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Artificial Intelligence–Enabled AML Technology and Transaction-Monitoring Efficiency: Evidence from Banking Institutions in Rajasthan

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Abstract

Rapid proliferation of digital banking has led to faster, greater and more complex transactions. While digital channels have made banking easier and efficient, they have at the same time provided new avenues for financial crime like money laundering. Traditional AML systems usually follow pre-defined rules, threshold-based transaction analysis and manual reviews. These systems may result in too many alarms, false alarms and inability to detect new patterns of transactions. In such an environment, AI, machine learning, automation of customer due diligence, real-time alarm generation, customer risk scoring and integrated analytics platforms are becoming increasingly significant aspects of AML compliance. In this current study, the influence of AML technology on transaction-monitoring effectiveness is assessed for selected banking organizations in the state of Rajasthan. For this research, a descriptive, analytical, correlational and cross-sectional research design was adopted. The main data were collected through the structured questionnaire survey, where 298 respondents in total number were selected from public, private and cooperative banking institutions. The subjects participating in the survey were AML and compliance officers, auditors, risk managers, forensic accountants and other finance control personnel. The questionnaire survey was conducted on the basis of five-point Likert scale, and the quantitative data was analyzed through the SPSS. The reliability of the instrument was established based on internal consistency, where Cronbach's Alpha was 0.910 for 40 items. From the regression analysis, a highly significant and positive correlation was found between AML technology adoption and transaction monitoring efficiency. $R = 0.837$, $R^2 = 0.701$, adjusted $R^2 = 0.700$, and $F(1,296) = 694.165$ were observed where $p < 0.001$. Thus, AML technology adoption accounted for 70.1 per cent of the variation in transaction monitoring efficiency. This study finds that Artificial Intelligence (AI) enabled monitoring, automated reporting, real-time surveillance, risk scoring, and data platforms are useful in making AML more efficient. However, the success of such tools requires good quality data, capability of employees, model validation, integration, and proper human control.

Keywords: *Artificial Intelligence, Anti-Money Laundering, Machine Learning, Transaction Monitoring, Banking Technology, Suspicious Transactions, Rajasthan.*

Introduction

The banks play a critical role in the process of economic development through savings mobilisation, credit creation, investment financing, payments services, and building trust within the

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financial system. Over the past decades, the banking sector has experienced significant changes. The introduction of mobile banking, internet banking, instant payment systems, electronic transfers of money, digital customers' registration, and other data-driven financial products has resulted in the increase of speed and accessibility of transactions. Digitalisation of the banking sector has also contributed to the growth in the number, frequency, variety, and geographic scope of financial transactions.

Such development has brought about challenges for anti-money laundering compliance. Money laundering is defined as the process of hiding or covering up of the source, ownership, transfer, and/or use of any funds which have been generated through criminal activity. Usually, it includes three phases: placement, layering, and integration. In case of the modern financial system, these stages can include many different bank accounts, shell companies, electronic payments systems, fake identities, intermediate accounts, international transfers of funds, etc. Such transaction chains may become too complicated to be verified manually.

Rule-based transaction monitoring systems have been in use by banks in the past. This type of monitoring system flags transactions based on certain criteria such as predefined thresholds, scenarios, customers, geographic location exposure, number of transactions, or any other risk factors. Rule-based monitoring is still relevant; however, it has certain weaknesses. Criminal behavior does not always operate within set thresholds. When a control rule is known, money will be divided, moved, layered, or structured in order to avoid being flagged by the rules.

Another problem associated with the transaction monitoring is alert fatigue. Transaction monitoring generates too many alerts, the majority of which is not related to the suspicious activities. Still, compliance officers are obliged to review such alerts, document their findings, escalate suspicious alerts and close those that are not considered suspicious. False positive alerts overloading distracts from the investigation of the risky transactions. Fragmentation of the customer information, lack of interaction between transaction monitoring, KYC, risk management, audit and case management systems contribute to this problem.

