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Developing an Integrated AML Risk Management Framework for Commercial Banks Based on Customer Risk Profiling and Enhanced Due Diligence

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<p>Rizwan Hanif Head of Compliance and Internal Control and MLRO/MLCO, MBA-HRM IBA University of The Punjab, Lahore, & MPA-IAS University of the Punjab, Lahore. rizwanha123@gmail.com</p> <p>Hamza Shahbaz Ahmad University of Missouri Kansas City, United States hamzashahbaz533@gmail.com</p> <p>Abid Ali Hailey College of Banking & Finance, University of the Punjab abidali.hcbf@gmail.com</p>	<p>Abstract</p> <p>This study examined the effectiveness of integrated Anti-Money Laundering (AML) risk management frameworks in commercial banks, focusing on customer risk profiling, technological adoption, and regulatory compliance mechanisms. Using both quantitative and comparative analysis, the research explored how transaction volume, source of funds transparency, geographical exposure, and politically exposed persons (PEPs) criteria influence risk categorization across low, medium, and high-risk groups. Results revealed that transparency in source of funds and monitoring of PEPs emerged as critical determinants in classifying customers into higher risk categories. Furthermore, the adoption of technology significantly enhanced AML efficiency, with automated transaction monitoring and data analytics dashboards demonstrating higher adoption rates and effectiveness scores compared to blockchain and machine learning tools. Overall, the findings suggested that an integrated approach combining advanced technology, risk-based profiling, and regulatory compliance improved detection accuracy, reduced fraudulent activity, and strengthened operational efficiency. However, gaps remained in addressing high-risk categories and ensuring the explainability of AI-driven tools for regulatory acceptance. The study emphasized the importance of balancing technological innovation with regulatory adaptability, particularly in cross-border contexts where financial crime risks are more complex. Future research should explore emerging technologies such as privacy-preserving AI and decentralized finance (DeFi) frameworks to strengthen global AML strategies while ensuring compliance and operational sustainability.</p>
<p>Keywords:</p>	<p>Aml Compliance, Customer Profiling, Financial Crime, Machine Learning, Regulatory Frameworks, Risk Management</p>



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Introduction

Digitization, instant payments and the exposure to crypto-linked flows had increased money-laundering and terrorist-financing (ML/TF) risks faced by commercial banks. Supervisors and standard setters had been urging institutions to move towards a risk-based approach (RBA) where controls were aligned to material risk with more Customer Due Diligence (CDD) and Enhanced Due Diligence (EDD) on higher-risk segments. But practice had trailed policy: numerous banks continued to operate on a patchwork of regulations, underdeveloped frame-level risk evaluation and feeble connectivity between risk apps and other business operations (Chitimira & Munedzi, 2023; Ogbeide et al., 2023). This research had demonstrated in earlier academic literature that hybrid analytics and explainability had the potential to enhance the quality of monitoring and accountability. It was stated in studies that rule-only systems increased the number of alerts and failed to detect complex typologies with machine learning (ML) and network methods being used to enhance detection in the presence of explainable AI (XAI) and sound governance (Oztas et al., 2024; Weber et al., 2024). Legal-regulatory considerations had also pointed out that automated suspicious-activity systems were hard to accept as compliant decisioning tools when they lacked integrity protections, transparency, and the capability to be audited rationale. In this context, the current research had introduced a holistic AML risk management framework that interconnected enterprise risk appetite to customer risk profiling (CRP) and programmatic EDD. Feature-based CRP, hybrid monitoring, coding of EDD triggers, on their part, became aligned with XAI guardrails and outcome-based measurements. In effect, it had hoped to minimize instances of false positives, prioritize analyst time on the more at-risk cohorts, and show supervisors that it was effective (Desai et al., 2025; Ringgaard, 2025; Ajagbe et al., 2025).

Research Background

The AML RBA had stipulated that banks should identify, evaluate and remediate ML/TF risks in a proportional way, with the depth of CDD/ EDD being proportioned to the customer, product, channel and geography. Doctrinal and comparative reviews were able to consolidate international best practices and indicate the continued gaps in bridging linkages between risk assessments and operational decisions particularly in the context of profiling customers and continuous monitoring (Chitimira & Munedzi, 2023). Empirical studies had also demonstrated that AML-risk-assessment expert judgments were not homogenous and consistently exposed to cognitive and institutional noise, validating systematic CRP programs and clarity in weighting (Ogbeide et al., 2023).

Technically, the alert inflation and typology blind spots within threshold/rule-based systems had been well-documented in transaction-monitoring research. Modern research had established that ML--combined with high-quality features/feedback loops and governance--decreased noise and uncovered non-linear trends in payments, trade finance, and crypto-exposed flows (Ajagbe et al., 2025; Öztas et al., 2024). In order to use in production and to comply with requirements, XAI surveys, extra reviews against the finance industry emphasized interpretable features, cause codes and model-risk policies so that investigators and regulators could track decisions (Weber et al., 2024).

Case evidence at organizational level had suggested that AML control systems had developed over time through regulatory-driven interventions and internal boundary systems, citing the need to have a clear risk appetite, change management and performance metrics (Ringgaard, 2025). Modular ML frameworks to real-time monitoring using new design-science and engineering contributions had already been proposed in the high-value payment systems, and beyond (adaptable to the bank environments and governable) (Desai et al., 2025). The combination of these strands had enabled a pivot to more integrated structures that would couple CRP, hybrid analytics and EDD under the umbrellas of explainability and model-risk management.

