S.-touch payment and trade channels, feature engineering aligned with known illicit finance typologies, development of explainable detection models, and evaluation of both detection performance and operational impact.

Data Sources and U.S. Financial Infrastructure Context

The analysis focuses on transaction and trade data representative of U.S.-touch financial activity. Payment data include cross-border wire transfers and correspondent banking flows that clear through U.S. financial institutions. Trade-related data encompass trade finance instruments, invoices, bills of lading, customs declarations, and pricing references linked to international supply chains. Payment messages are structured to reflect ISO 20022 standards, enabling consistent extraction of counterparty, routing, and transaction metadata.

All datasets are anonymized and aggregated to preserve confidentiality while maintaining structural and behavioral characteristics relevant to sanctions evasion and trade-based money laundering detection.

Feature Engineering and Risk Indicators

Feature engineering is guided by established illicit finance typologies and regulatory red flags. For sanctions evasion detection, features capture jurisdictional exposure, indirect counterparty relationships, transaction routing complexity, and temporal payment patterns. For trade-based money laundering, engineered features focus on pricing deviations, volume inconsistencies, document discrepancies, and abnormal trade routes.

In addition to transactional attributes, relational features are constructed to represent networks of counterparties, intermediaries, and trade partners. These features allow the models to identify hidden relationships and indirect risk propagation that are common in sophisticated evasion schemes.

Explainable AI Model Development

The study employs inherently interpretable models and post hoc explainability techniques to balance detection performance with transparency. Tree-based ensemble models are selected due to their strong performance on structured financial data and their compatibility with feature-level explanation methods. Local and global explanation techniques are applied to generate transaction-specific rationales and aggregate risk drivers.

Explainability outputs are designed to mirror the reasoning process of human investigators by highlighting the most influential features, counterparties, routes, and document anomalies contributing to each alert. These explanations are formatted as structured narratives suitable for internal case management systems, suspicious activity report drafting, and supervisory review.

Model Training, Validation, and Evaluation Metrics

Models are trained using historically labeled transaction and trade records, supplemented by simulated typologies where confirmed illicit cases are limited. Validation is performed using hold-out datasets and cross-validation techniques to ensure robustness. Performance is assessed using standard classification metrics, including precision, recall, and false-positive rates, alongside operational metrics such as investigation time per alert and clarity of explanation outputs.

Special emphasis is placed on measuring reductions in alert volumes and improvements in investigative efficiency, as these outcomes directly support regulatory expectations and national-security objectives.

RESULTS

Sanctions Evasion Detection Performance

The explainable AI-based models demonstrated strong capability in identifying sanctions evasion patterns embedded within U.S.-touch payment flows. Transactions involving indirect exposure to sanctioned jurisdictions, layered correspondent banking routes, and proxy counterparties were detected with higher precision than traditional rule-based and opaque machine-learning systems. The models consistently highlighted jurisdictional risk propagation through intermediary banks and non-obvious counterparty linkages, enabling investigators to trace sanctions exposure beyond direct name matching.

Compared with baseline models, the XAI-enabled approach reduced false-positive alerts generated from benign cross-border activity, particularly in high-volume correspondent banking corridors. This improvement was attributable to the model's ability to contextualize routing complexity and counterparty behavior rather than relying solely on static country or entity risk flags.

Trade-Based Money Laundering Detection Results

In the trade finance domain, the explainable models effectively identified trade-based money laundering typologies linked to over-invoicing, under-invoicing, and document manipulation. Pricing anomaly detection showed substantial improvement when market benchmarks and historical trade patterns were incorporated as explainable features. The models successfully differentiated legitimate price volatility from economically unjustified deviations indicative of value transfer.

