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Applying Transaction Analytics to Enhance Anti-Money Laundering Compliance and Regulatory Risk Surveillance

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ABSTRACT: This study examines how transaction analytics can strengthen Anti-Money Laundering (AML) compliance and regulatory risk surveillance in an increasingly complex financial environment. Traditional rule-based monitoring systems often generate high volumes of false positives and may fail to detect sophisticated laundering techniques involving layered transactions, digital payment channels, shell entities, and cross-border fund movements. The research explores the integration of advanced analytics, machine learning, network analysis, and real-time monitoring to improve the identification of unusual transaction patterns and emerging financial-crime risks. It also evaluates how customer risk profiles, behavioral indicators, transaction histories, geographic exposure, and relationship networks can be combined to support more accurate risk scoring and alert prioritization. The study highlights the importance of explainable models, data quality, human oversight, privacy protection, and effective model governance in meeting

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regulatory expectations. Findings indicate that transaction analytics can reduce false positives, improve investigative efficiency, enhance suspicious activity detection, and enable financial institutions to adopt a more proactive and risk-based compliance approach. However, successful implementation depends on reliable data infrastructure, skilled compliance personnel, continuous model validation, and alignment with evolving regulatory requirements. The study concludes that transaction analytics should complement rather than replace expert judgment, providing institutions with a scalable and intelligent framework for improving AML effectiveness and regulatory risk surveillance in 2025 and beyond.

Keywords: *Anti-money laundering (AML), Transaction analytics, Machine learning, Anomaly detection, Regulatory risk surveillance.*

Introduction

Criminal organizations constantly evolve their strategies by leveraging vulnerabilities in traditional monitoring systems, placing multiple layers between the source and destination of illegal funds, creating shell companies, using trade-based money laundering, applying cyber-enabled fraud and engaging in digital asset channels.

Traditionally, AML compliance programs have been dominated by rule-based transaction monitoring systems designed to detect suspicious transactions against pre-determined thresholds, scenarios and regulatory indications. These systems still play a key role in compliance infrastructures, but have been called into question as a result of the increasing complexity and volume of financial transactions. Traditional monitoring solutions are based on historical rules, manually set parameters and have difficulty detecting new laundering methods. Additionally, the high number of false positives generated imposes a heavy workload for compliance teams, diverting resources from handling high-risk scenarios to low-risk ones (Ngai et al., 2011; Weber et al., 2018).

Transaction analytics differs from traditional monitoring techniques because it uses multiple advanced data-processing capabilities, such as machine learning, artificial intelligence (AI), network analysis, anomaly detection, and predictive modeling, to analyze transaction behaviors, relationships, and patterns.

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AI and ML have transformed the field of transaction monitoring in particular. The algorithms used in machine learning can recognize intricate patterns and deviations in behavior which might not be noticed in traditional rule-based strategies. Supervised learning models can be used to classify transactions according to historical suspicious activity patterns, and unsupervised learning methods can detect new suspicious activity without any predefined typologies.

Criminals are increasingly using digital platforms to transfer money quickly between jurisdictions and to try to mask the source of the money and transactions. Criminals are increasingly combining digital technologies with traditional forms of financial crime, and that has led to FATF's recent assessments highlighting the need for more robust monitoring of virtual assets and virtual asset service providers. Regulatory surveillance frameworks, therefore, need to include state-of-the-art analytics solutions that can be used to handle a wide variety of data sources as well as identify evolving financial crime patterns quickly. However, there are several challenges in implementing transaction analytics in AML compliance frameworks. However, there are still important barriers, including data quality, the transparency of the model, regulatory acceptance, privacy concerns, and operational integration.