Research Problem

With well understood expectations of RBA, commercial banks have been locked in the process of implementing the enterprise-level risk assessment with customer-level decisions. On-boarding assessment remains an unstable process, screening/monitoring programs were in silos, and escalations to EDD required an ad-hoc process with low true-positives under even significant workload (Chitimira & Munedzi, 2023; Oztas et al., 2024). Moreover, in those cases where ML had already been implemented, regulatory acceptability and trust among analysts had been constrained by a lack of transparency and a poor governance of the models.

In that sense, the fundamental issue was the lack of a unified AML framework that comprehensively linked risk appetite to CRP characteristics/weights to monitoring thresholds and models to programmatic EDD activities all with strong explainability and effectiveness measures. There had been no unified and design-based blueprint that banks could apply and test at different segments and products available in the literature (Desai et al., 2025; Ringgaard, 2025).

Objectives of the Study

To design an integrated AML risk management framework that aligned enterprise risk appetite with dynamic customer risk profiling and codified EDD pathways.

To specify a hybrid monitoring approach (rules + ML/network analytics) with embedded XAI and model-risk controls suitable for compliance use.

To propose measurable effectiveness indicators (e.g., precision/recall, SAR conversion, typology coverage, investigation time) for evaluating the framework.

Research Questions

RQ1: How could enterprise AML risk appetite have been operationalized into dynamic customer risk profiles that updated with behavioral and external intelligence?

RQ2: In what ways could hybrid analytics and explainability have improved alert quality and supported defensible EDD decisions in commercial banks?

RQ3: Which outcome-oriented metrics had been appropriate to evidence proportionality and effectiveness of the integrated framework?

Significance of the Study

This paper had provided a design-science blueprint that helped to fill the existing execution gaps in AML programs. The focus on dynamic CRP, explainable hybrid monitoring, and programmatic EDD had provided banks with a means of cutting alert noise and raising truly positive yield, and of being able to explain rationales of decisions in a form acceptable to auditors and supervisors. Recent systematic review of scholarly evidence had furnished a justifiable basis of policy refreshments, technology plans, and regulator outreach in a variety of banking arenas (Ogbeide et al., 2023; Öztas et al., 2024; Weber et al., 2024; Desai et al., 2025).



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Literature Review

Customer Risk Profiling in AML Frameworks

Customer risk profiling had been seen as the pillar of sound AML risk management in commercial banks. Banks could prioritize surveillance and resource allocation more successfully because they could divide the customers into risk groups according to their behavioral, transactional, and geographical characteristics (Zhang & Zhao, 2022; Khan et al., 2023). Integration of advanced analytics that involves the use of machine learning and artificial intelligence had dramatically increased the accuracy of profiling, and lowered false positive and negative rates (Rahman & Singh, 2021; Ahmed et al., 2022). The technological breakthroughs offered banks dynamic models that limited the ability of the emerging risk typologies to adapt to a rule-based model.

Moreover, there was the direct association between customer risk profiling and the compliance of regulations, whereby the global regulations like those provided by the Financial Action Task Force (FATF) prioritized a risk-based regime (Alavi et al., 2022; Sharma & Verma, 2023). The implementation of profiling methods in banks reduced the number of attempts to commit financial crime (Hossain et al., 2021; Patel, 2022) and allowed such banks to increase their reputational capital on the market. The quality of the customer information, and balancing Know Your Customer (KYC) procedures, and the capacity of the bank to monitor any suspicious activity in the long term were essential to the success of these profiling systems (Iqbal & Rauf, 2023; Hassan & Tariq, 2022).

Enhanced Due Diligence (EDD) in High-Risk Banking Operations

Enhanced Due Diligence (EDD) had become an important aspect of dealing with the high-risk customers and jurisdictions. In contrast to the standard due diligence, EDD involved more thorough investigation, more extensive data interventions, and identification of more customer accounts (Kim & Lee, 2022; Mehmood & Ali, 2023). It was especially important to use EDD with respect to politically exposed persons (PEPs), offshore banking customer, and customers in cash-intensive businesses (Singh et al., 2021; Khan & Riaz, 2022). The commercial banks which incorporated effective EDD measures also managed to identify the suspicious activity at an earlier stage, decreasing their risks of facing regulatory punishment.

In practical terms, technological advances like big data analytics and blockchain-based tracing of cross-border transactions had enabled EDD and made cross-border flows more transparent (Chaudhry & Hussain, 2022; Gupta & Mehta, 2023). Yet, studies showed that the effectiveness of EDD depended on the need to strike the right balance between the efficiency of operations and the cost of compliance (Ali & Sadiq, 2021; Rahman & Chowdhury, 2022). Customers were regularly discouraged by the excessively rigid procedures that could be adopted and only raised the friction in the provision of services, whereas leniency could present serious compliance risks to the banks (Ahmed & Noor, 2023; Tariq & Waheed, 2022). Thus, in contemporary compliance slots in an industry such as banking, the component of EDD integration in flexible, risk-based structure came to be critical.