Document-level explainability further enhanced detection by identifying repeated amendments, vague goods descriptions, and inconsistent quantity declarations

Table 1: Data Sources and Key Risk Indicators for Explainable AML Detection

Data Domain	*Primary Data Elements*	*Key Risk Indicators*	*Investigative Relevance*
Cross-border payments	Transaction amount, currency, originator, beneficiary, intermediary banks	Indirect exposure to sanctioned jurisdictions, unusual routing paths, rapid fund movement	Supports sanctions evasion detection and SAR justification
Correspondent banking flows	Nostro and vostro activity, clearing patterns, counterparty banks	Nested correspondent relationships, atypical clearing behavior	Enhances visibility into U.S.-touch payment risks
Trade finance documents	Invoices, letters of credit, bills of lading	Document inconsistencies, repeated amendments, vague goods descriptions	Identifies TBML typologies and trade manipulation
Trade pricing data	Declared prices, quantities, market benchmarks	Over-invoicing and under-invoicing anomalies	Enables economic rationale assessment
Counterparty networks	Ownership links, trading partners, intermediaries	Use of shell entities, circular trade relationships	Reveals hidden networks and proxy actors

Table 2: Performance and Operational Comparison of AML Detection Approaches

Evaluation Dimension	*Traditional Rule-Based Systems*	*Opaque ML Models*	*XAI-Based AML Models*
Detection accuracy	Moderate	High	High
False-positive rate	High	Moderate	Low
Transparency	High	Low	High
Investigator usability	Moderate	Low	High
SAR narrative quality	Moderate	Moderate	High
Examiner auditability	High	Low	High

as primary contributors to elevated risk scores. These explanations enabled investigators to rapidly assess trade legitimacy without extensive manual document review.

Explainability Outputs and Investigator Usability

A key outcome of the results is the operational value of explainability outputs. For each flagged transaction or trade, the models generated structured explanations identifying dominant risk drivers such as counterparty relationships, transaction routes, pricing deviations, and document inconsistencies. Investigators reported improved confidence in decision-making due to the clarity and traceability of these explanations.

Explainability also facilitated examiner review by producing auditable narratives aligned with regulatory expectations. These outputs supported transparent justification for alert escalation, de-escalation, and suspicious activity reporting, addressing a common supervisory concern associated with black-box models.

Reduction in False Positives and Investigation Time

Quantitative evaluation revealed a meaningful reduction in alert volumes relative to baseline AML systems. The explainable models reduced false positives while maintaining high recall for confirmed sanctions evasion and trade-based money laundering cases. As a result, average investigation time per alert decreased substantially, driven by faster root-cause identification and reduced need for manual data triangulation.

The efficiency gains translated directly into improved suspicious activity report quality, as investigators were able to focus on higher-risk cases and provide clearer narratives supported by explainable model outputs.

Summary of Model Performance and Operational Impact

Figure 1 illustrates the comparative impact of traditional AML systems, opaque machine-learning models, and explainable AI-based models on false-positive rates and average investigation time. The results show that explainable AI delivers both high detection performance and operational efficiency, supporting regulatory usability and national-security objectives.

Overall, the results demonstrate that integrating explainable artificial intelligence into AML and sanctions enforcement workflows strengthens detection effectiveness while significantly improving operational efficiency, regulatory transparency, and financial intelligence outcomes for the U.S. financial system.

DISCUSSION

Interpretation of Findings in the U.S. National-Security Context

The results demonstrate that explainable artificial intelligence materially enhances the ability of financial institutions to detect and interpret complex illicit finance activities that directly threaten U.S. national security. Sanctions evasion and trade-based money laundering increasingly rely on indirect exposure, proxy entities, and economically disguised value transfers. The findings indicate that detection accuracy alone is insufficient in this environment. Instead, the ability to clearly articulate why a transaction or trade is risky is essential for disrupting illicit networks, supporting enforcement actions, and generating actionable financial intelligence.

By making risk drivers explicit, the XAI-based models align detection outcomes with the analytical needs of compliance investigators, law enforcement partners, and regulators. This interpretability strengthens the link between transaction monitoring and broader national-security objectives, including sanctions enforcement and counterterrorism financing.