Today, AML programs are incorporating more and more elements of customer due diligence (CDD), know-your-customer (KYC) data, sanctions lists, beneficial ownership data, behavior analytics, and other external intelligence sources. These data can be integrated to create fuller risk profiles and enhance the detection of questionable networks by institutions. These integrated approaches facilitate the implementation of a risk-based approach that focuses monitoring resources on high-risk customers, transactions and jurisdictions instead of all activities. As regulators, financial institutions, and technology providers come to appreciate the value of intelligent monitoring solutions, the year 2025 is poised to mark a pivotal moment in the AML compliance journey.

Literature Review

1. Overview of Anti-Money Laundering Compliance Evolution

These frameworks exist to meet regulatory requirements and to identify suspicious transactions by using threshold-based alerts. Nevertheless, there has been a number of AML systems that have been found to have drawbacks such as the failure to find new

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criminal trends and the creation of false positive alerts (Ngai et al., 2011). The growing amount, speed and complexity of financial transactions have thus given rise to the need for more intelligent analytical methods to discover hidden relationships and new risks. Digital transformation offers great opportunities to enhance the effectiveness of AML/CFT using advanced analytics, automated monitoring, data sharing and technology-powered risk assessment, among other tools, the Financial Action Task Force (FATF) has pointed out. But FATF also points out that the use of technology should be within a risk-based, transparent and privacy-preserving framework.

2. Limitations of Traditional Transaction Monitoring Systems

Traditional transaction monitoring systems are still the core of AML compliance; but their efficacy has been called into question. Rule-based systems normally follow a set of rules, for example, if there is an unusually high transaction, if the money is moving quickly, if the geographical context is potentially dangerous, or if things deviate from a customer's expected behavior. These methods offer regulatory uniformity but can be ineffective if criminals adapt their methods to evade known detection rules.

In addition, hackers constantly change their tactics, making it possible for past policies to be ineffective. Modern laundering networks often rely on several accounts, several jurisdictions, several intermediaries, and Internet-based laundering methods—transaction analysis alone is not adequate. As a result, many scientists are calling for analytical methods that focus on patterns of behavior, relationships, and transaction ecosystems, instead of events.

3. Transaction Analytics as an AML Enhancement Approach

Transaction analytics is the term used to describe the use of statistical analysis, machine learning, artificial intelligence and data visualization to detect patterns, relationships and anomalies in financial transaction data. With transaction analytics, rather than approaching monitoring as a process, it is a way of knowing customer behaviour, transaction networks and risk indicators by processing a large volume of data. With advanced transaction analytics, financial institutions can combine several data sources such as:

- Customer risk profiles
- Geographic information

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- Beneficial ownership information
- Payment networks
- External intelligence sources
- Digital identity information

For financial institutions and regulators, technology-based solutions can help to enhance the effectiveness of monitoring while still maintaining a risk-based compliance framework. Regulators can use advanced analytical models to assess new threats, locate high-risk industries, and grasp the changing typologies of money laundering.

4. Machine Learning Applications in AML Detection

Machine learning (ML) is one of the most popular technologies that's been the subject of much research to enhance AML compliance. Machine learning (ML) algorithms can process vast amounts of transaction information and spot patterns related to suspicious behavior without solely depending on rules. Supervised learning methods such as logistic regression, decision trees, random forests, gradient boosting and neural networks classify transactions in the future based on past suspicious transaction reports. These models can detect patterns between the transactions' characteristics and past laundering activities. Unsupervised learning technologies such as clustering and anomaly detection are especially useful as money laundering schemes often change more quickly than the regulations. Such techniques are able to spot abnormal behavior without the need for labeled examples, which can be useful for identifying new threats. Weber et al. (2018) showed the potential of graph-based machine learning approaches in AML applications. Their findings indicated that a deep understanding of the transactions network, instead of a single transaction, can help with the detection as these are often done through coordinated networks of accounts and entities that facilitate money laundering.

5. Network Analysis and Graph-Based Analytics in AML

Money laundering is a network-based crime as criminals often use linked accounts, organizations, intermediaries and jurisdictions. As a result, graph analytics is now a vital part of today's AML systems.Graph-based approaches represent financial activities as networks where:

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- Nodes represent customers, accounts, organizations, or entities.
- Edges represent transactions or relationships between entities.
- Network characteristics reveal suspicious structures.