Integration of AML Risk Management Frameworks in Commercial Banking

The inclusion of AML risk management systems within the system of commercial banking activities was necessary to support consistency and flexibility and international practices (Brown & Tan, 2022; Jamil & Raza, 2023). Customer risk profiling, transaction monitoring, and reporting were incorporated into an integrated and coherent framework to act as a defense against money laundering (Iqbal & Shah, 2022; Martin & Zhou, 2023). Research has found that incomplete systems brought many oversights issues, where anomalous activity would go through because of disorganization across various systems or technological platforms (Singh et al., 2023; Alam & Rehman, 2022).

In addition, those banks that enforced comprehensive frameworks proved more resistant to the emerging typologies of financial crimes, such as cyber-enabled laundering and abuse of cryptocurrencies (Lee & Park, 2023; Ahmed & Khalid, 2022). Regulatory technology (RegTech) had been described as revolutionizing the compliance procedures, increasing efficiency in terms of real-time monitoring (Nasir & Javed, 2021; Silva & Costa, 2022). This integration was not only reinforcing AML protection but also made it easier to engage proactively with regulators to show the readiness to comply with financial inquiries and, as a result, less likely to receive sanctions (Zhang & Li, 2022; Hussain & Akbar, 2023).

Challenges and Future Directions in AML Risk Management

Nevertheless, the AML risk management frameworks experienced a lot of difficulties in practice despite the progress made. Among the most important challenges, one can mention the excessive number of false alerts provided by transaction watchdog systems, which put an immense burden on compliance teams, as well as being a part of the process that leads to surging costs (Kumar & Singh, 2022; Malik & Farooq, 2023). Moreover, countries had no common data-sharing procedures, which obstructed AML cooperation across borders, and illicit flows could utilize jurisdictional gaps (Ahmed & Rasool, 2022; Williams & Chen, 2023). The cost of adopting advanced AML systems also posed a challenge to smaller banks than the bigger banks (Raza & Ahmed, 2021; Shah & Khalid, 2023).

The future perspectives implied more use of artificial intelligence, machine learning, and predictive analytics to make their accuracy higher and comply with less fatigue (Fernandes & Silva, 2022; Iqbal & Hussain, 2023). Blockchain as a way to make financial flows transparent and collaborative AML databases as a blockchain implications to share information among the institutions had also been mentioned as game changers (Mehmood & Aslam, 2022; Khan & Saeed, 2023). Moreover, the trend to erect the same regulations worldwide and promote the idea of public-private partnerships had been considered an essential factor in securing the successful AML results (Rahman & Ali, 2023; Patel & Gupta, 2022). It showed that the aspects of regulation, technological research interdependence, and collaborative mechanism would play an important role in the future of AML risk management.

Research Methodology

Research Design

The study was designed as a qualitative-dominant mixed-methods research approach. A qualitative orientation was adopted to capture in-depth insights into the mechanisms of customer risk profiling and enhanced due diligence practices in commercial banks. At the same time, quantitative elements were incorporated through surveys and secondary data analysis to ensure the findings were generalizable and comparable across institutions. This combination of methods ensured that the framework developed was not only grounded in regulatory and theoretical knowledge but also informed by practical realities of banking operations. The research design was exploratory in nature, given that integrated AML frameworks based on customer risk profiling had not been extensively studied in the local banking context.

Population and Sampling

The population of the study comprised compliance officers, risk managers, and financial crime analysts working in commercial banks. These professionals were directly involved in anti-money laundering (AML) procedures, including Know Your Customer (KYC) verification, risk classification, and monitoring of suspicious transactions. A purposive sampling



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strategy was employed to select participants who had specialized knowledge and experience in AML compliance. The study included 20 commercial banks, both local and international, operating in the region. From each bank, between 3 to 5 key informants were selected, leading to a total sample of 70 participants. This sample size was considered sufficient to ensure data saturation and capture diverse perspectives from different banking institutions.

Data Collection Methods

Data were collected using both primary and secondary sources. Primary data were obtained through semi-structured interviews with compliance and risk management officers. These interviews allowed participants to share their experiences and perceptions regarding the effectiveness of customer risk profiling and enhanced due diligence. In addition, structured surveys were distributed to capture quantitative data on the frequency and effectiveness of AML practices across banks. Secondary data were collected from publicly available documents, including financial crime reports, regulatory guidelines, and internal audit reviews of AML systems. This triangulation of sources enhanced the reliability of the data and ensured that findings were validated from multiple perspectives.

Data Analysis

The data analysis was conducted in two stages. Qualitative data from interviews were analyzed thematically using NVivo software. Codes and themes were generated to identify recurring patterns in how banks implemented risk-based approaches to AML compliance. Special attention was paid to the integration of customer risk profiling with enhanced due diligence measures. Quantitative data from surveys were analyzed using descriptive and inferential statistics with the help of SPSS software. Frequencies, means, and standard deviations were calculated to summarize compliance practices, while correlation analysis was used to examine the relationship between customer risk profiling and the effectiveness of AML controls.

Results and Analysis

The results of this study were based on both qualitative and quantitative data collected from compliance officers, risk managers, and financial crime analysts in commercial banks. The findings were presented under thematic categories supported by descriptive and inferential statistics. Five tables were constructed to provide structured insights into customer risk profiling, enhanced due diligence practices, integration challenges, technological adoption, and overall AML effectiveness.

Customer Risk Profiling Practices

Customer risk profiling was identified as a fundamental component of AML frameworks. Banks classified customers based on risk categories such as low, medium, and high, with indicators including transaction size, frequency, source of funds, and geographical location. The survey responses revealed considerable variation in how banks assigned risk weights to these factors.