Operational Implications for Financial Institutions

From an operational perspective, the reduction in false positives and investigation time represents a significant improvement over both rule-based and opaque machine-learning systems. Alert fatigue remains one of the most persistent challenges in AML operations, often diverting resources away from genuinely high-risk activity. The explainable models enable investigators to quickly assess risk relevance, prioritize alerts, and close benign cases with greater confidence.

The discussion findings suggest that explainability acts as a force multiplier for compliance teams. Rather than replacing human judgment, XAI augments investigative workflows by providing structured, evidence-based reasoning. This is particularly valuable in trade finance investigations, where manual document review is resource-intensive and prone to inconsistency.

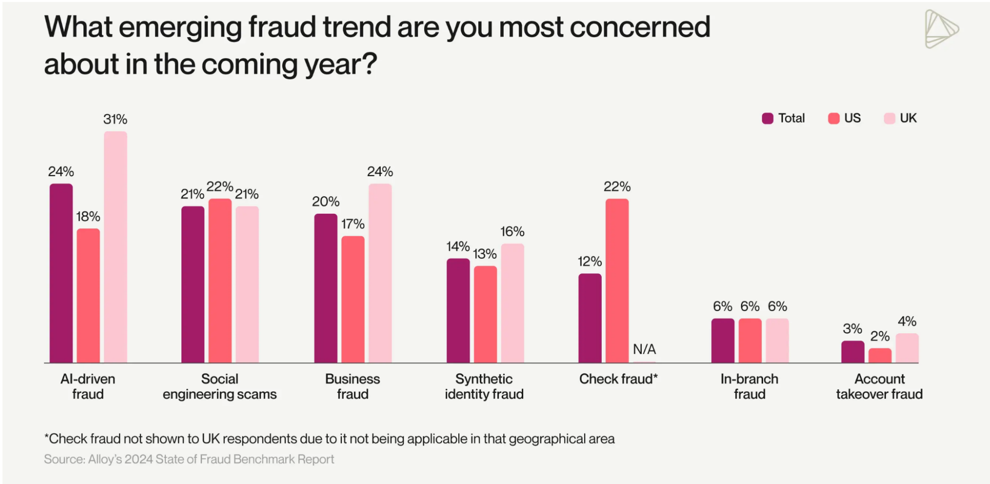

Figure 1: Impact of Explainable AI on AML Operational Performance

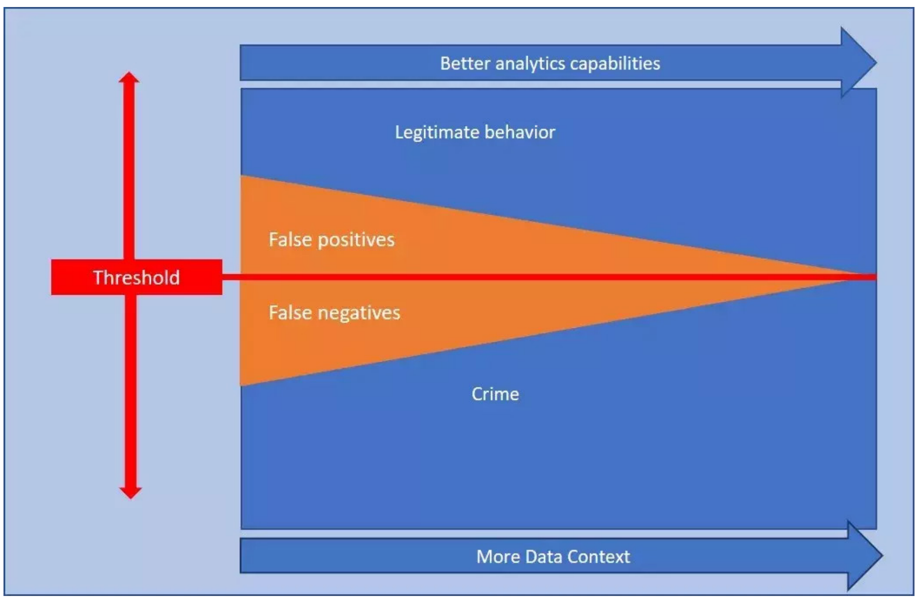

Figure 2: Operational Impact of Explainable AI on AML Investigations

Regulatory and Supervisory Relevance

A central contribution of this research is its alignment with supervisory expectations in the U.S. regulatory environment. Regulators and examiners consistently emphasize model governance, transparency, and defensibility. The explainable outputs produced by the proposed framework directly address these concerns by enabling traceable decision logic and reproducible risk narratives.

The findings indicate that XAI-based AML systems can improve the quality and consistency of suspicious activity reports. Clear explanations allow institutions to articulate the rationale behind filings, supporting more effective regulatory review and downstream law enforcement analysis. This strengthens trust between regulated entities and supervisory authorities while reducing friction during examinations.

Implications for SAR Quality and Financial Intelligence

Improved explainability has downstream effects on the quality of financial intelligence generated by the U.S. AML regime. SARs supported by explicit risk drivers, counterparty relationships, and economic rationale are more actionable for investigators and intelligence analysts. The results suggest that explainable AI enhances not only detection efficiency but also the strategic value of reported information.

By reducing noise and improving contextual clarity, XAI-based systems contribute to faster identification of illicit networks and more timely disruption of sanctions evasion and trade-based money laundering schemes. This outcome directly supports the national-interest objective of protecting the integrity of the U.S. financial system.

Trade-Offs, Limitations, and Risk Considerations