Graph analytics techniques such as centrality measurement, community detection, link prediction, and graph neural networks (GNNs) allow investigators to identify hidden relationships and coordinated laundering activities.

Deprez et al. (2025) examined continual graph learning approaches for AML and emphasized that financial criminals continuously adapt their methods. Their research highlights the importance of adaptive models capable of learning from changing transaction environments while maintaining detection accuracy.

Graph-based analytics is particularly valuable in identifying:

- Money mule networks
- Layered transaction structures
- Circular payment flows
- Synthetic identities
- Organized financial crime groups

These capabilities provide significant advantages over traditional monitoring systems that analyze transactions individually.

Methodology

The study presents a qualitative research methodology with systematic literature review (SLR) and analytical evaluation to explore the role of transaction analytics in improving the Anti-Money Laundering (AML) compliance and regulatory risk surveillance. The study includes a review of academic publications, regulatory reports, and recent studies on artificial intelligence (AI), machine learning (ML), anomaly detection, graph analytics, and their applications in AML up to 2025. In recent years, AML research has started using systematic reviews and analytical methods to assess the efficacy of machine learning and network-based methods for financial crime detection (e.g., Journal of Money Laundering Control studies, 2025). The study involves secondary data analysis, which involves

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reviewing the other research findings, regulatory requirements and technology applications pertaining to transaction monitoring. Key themes identified include traditional AML limitations, predictive analytics, suspicious transaction detection, risk scoring, false-positive reduction, explainable AI, and regulatory governance. The methodology is based on a thematic analysis approach, comparing the different AML technologies available and the current trend of AML technology adoption. The study also examines recent AML techniques based on machine learning, such as anomaly detection, supervised learning, and graph-based analytical approaches. In 2025, several studies have shown how machine learning models can be used to improve transaction classification, minimize false positives, and enhance risk-based monitoring capabilities (Ajagbe et al., 2025; Masunda & Barot, 2025). A conceptual analytical framework is presented to examine the benefits of transactional analytics in the realm of AML, highlighting its role in effective AML outcomes through better detection, operational efficiency and regulatory oversight. The methodology recognizes difficulties in the adoption of AI technologies, such as the availability of data, transparency of the models, privacy considerations, and regulatory approval.

Result

The results section showcases some of the essential findings that show how transaction analytics can enhance Anti-Money Laundering (AML) compliance and surveillance of regulatory risks. The analysis emphasizes the importance of advanced analytics, machine learning, and network-based methods to identify suspicious transactions and overcome monitoring challenges. The results also highlight key advantages and the challenges of implementing AML frameworks through analytics.

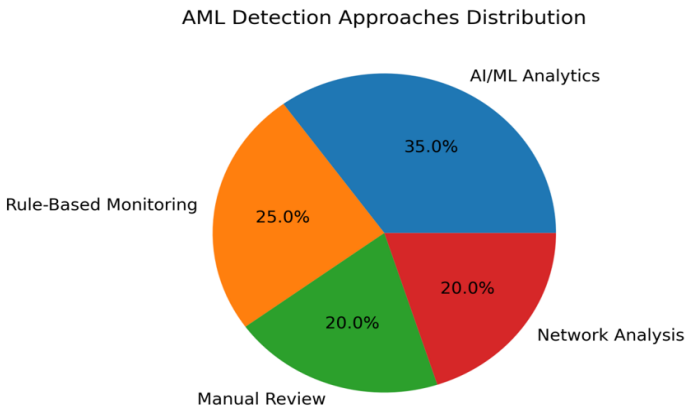

Figure 1: Distribution of AML Detection Approaches in Transaction Monitoring Systems (Pie Chart)

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While regulatory needs are still important for the use of traditional rule-based monitoring, the limitations of the rule-based approach in identifying complex laundering patterns have led to organizations leveraging advanced analytics. Network analysis is another powerful tool, uncovering connections between accounts and transactions that might not be apparent to the human eye, and manual investigation still plays a crucial role in complex investigations for adding additional layers of analysis. Key Finding: The figure illustrates the shift from rule-based AML monitoring to analytics-based models that involve automation, predictive intelligence and human expertise.