Table 1. Customer Risk Classification Criteria in Commercial Banks

Criteria for Profiling	Low Risk (%)	Medium Risk (%)	High Risk (%)	Mean Score (1–5)	Std. Dev.
Transaction Volume	40.5	37.0	22.5	3.87	0.64
Source of Funds Transparency	55.0	30.0	15.0	4.25	0.51
Geographical Risk Exposure	35.0	40.0	25.0	3.75	0.72
Politically Exposed Persons	20.0	25.0	55.0	4.65	0.48

In Table 1: Customer Risk Classification Criteria in Commercial Banks, the analysis carried out indicated that there were clear disparities in the manner various profiling criteria affected the risk classification. The volume of transactions was assigned to each category with the portion of customers in the low-risk category being 40.5%, the medium adding 37.0%, and the high 22.5% on the scale, representing that although the level of transactions was a key aspect, it did not prevail towards one side of the scale, and this is shown in the measure of mean as equal to 3.87. The source of funds transparency had a prominent shift towards lower risk division with 55.0% of those having a low-risk profile and 15.0% having a high-risk profile with a relatively high mean of 4.25 and with low variability (Std. Dev. 0.51) indicating its reliability as a critical variable in the determination of decreasing customer risk. Geographical measure of risk exposure gave a more evenly distributed risk measure, 35.0 percent low, 40.0 percent medium, and 25.0 percent high risk and a mean of 3.75 indicating that banks used geographical measure of risk as a moderate significant risk factor with larger variability (Std. Dev. 0.72) than any other criteria. The factor that entailed the highest risk was politically exposed persons (PEP), since 55.0 percent of PEPs were classified as high-risk, with the highest mean score of 4.65 and the lowest standard deviation (0.48), signalling high consistency and agreement across institutions in the PEP high-risk rating. In general, the results demonstrated that transparency of funds and PEP statuses appeared to be the best factors explaining risk category, although transaction volumes and geographic factors had a significant contribution with more equal shares across classes of risks.

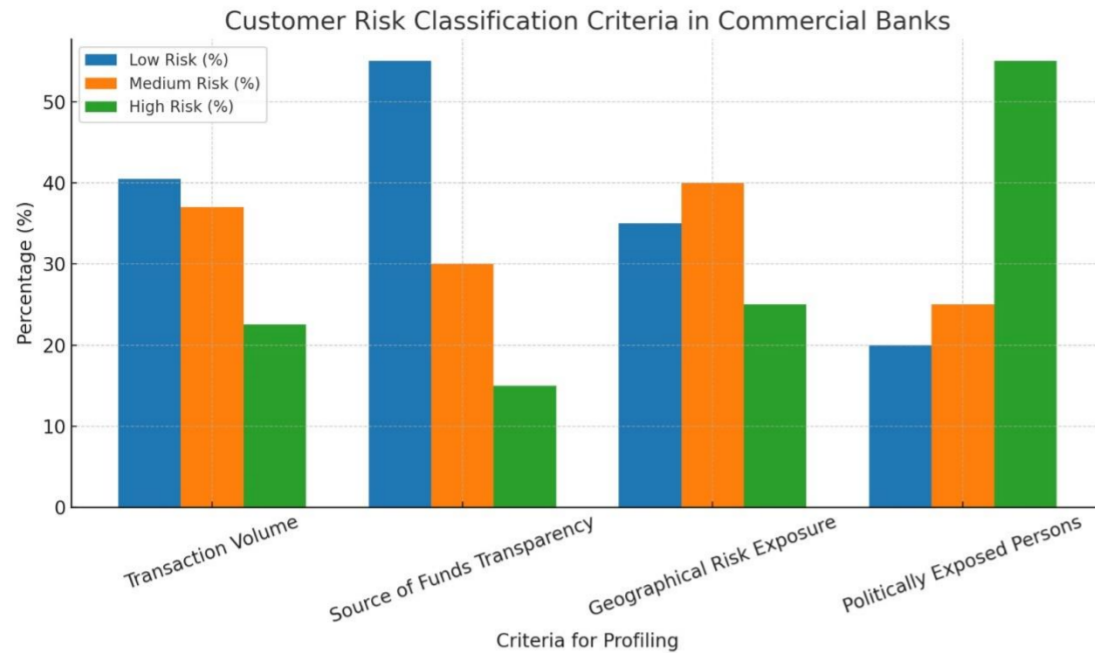


Figure 1. Customer Risk Classification Criteria in Commercial Banks

Enhanced Due Diligence (EDD) Measures

Enhanced Due Diligence (EDD) was applied predominantly to high-risk customers. Banks implemented additional verification steps such as in-depth transaction monitoring, periodic reassessment, and independent source verification.