Alternative solution to the problem is to use artificial intelligence and machine learning. While rule-based solutions focus only on the rules, AI technology can identify behavioral patterns, analyze transactions and previous transactions, discover hidden connections and investigate unusual cases. Machine learning algorithms can be taught to identify correlations between different factors that are individually insignificant but important in the combination. Network and link analysis is used to establish relations between customers, accounts, beneficiaries, firms, locations, devices and transactions.

But the technology in this paper is not just limited to AI; instead, it involves many technologies such as AI and machine learning-based transaction monitoring systems, automated electronic know your customer/ customer due diligence systems, real-time alerting system, automated suspicious transaction reporting, database management, customer risk scoring, compliance dashboard, and upgrading of AML tools, etc. The question posed by the study is whether the introduction of these technologies helps increase transaction-monitoring efficiency.

The context of the research is Rajasthan, where there exist public sector, private sector, and cooperative banks in urban, semi-urban, and regional markets. There being differences in infrastructure, customer base, staffing, organization capability, and technology adoption makes Rajasthan an appropriate context for studying AML technology.

Need and Relevance of the Study

The reason why technology-assisted AML monitoring is needed lies in the nature of financial crimes themselves. Transactions could happen very quickly and frequently via multiple channels. Suspicious transactions could be conducted through multiple accounts or transactions could be purposefully structured below the reporting levels. The manual alert monitoring system would fail to cover every transaction, business relationship, and related financial organizations in such cases.

The proposed research would have a practical application because an inefficient AML monitoring system would create serious issues within the area of compliance. In case the alerts are not tuned properly, then specialists would spend a lot of time analyzing usual transactions. Too many operations would increase the costs of the compliance procedure and the risk of ignoring important issues. Technology could help in this situation by prioritizing the alerts and identifying unusual behaviors of customers.

It is also significant from the standpoint of regulation. There are various responsibilities that banks must assume, such as customer identification, customer due diligence, risk profiling, transaction monitoring, record keeping, and suspicious transaction reporting. Technology may play a role here, but if managed incorrectly, it may lead to compliance problems. Compliance officers and regulators cannot always easily explain decisions generated by an unexplainable, unvalidated, and unsupervised AI system. Thus, the technology becomes significant not just as an innovation but also as the element of the larger governance and control process.

The regional significance of the research becomes obvious too. The banking system of Rajasthan consists of banks with various technological abilities and organizational forms. Public sector banks possess wide branch networks, private banks tend to embrace digital technologies quickly, and cooperative banks play a vital role in regional communities. It makes sense to analyze all three types of banks.

Review of Literature

The existing literature on AML technology seems to acknowledge the inability of traditional monitoring systems to handle large volumes of complex data sets. The recent works have thus considered artificial intelligence, machine learning, network analysis, automated transaction monitoring, and data integration as means to facilitate the process of crime detection.

Zhang, Chen, and Kumar (2025) considered graph-based network analysis for discovering complicated associations of money laundering. They found out that using graph models makes it possible to uncover associations and indirect connections that would be overlooked during individual account monitoring. Network analysis proved to be especially helpful in detecting layering activities and connections between seemingly unrelated transactions.

Singh & Mehta (2024) have analysed the application of artificial intelligence in AML programs. It was discovered that predictive analytics and automated alerts can help to decrease false positives, facilitate alert prioritization and speed up the process of detecting suspicious activities. The results provided by Singh & Mehta (2024) also include information about the dependence of performance of AI systems on continuous training and access to the appropriate data.

Williams, Brown & Taylor (2023) have made comparison between machine learning and traditional financial crime detection techniques. The results provided by the authors show that machine learning can help to detect more complicated patterns, eliminate the need for manual work and improve prediction precision. Nevertheless, issues concerning quality, transparency, and explainability of the model were discovered.