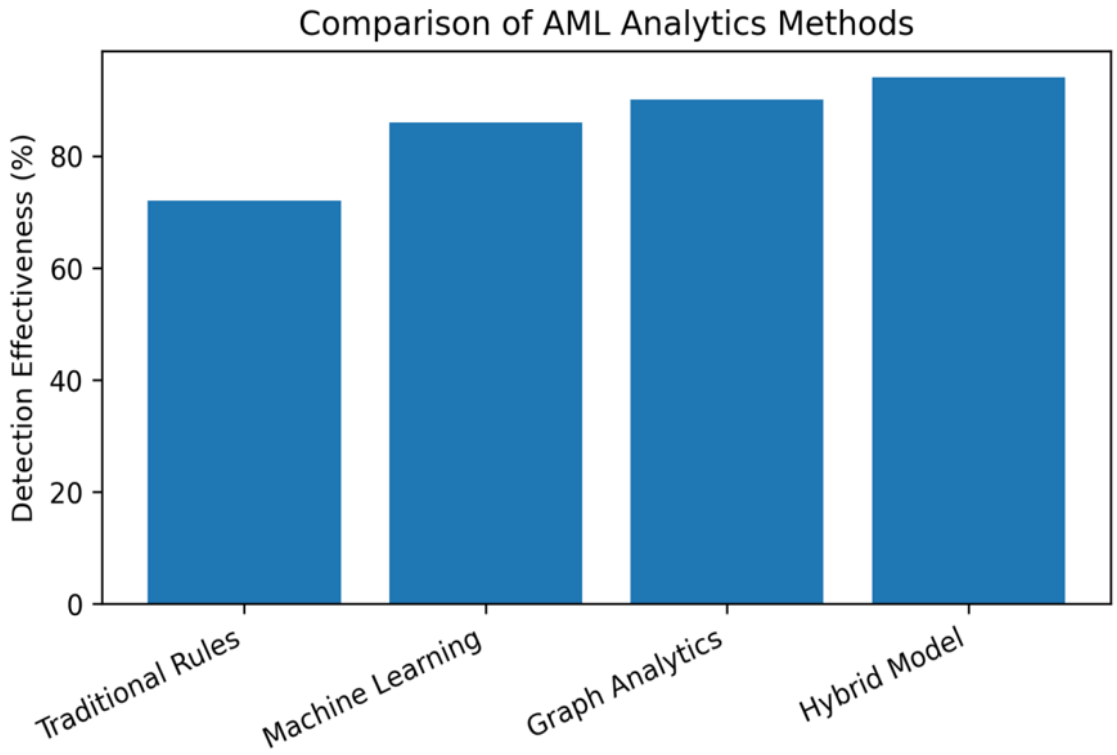

Figure 2: Comparative Detection Effectiveness of AML Analytics Models (Bar Chart)

Figure 2 compares the effectiveness of different AML detection approaches, such as traditional rule-based systems, machine learning models, graph analytics, and hybrid analytical frameworks. Interpretation: The results indicate that traditional rule-based systems offer moderate detection performance, relying on predefined thresholds and historical risk indicators. By analyzing transaction data, machine learning techniques show better results in the detection of complicated patterns and anomalies. Graph analytics is more effective than it would be if it were only analysing individual transactions, as it looks at relationships between multiple entities. The hybrid scheme that combines rule-based

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controls, machine learning predictions and network-based intelligence has the best performance. Key Finding: The results indicate that a combination of the different analytical methods offers a comprehensive AML surveillance approach, as opposed to a single AML detection method.