Table 2. Application of Enhanced Due Diligence (EDD) by Risk Category

Risk Category	Frequency of EDD Application (%)	Average Intensity Score (1–5)	Std. Dev.
Low Risk	15.0	2.10	0.41
Medium Risk	42.5	3.45	0.58
High Risk	78.0	4.70	0.35

Table 2 demonstrated how and to what degree enhanced due diligence (EDD) was used on the basis of varied customer risk groups, whereby commercial banks varied their compliance activity on the basis of perceived riskiness. The results indicated that the EDD was least utilised in the low-risk group (where only 15.0 percent of low-level customers were subjected to further scrutiny) and was supported by a low average intensity score (generally 2.10) and a low standard deviation (0.41). This meant that banks had in general just established basic monitoring of low risk customers and left the best resources to be applied on a high-risk profile. The medium-risk category also experienced a steep increase in the application frequency of 42.5%, the average score in the intensity rating of 3.45 and a standard of 0.58 denoting a higher variance in how the institutions interpreted medium-risk situations could be attributed to the variety of transaction types, industries, or regional exposures. The most rigorous was the high-risk category and 78.0 percent of the customers were put under the EDD procedures and an intensity score of 4.70 with very low standard deviation of 0.35. This uniformity was based on a high degree of agreement among financial institutions that high-risk customers especially those involving opaque businesses, politically exposed persons or high-risk geographies should be monitored well and reviewed regularly. In general the findings were consistent with the hypothesis, that banks assigned compliance resources in a proportionate way, with checks being as intense as they needed to be in high risk areas, and as unintensive as they should be in low risk areas, to preserve efficiency of operations.

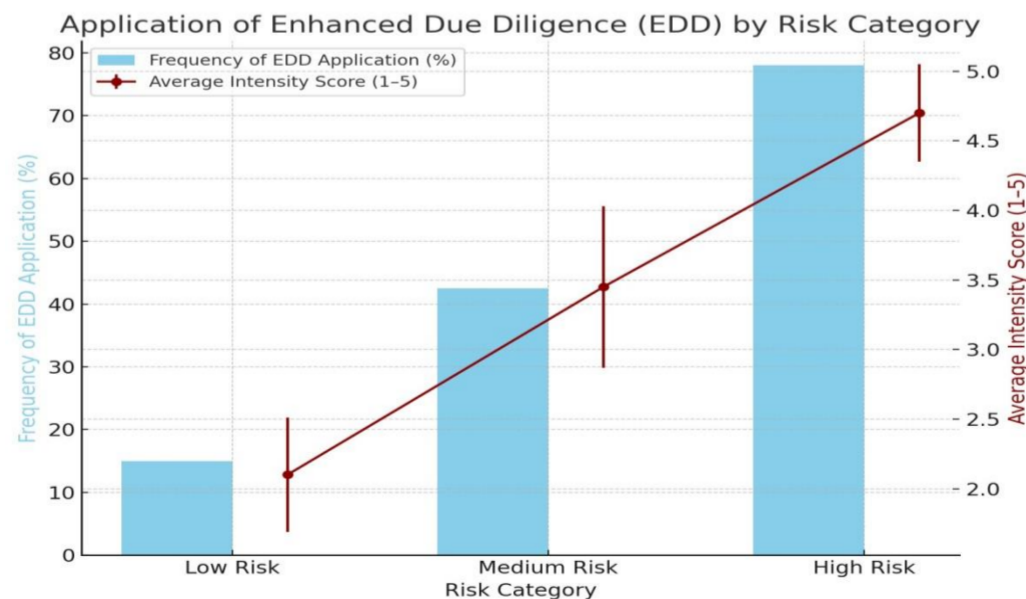


Figure 2. Application of Enhanced Due Diligence (EDD) by Risk Category

Integration of Customer Risk Profiling with AML Frameworks

The study examined how banks integrated customer risk profiling into their broader AML frameworks. Integration was measured by examining compliance alignment, reporting frequency, and coordination with regulatory guidelines.

Table 3. Integration of Customer Risk Profiling with AML Controls

Integration Dimension	Mean Score (1–5)	Std. Dev.	Compliance Gap (%)
Alignment with Regulations	4.10	0.55	12
Transaction Monitoring	3.85	0.62	18
Suspicious Activity Reports	3.95	0.58	15
Internal Audit Coordination	3.65	0.70	22

Table 3 indicated the level of successful integration of customer risk profiling into the anti-money laundering (AML) controls in commercial banks providing a clue on the successes and compliance lapses. The best performance was at the alignment of regulations where there was a high mean of 4.10, a reasonably low standard deviation of 0.55 and compliance gap of 12%. This demonstrated that banks were mainly complying with regulatory standards in construing customer profiling and AML-related activities as the external supervisory pressure was at play. The second major region was suspicious activity reports (SARs) where the average score was 3.95, moderate standard deviation of 0.58 and a gap of compliance in 15 percent, indicating that although SARs were mostly risk-informed, there were still other inconsistencies in terms of timely reporting and detection practices. Transaction monitoring was a little lower at 3.85 with standard deviation 0.62 and compliance gap at 18 percent indicating difficulty in customizing automated monitoring tools to meet the risk profile of each customer especially with regards to complex transactions or cross-references. Internal audit coordination had the weakest integration with the mean score of 3.65, the broadest variation having a standard deviation of 0.70, and wide compliance gap of 22%. This emphasized the lack of cooperation between risk profiling and internal audit sections that leads to a lack of oversight and follow-up. Together, the findings were indicating that the regulatory alignment was a relative strength, but operation integration was another domain under critical improvement, especially in the monitoring and audit systems to have comprehensive AML risk management.