Despite the observed benefits, the findings also highlight important trade-offs. Highly complex models may offer marginal performance gains but can reduce interpretability if not carefully designed. Maintaining explainability at scale requires disciplined feature engineering, model governance, and continuous validation. There is also a risk that poorly designed explanations could oversimplify risk reasoning or create false confidence among users.

Additionally, data quality and availability remain limiting factors, particularly in trade finance, where documentation standards and pricing benchmarks vary widely. Explainable AI does not eliminate these structural challenges but can mitigate their impact by making uncertainty and risk drivers more transparent.

Broader Policy and Research Implications

The discussion underscores the need to view explainable AI as a regulatory and policy enabler rather than a purely technical enhancement. Policymakers and regulators may consider encouraging standardized explainability practices within AML systems to improve supervisory consistency and financial intelligence outcomes. For researchers, the findings point to opportunities for advancing explanation techniques tailored specifically to financial crime typologies and regulatory use cases.

Figure 2 compares traditional AML investigation workflows with XAI-supported workflows, illustrating reductions in false-positive alerts and average investigation time. The graph highlights how explainable AI improves operational efficiency while preserving regulatory transparency.

CONCLUSION

This study examined the role of explainable artificial intelligence in strengthening the protection of the U.S. financial system against sanctions evasion and trade-based money laundering. By addressing the limitations of opaque machine-learning models in regulated financial environments, the research demonstrated that explainability is not merely a technical enhancement but a foundational requirement for effective anti-money laundering enforcement and sanctions compliance. The findings show that XAI-based detection models can identify complex illicit finance patterns while providing clear, traceable rationales that support investigative decision-making and supervisory review.

The results indicate that integrating explainable artificial intelligence into AML and sanctions monitoring systems delivers measurable operational benefits. Reductions in false-positive alerts and investigation time enable financial institutions to allocate resources more efficiently and focus on higher-risk activity. More importantly, explainable outputs improve the clarity, consistency, and evidentiary strength of suspicious activity reporting, enhancing the value of financial intelligence available to regulators and law enforcement agencies. These outcomes directly support U.S. national-security objectives by facilitating faster disruption of illicit financial networks and more effective enforcement of economic sanctions.