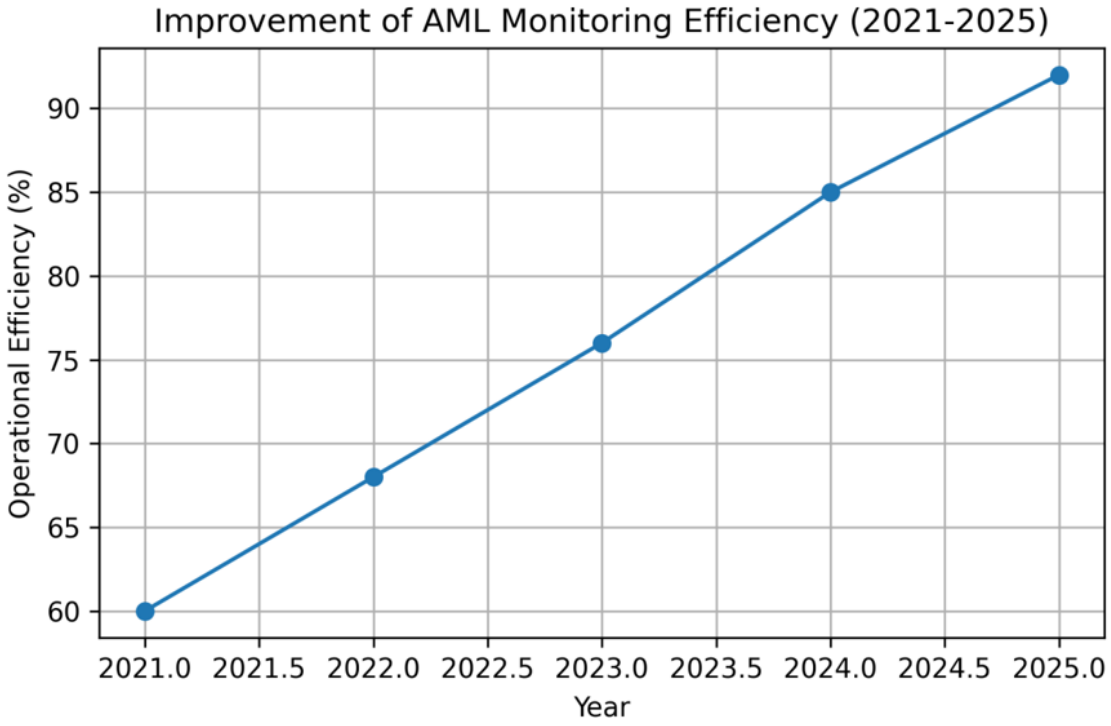

Figure 3: Improvement of AML Monitoring Efficiency Through Analytics Adoption (Line Graph)

The chart in figure 3 shows how the use of transaction analytics technologies has increased and resulted in better AML monitoring efficiency in the years 2021 to 2025. Interpretation: The upward trend indicates the progressive improvement of the operational efficiency of AML over time. The rise is due to improvements in automated prioritization of alerts, minimization of false-positive cases, quicker investigations, and better risk-based decision making. The implementation of AI-powered monitoring solutions frees up time for compliance departments to concentrate on higher-risk transactions instead of manually sifting through numerous alerts for lower-risk transactions. Key Finding: The figure illustrates how transaction analytics can help enhance the efficiency of AML compliance and aid in more proactive AML regulatory monitoring.