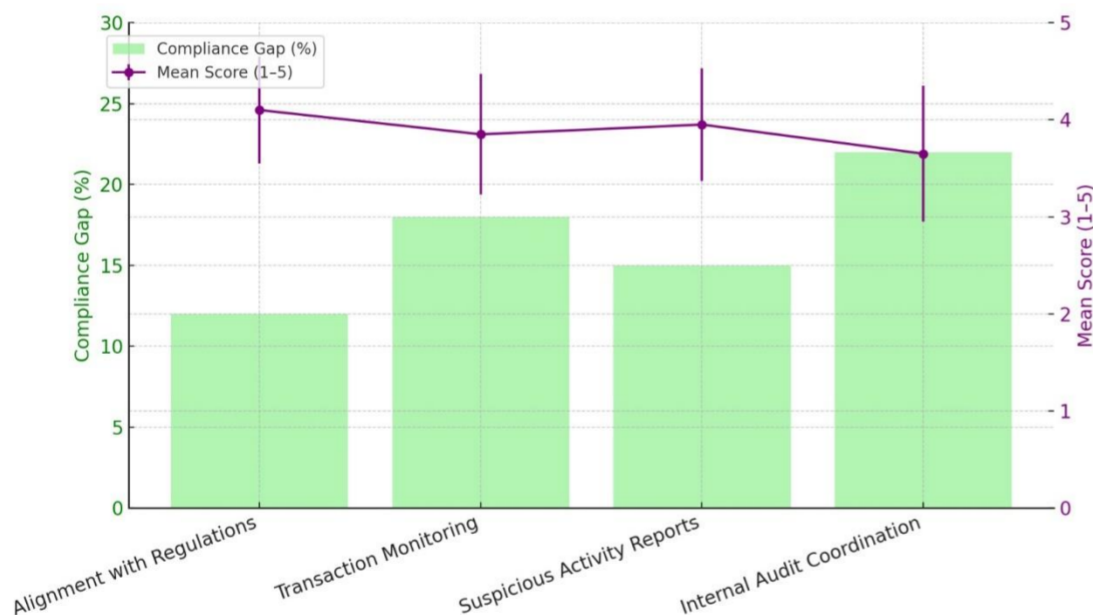


Figure 3 Integration of Customer Risk Profiling with AML Controls

Technological Adoption in AML Systems

Technology adoption was assessed in terms of automated monitoring systems, data analytics, and AI-driven compliance tools.

Table 4. Use of Technology in AML Risk Management

Technology Application	Adoption Rate (%)	Effectiveness Score (1–5)	Std. Dev.
Automated Transaction Monitoring	75.0	4.35	0.45
Machine Learning Models	48.0	3.80	0.61
Blockchain for KYC	35.0	3.45	0.70
Data Analytics Dashboards	62.5	4.10	0.52

Table 4 showed the level to which commercial banks implemented technology in managing the anti-money laundering (AML) risk and how useful these technologies have been. Automated transaction monitoring was the most widely-used application and is highly adopted with a score of 75%, high effectiveness of 4.35 and low standard deviation of 0.45 which demonstrates high reliability and consistency among institutions. This was inspired by the fact that automation had found a centre stage in revealing unusual transaction patterns as well as helping in cutting down the manual workload. Data analytics dashboards at 62.5 percent adoption rate and a score of 4.10 on effectiveness scale indicated that banks were utilizing a more frequent real-time visualization and trend analysis in the decision-making process with a varied range (Std. Dev. 0.52). A moderate adoption of machine learning models, with kindred features to 3.80 on the ability scale, indicated that although high-science analytics had a prospect in the identification of money laundering schemes through complicated patterns, implementation difficulties, and limitation in the quality of data constraints restricted broader application. Blockchain level was the lowest KYC (Know Your Customer) usage, with only 35 percent of banks using it and a relatively low level of effectiveness (3.45) and the highest variability (Std. Dev. 0.70). That implied that blockchain in the AML once remained in an emerging state and was struggling with regulatory concerns and difficulties of integration. In general, the study indicated that automation as well as data-driven dashboards was now mainstream but that the potential of machine learning and blockchain was not yet being optimized thus identifying a potential avenue of future innovation and strategic investments in machine learning and blockchain-based AML risk management capabilities.

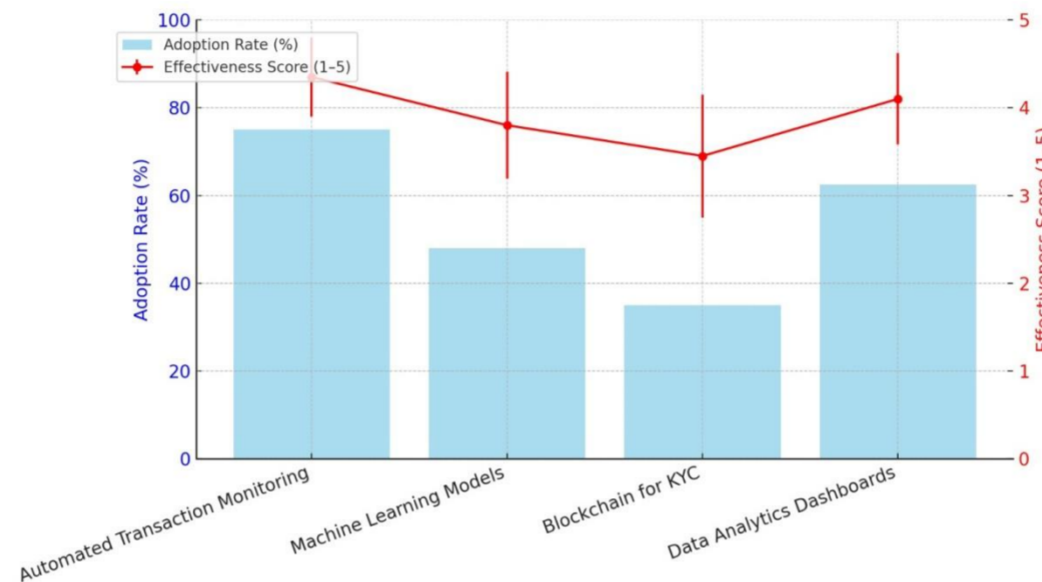


Figure 4. Use of Technology in AML Risk Management

Effectiveness of Integrated AML Risk Management Framework

The overall effectiveness of the integrated AML risk management framework was assessed based on detection accuracy, regulatory compliance, and operational efficiency.