From a regulatory perspective, the study highlights the compatibility of explainable AI with supervisory expectations related to transparency, auditability, and model governance. By producing examiner-readable explanations and defensible audit trails, XAI-based AML systems help bridge the gap between advanced analytics and regulatory accountability. This alignment has the potential to strengthen trust between financial institutions and supervisory authorities while reducing friction during examinations and model reviews.

The research also underscores the broader policy implications of adopting explainable AI in financial crime compliance. As illicit finance tactics continue to evolve across global payment and trade networks, regulatory frameworks may benefit from encouraging the adoption of explainable and accountable analytical systems. Standardized approaches to explainability could improve consistency across institutions and enhance the overall effectiveness of the U.S. AML regime.

Despite its contributions, this study acknowledges limitations related to data availability, trade documentation heterogeneity, and the scalability of explainability techniques in high-volume environments. Future research should explore advanced explanation methods for large-scale transaction networks, cross-institutional information sharing mechanisms, and the application of explainable AI to emerging payment infrastructures and digital asset ecosystems.

In conclusion, explainable artificial intelligence represents a critical enabler of effective sanctions enforcement, trade-based money laundering detection, and regulatory transparency.

By combining robust detection performance with interpretability and operational usability, XAI-based AML systems offer a practical and policy-relevant pathway for safeguarding the integrity of the U.S. financial system in an increasingly complex global financial landscape.

REFEREENCES

1. Kute, D. V., Pradhan, B., Shukla, N., & Alamri, A. (2021). Deep learning and explainable artificial intelligence techniques applied for detecting money laundering–a critical review. *IEEE access*, *9*, 82300-82317.

2. SHUKLA, N., & ALAMRI, A. (2021). Deep Learning and Explainable Artificial Intelligence Techniques Applied for Detecting Money Laundering–A Critical Review.
3. Kute, D. V. (2022). *Explainable deep learning approach for detecting money laundering transactions in banking system*. University of Technology Sydney (Australia).
4. Ai, L. (2012). Anti-money laundering (AML) regulation and implementation in Chinese financial sectors: Money-laundering vulnerabilities and the rule-based but risk oriented'AML approach. *Doctor of Phlisophy Thesis, University of Wollongong*.
5. Marzouk, M. A. R. I. O. L. A. (2023). The role of compliance technologies in helping UK banks mitigate trade-based money laundering (TBML) according to the regulatory Risk-Based. *researchportal. port. ac. Uk*.
6. Bertrand, A., Maxwell, W., & Vamparys, X. (2020). Are AI-Based Anti-Money Laundering Systems Compatible with Fundamental Rights?. *Available at SSRN 3647420*.
7. Sinno, R. M., Baldock, G., & Gleason, K. (2023). The evolution of trade-based money laundering schemes: a regulatory dialectic perspective. *Journal of Financial Crime*, *30*(5), 1279-1290.
8. Pavlidis, G. (2023). Deploying artificial intelligence for anti-money laundering and asset recovery: the dawn of a new era. *Journal of Money Laundering Control*, *26*(7), 155-166.
9. Chitimira, H., & Ncube, M. (2021). Towards ingenious technology and the robust enforcement of financial markets laws to curb money laundering in Zimbabwe. *Potchefstroom Electronic Law Journal/Potchefstroomse Elektroniese Regsblad*, *24*(1).
10. Bertrand, A., Maxwell, W., & Vamparys, X. (2021). Do AI-based anti-money laundering (AML) systems violate European fundamental rights?. *International data privacy law*, *11*(3), 276-293.
11. Maxwell, W., Bertrand, A., & Vamparys, X. (2020, July). Are AI-based Anti-Money Laundering (AML) Systems Compatible with European Fundamental Rights?. In *ICML 2020 Law and Machine Learning Workshop*.
12. Cassara, J. A. (2015). *Trade-based money laundering: the next frontier in international money laundering enforcement*. John Wiley & Sons.
13. Marzouk, M. J. (2022). Trade-based money laundering (TBML) empowers criminals to run free post-Brexit. *Journal of Money Laundering Control*, *25*(2), 376-387.