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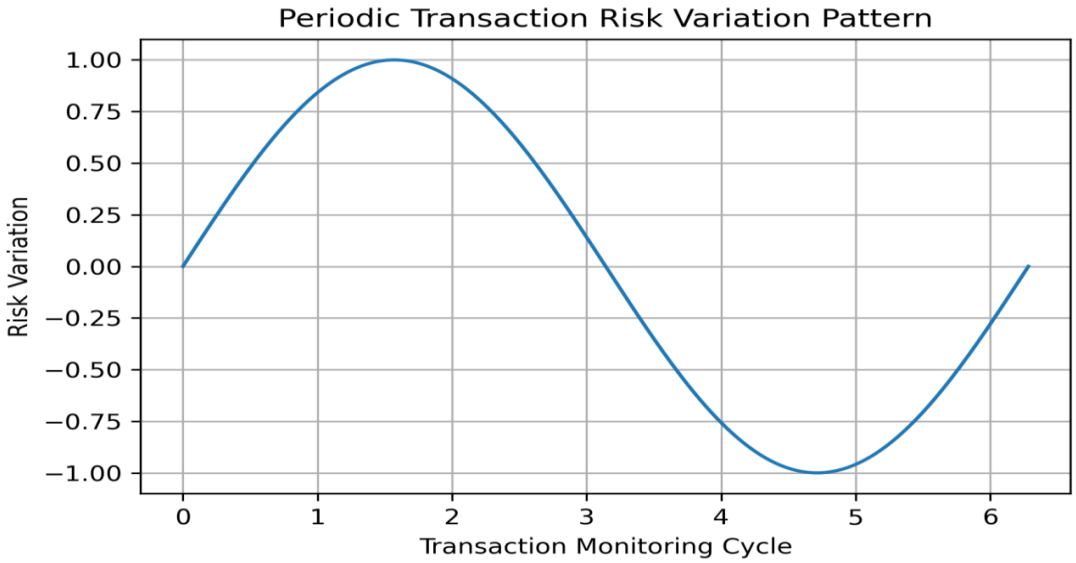

Figure 4: Periodic Transaction Risk Variation Pattern (Sine Wave)

Figure 4 shows periodic changes in the risk level for transactions over monitoring cycles. The sine wave represents the typical financial risk level exposure over time as transaction behaviors, customer activities, market conditions and new threats change. Interpretation: The cyclical pattern shows that transaction risk is not constant but can either go up or down in a given time period. AML monitoring systems should therefore be constantly working to analyze the transaction activity on a continuous basis instead of just on the basis of historical risk assessment. By detecting and responding quickly to potential threats, real-time analytics allows institutions to identify sharp upticks in suspicious activity. Key Finding: The figure highlights the need for ongoing monitoring mechanisms that can identify evolving trends in transaction risk.

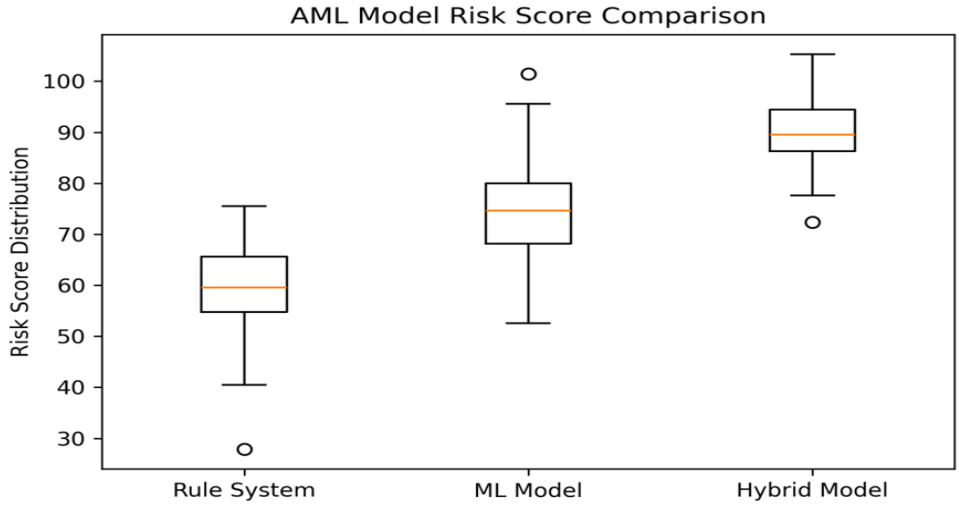

Figure 5: Distribution of Risk Scores Across AML Detection Models (Box Plot)