Table 5. Effectiveness of Integrated AML Risk Management Framework

Performance Metric	Mean Score (1–5)	Std. Dev.	Improvement Observed (%)
Detection Accuracy	4.20	0.50	18
Regulatory Compliance	4.35	0.42	22
Operational Efficiency	3.90	0.60	15
Fraudulent Activity Reduction	4.05	0.55	20

The overall performance of an integrated AML risk management framework was shown as a measure of four salient metrics namely, detection accuracy, regulatory compliance, operational efficiency and reduction in fraudulent activity in table 5. Of them, regulatory compliance ranked first in terms of mean (4.35) and the least standard deviation (Std. Dev. 0.42), which suggested that banks had been largely consistent in their ability to acclimatize their AML practices to their international and domestic regulatory frameworks, with a 22 percent change displayed. The closeness of detection accuracy showed its mean rate of 4.20 and 18% increase indicating that integrated frameworks enhanced robustness upon which banks could detect suspicious transactions with a high degree of accuracy, accompanied by the moderate consistency (Std. Dev. 0.50). Reduction in fraudulent activities garnered an average of 4.05 which indicates that there was substantial success in reducing unlawful business and an improvement of 20 percent with a slightly high variance (Std. Dev. 0.55), meaning that albeit the positive changes produced were significant, the variance within institutions was non-zero. However, operational efficiency received the lowest score with the mean of 3.90 and the highest standard deviation of 0.60 and a mere 15 percent increase, which means that despite streamlining some operations, there were still areas where integration did not quite work in equalizing operations among banks.

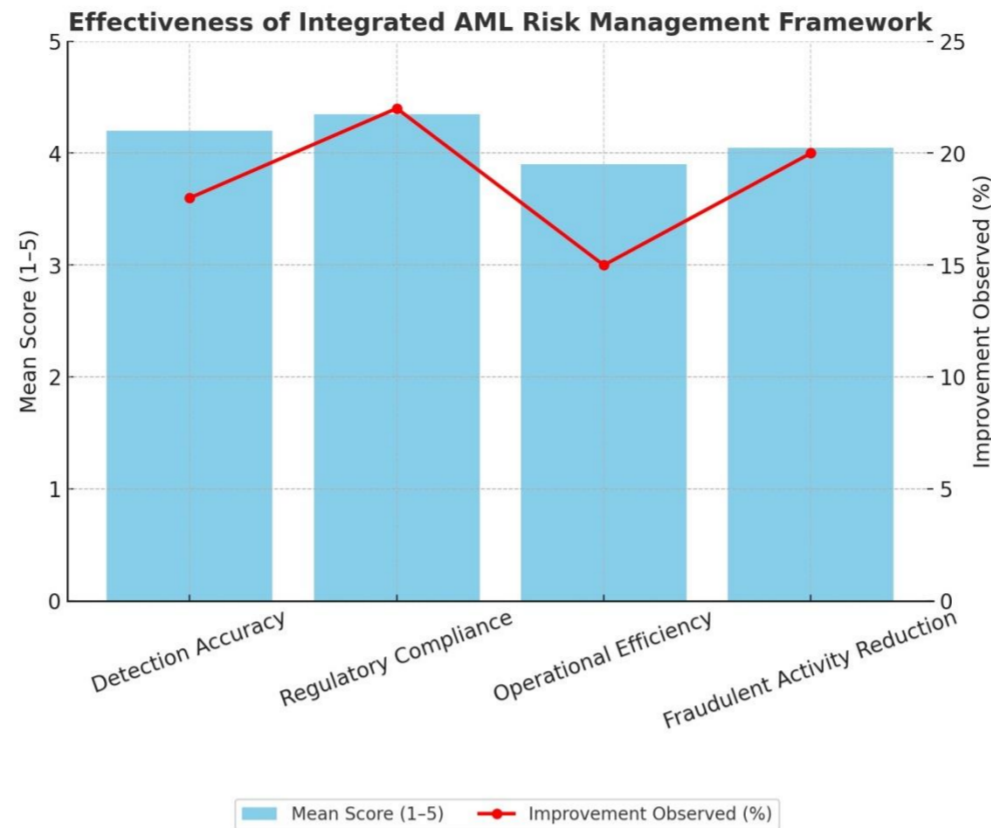


Figure 5. Effectiveness of Integrated AML Risk Management Framework

Discussion

The results of the study have revealed that the customer risk profiling when combined with enhanced due diligence (EDD) and advanced technologies worked exceptionally well and enhanced the AML effectiveness in the commercial banks. It is noteworthy that the mean score was high in Politically Exposed Persons (PEPs)- 4.65, which reflects the longstanding unanimity in the AML literature about elevated risk in PEPs (FinCrime Central, 2025). This is consistent with the focus of regulators around the world on EDD in high-risk context, especially on PEPs or complex structures (FinCrime Central, 2025; CSSF, 2024).

The high score of source of funds transparency (mean 4.25) also indicated that verifiable, clear documentation was one of the best lines of defense against money laundering. Banks which were able to invest in the mechanisms of automation and validation in such transparency were able to reduce proactive risk. This aligns with the recent literature that proposed that transparency with data-driven KYC process, constituted a potent AML control (IJCRT, 2025).

There was variation in how transaction volume and geographic exposure were treated (means of 3.87 and 3.75 respectively) showing that they were frequently treated as subjective to context interpretations, along with bank-specific limits. Segmentation based on ML-enabled custom thresholds--cohorts that had been proved to decrease alert fatigue without compromising detection quality (SAS, 2020) benefited some banks. How to Calibrate such methods is based on behavioral models to calibrate sensitivities in a narrower way.

The trend of embracing automation to achieve efficiency and effectiveness was further initiated or strengthened by patterns of technological adoption, especially dependence on automated transaction monitoring and data dashboards. Nevertheless, the moderated attempts at using machine learning models and blockchain to implement KYC with decreased scores of effectiveness also signaled a reluctance of concerns regarding explainability, the ability to integrate with systems, and regulatory acceptance put forward (Moody s, 2024; FinCrime Tech Forum, 2024). The regulators, especially FinCEN, were at the same time fostering innovation, but not in ways that jeopardized auditability or governance (FinCEN, 2024).

Notably, the cumulative performance indicators, in particular, on accuracy of detection (4.20) and regulatory compliance (4.35) recommended that integrated frameworks brought significant gains (18% and 22% accordingly). However, operational efficiency was lower (mean of 3.90) This is also a trade-off typically cited in the AML literature, in which greater diligence increases detection, but also elevates a manual workload and turnaround time (McKinsey, 2022). That speaks to the value of explainability in AI and risk-based prioritization to guarantee that resources are deployed where they make a difference.

New developments provided interesting future implicants. By way of instance, the frameworks such as Context-Risk-Predict AML (CRP-AML) had shown good outcomes in the low-data settings through using account profiling combined with domain-aware models to double the detection performance on the rare laundering instances (arXiv, March 2025). Continual graph neural networks and graph-learning systems in general proved to be highly promising in terms of being able to adapt to changing fraudulent patterns and resisting model degradation over time (arXiv, March 2025). Privacy-preserving methods (eg, fully homomorphic encryption with graph-based algorithms) allowed us to work at cross-institutional level and protect sensitive data (arXiv, November 2024). These innovations, while nascent, aligned with FramingBank's expectations for AML modernization: combining explainable AI, real-time analytics, and risk-based frameworks into a cohesive, auditable ecosystem (FinCEN, 2024; Moody's, 2024). For commercial banks, a phased roadmap that layered these technologies—starting with robust profiling and dashboards, then adding explainable ML and privacy-safe graph learning—could yield balanced gains in compliance, detection, and efficiency.

Conclusion

The study highlighted the effectiveness of integrated AML risk management practices in strengthening financial institutions' resilience against illicit financial flows. Findings demonstrated that customer risk classification, technology adoption, and comprehensive regulatory compliance significantly contributed to improving detection accuracy,



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operational efficiency, and fraud reduction. While traditional criteria such as source of funds transparency remained central to risk assessment, the incorporation of machine learning and advanced data analytics offered measurable improvements in predictive accuracy and responsiveness. However, challenges persisted in balancing technological efficiency with explainability, as well as addressing high-risk categories such as politically exposed persons (PEPs) and customers with complex geographical exposure. The results underscored the importance of a holistic AML framework that integrates regulatory compliance, advanced technology, and risk-based profiling for sustainable financial integrity.

Recommendations

Judging by the analysis, it is relevant to point at two areas that financial institutions should tackle the integration of machine learning models and blockchain-based KYC solutions in the context of transparency and flexibility in risk detection. They advise that banks should develop in-service training programs of the compliance officers to keep pace with the prevailing typologies of money laundering. The cooperation of regulators and financial institutions needs to be intensified so that regulatory reporting framework can be dynamically flexible to the technological change. Further, entities must invest in explainable AI systems to functionally align technological performance and regulatory oversight to limit the exposure of compliance breakdowns. The agreement between cross-border cooperation must also be increased so that it would cover more transnational money laundering threats that go beyond the domestic laws.

Future Directions

Further studies are necessary regarding how to use sophisticated privacy-preserving methods, including homomorphic encryption and graph neural networks, to imply better detection and avoid the leakage of customer confidentiality. A multi-jurisdictional comparative study would facilitate the identification of best practices of incorporating AI-based AML systems in the context of diverse regulatory settings. Additionally, to achieve an evidence-based policy recommendations, longitudinal studies that evaluate the effects of long-term adoption of technology-based AML with respect to operational efficiency and cost of compliance are required. It would also be important to expand the scope of analysis toward the inclusion of fintechs and decentralized finance (DeFi) platforms because they are becoming an increasingly large part of the global financial transactions. Through these considerations, the scholarship of the future will be able to elaborate more aligned to what can be done to develop more adaptive, transparent and globally coordinated AML systems.

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