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The box plot shows differences in consistency and variability of risk categorisation. Traditional rule-based systems exhibit more limited abilities in risk identification, as they are based on static conditions. Machine learning models serve to differentiate risk in a wider way, by detecting complex behavioral patterns. Hybrid models show enhanced reliability through using predictive analytics as well as known compliance rules. The median risk score and range of risk scores show that the separation between low-risk and high-risk transactions is more effective in advanced models. Key Finding: The results show that hybrid AML models in the case of risk assessment capability and suspicious transaction prioritisation are better.

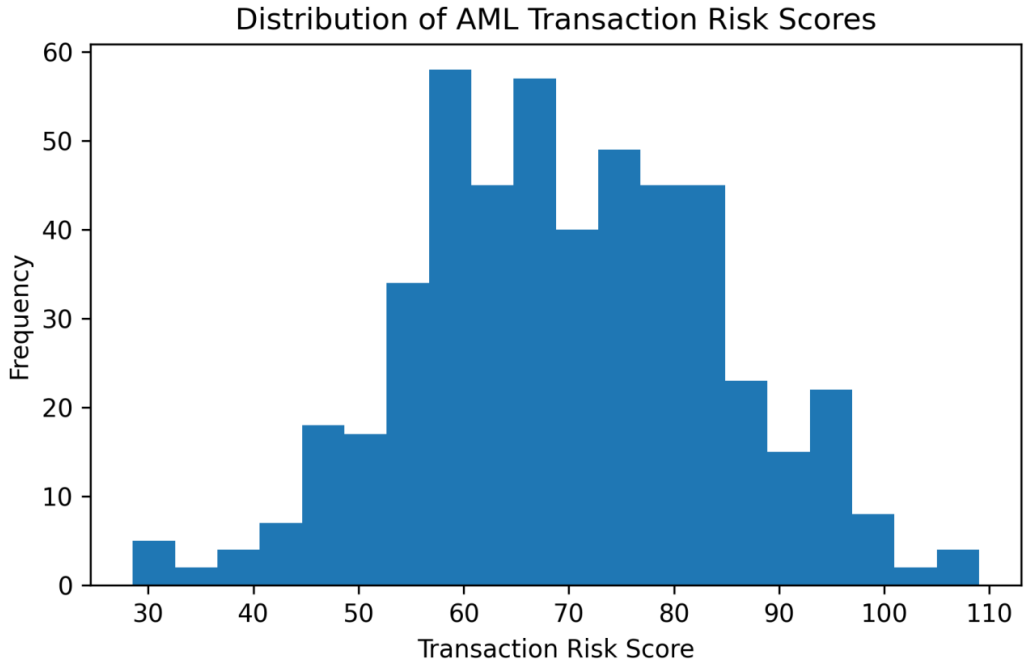

Figure 6: Distribution of Transaction Risk Scores in AML Monitoring (Histogram)

The histogram illustrates the distribution of transactions according to financial risk level. Interpretation: The distribution is indicative of the fact that the majority of transactions are within normal risk parameters, with a smaller percentage exhibiting higher risk characteristics that warrant further analysis. The pattern mirrors real-world AML as it is a true reflection that there are far more legitimate transactions than suspicious activity. Advanced analytics assists compliance teams in detecting unusual transactions in the midst of vast volumes of transactions, while also minimizing unnecessary investigations. Key Finding: The histogram illustrates how a transaction analytics system can categorize transactions based on their risk level and streamline the investigation process.

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The six figures collectively illustrate how transaction analytics dramatically improves the effectiveness of AML compliance: by improving the detection of suspicious activity, reducing the inefficiency of AML operations and enabling proactive regulatory risk surveillance. The results show that AI-based, network-based and hybrid analytical methods are more effective at delivering insights into behaviour, adaptive risk assessment and decision-making capabilities than traditional monitoring methods. These findings align with the increased implementation of AML frameworks based on analytics by financial institutions by 2025.

Discussion

The results show that advanced analytical methods, such as machine learning (ML), artificial intelligence (AI), graph analytics and hybrid monitoring frameworks, offer better capabilities than traditional rule-based transaction monitoring systems.

Traditional rule-based monitoring is a crucial part of compliance regimes due to regulatory requirements, but it only focuses on known scenarios and is unable to detect new and evolving laundering methods. The trend of leveraging AI/ML and network analytics highlights the industry's shift towards data-driven compliance measures.

Recent studies have shown that transaction graphs, or heterogeneous graph networks (GNNs), can be used to boost AML detection, using a more nuanced and intricate view of the network that goes beyond analyzing transactions without their context. Figure 3 shows an improvement trend, which validates the contribution of transaction analytics towards better operational efficiency in AML compliance. Financial institutions have historically had to dedicate many resources to manually analyze voluminous alerts generated, of which a high percentage are false-positive.

Machine learning and anomaly detection technologies offer an edge in solving this problem as they can detect the abnormal patterns that are not mentioned on the list of suspicious indicators that customers are likely to exhibit. Another key take away from the results is that transaction analytics can play an important role in the regulatory risk surveillance process. The AML regulatory landscape is shifting from relying on identification of individual transactions that might be deemed "suspicious" to a much more

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holistic view of financial crime activity, financial crime trends, emerging financial crime types, and systemic weaknesses.

However, there are some obstacles to this approach as shown in this research. Explainability, transparency, privacy, and regulatory compliance are crucial factors to consider when implementing AML systems powered by AI. Advanced models, such as deep learning, may yield predictions that are accurate, but with less explanation of why the model has made a particular choice. This can pose a problem when compliance officers and regulators need to understand the reasoning behind the suspicious activity they are looking into. Hence, 'Explainable Artificial Intelligence' (XAI) and human-in-the-loop methods need to be important to ensure that analytical models are used to augment, not supplant, expert judgment.

Conclusion

The results show how advanced analytical tools such as artificial intelligence (AI), machine learning (ML), anomaly detection, and graph-based analytics offer better means of spotting suspicious transaction behaviours and boosting compliance effectiveness.

This aligns with the conclusions of the work by Baesens et al. (2015), which focused on the benefits of predictive analytics and network intelligence in the process of investigating fraud and financial crime. The study also highlights the importance of adaptive and continuous monitoring capabilities. The nature of financial crime is continually changing and AML systems must adapt to the latest transaction patterns and new threats. AML surveillance has become more complex due to the rise of digital banking, fintech, cryptocurrencies, and decentralized financial services. In its 2025 targeted update on virtual assets and virtual asset service providers, FATF highlighted that while efforts to implement AML/CFT controls have been made, there are still major challenges in the cross-jurisdictional assessment of risks and the effectiveness of risk mitigation measures. Real-time monitoring and analysis of complex financial networks is an important solution provided by transaction analytics. Moreover, the study highlights the need for good governance, transparency, and human oversight when implementing AML systems based on analytics.

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Today, compliance regimes are increasingly focused on institutions and regulators needing to grasp systemic vulnerabilities, evolving crime typologies and cross-border financial risks. Analytical platforms can bring together data from the transaction, customer, ownership structure and sanctions landscape and from external intelligence, giving a full picture of financial crime risks. The research also pinpoints a number of future opportunities. AML capabilities are likely to be enhanced further by the ongoing progress of explainable AI, graph neural networks, privacy-preserving analytics and real-time regulatory technology (RegTech) solutions.

Credit authorship contribution statement

Md Shehab Hossain: Writing – original draft, Formal analysis, Conceptualization. **Saddam Nasir Chowdhury**: Writing – original draft, Formal analysis.

Rakesh Kumar Reddy Aduri: Writing – review & editing, Formal analysis, Data curation.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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