Anderson and Liu (2025) studied the use of data analytics alongside forensic accounting. Their findings revealed that the convergence of investigative skills and technological capabilities could contribute to enhanced detection in real time and reduce false alarms. It was stated that data analytics is effective when its results are evaluated by experts that are knowledgeable about financial transactions, behavioral indicators, regulation, and investigation practices.

The development of technology-assisted AML systems has been of interest for Indian scholars as well. Pillai and Deshmukh (2025) explored AI-driven AML systems in Indian banks. According to their findings, AI-based surveillance helps to identify transaction patterns that cannot be easily recognized and decrease the number of tasks to be performed manually. However, the integration issues, dependence on data, and investigative validation still constitute significant limitations.

Banerjee and Thomas (2024) explored the efficiency of transaction-monitoring systems in Indian banks. Their findings revealed that automation helped to increase the pace of transaction screening and enhance the capabilities of detection. Meanwhile, the high rate of false positives and insufficient coordination between the monitoring and investigative functions decreased the practical significance of alerts generated by the system.

Joshi and Kapoor (2023) examined the application of data analytics and machine learning in AML risk management. It identified that machine learning algorithms can help in assessing the risks associated with clients, pattern recognition and early detection of suspicious behavior. Yet, they also highlighted problems related to the opaqueness of algorithms and poor coordination with forensic investigations.

The regional literature related to the state of Rajasthan remains nascent. Kalla's research on the role of artificial intelligence in banking in Rajasthan, in terms of its performance and decision-making processes in both public and private sector banks, set the stage for the emergence of the topic of artificial intelligence in the field of banking. Although not restricted to AML, it provided the necessary groundwork at the regional level to understand the use of technology in AML. Chauhan and Pandey (2025) have also witnessed the growing trend towards digital finance in urban Rajasthan.

These literature findings reveal three major observations. Firstly, artificial intelligence and machine learning have significant capabilities for improving the detection of money laundering. Secondly, only technology itself will not be sufficient for ensuring efficient compliance. Its functioning will require reliable information, proper algorithm creation, implementation, technical skills of the personnel, and human decision making. Thirdly, there is a lack of empirical studies assessing the statistical impact of adopting AML technologies on transaction-monitoring efficiency in Rajasthan-based banks.

Research Gap Identified

Present day research either deals with the application possibilities of artificial intelligence in terms of its technological capabilities or mentions AML regulation compliance in abstract terms. The present-day literature regarding this subject matter often consists of either algorithm design or policy recommendations. Not many people analyze how much technology can actually contribute in accordance with the views of the bankers regarding alert handling, suspicious activities detection, fast reporting, and risk customer management.

There is also a geographic problem. Research that focuses on AML technology in Rajasthan is rare. Regional banks have different branch structure, customer base, digital maturity, workforce, and compliance expertise. Findings from multinational banks or advanced digital environments should not automatically be applied to all banks that operate in Rajasthan.

Finally, there is also a methodological gap. Many researchers offer descriptive findings without quantifying the portion of transaction monitoring effectiveness that can be explained by technology use. The current research fills this gap by using regression analysis based on 298 responses from bankers.

Objective of the Study

The principal objective of the paper is:

- To assess the impact of AML technology adoption, including AI and machine-learning-based monitoring, on transaction-monitoring efficiency and suspicious-activity detection in selected banking institutions operating in Rajasthan.

Hypotheses of the Study

- **Null Hypothesis—H_0:** AML technology adoption has no significant impact on transaction-monitoring efficiency in banks.
- **Alternative Hypothesis—H_1:** AML technology adoption has a significant positive impact on transaction-monitoring efficiency in banks.

Research Methodology

- **Research Design**

A research design involving description, analysis, correlation, explanation and cross-sectional was employed in this study. Description was used in describing the institutional and professional profiles of the participants and in summarizing the perception of the participants on the use of AML technology. Analysis and correlation designs were used in assessing the relationship between technology and transaction monitoring. A quantitative design was employed in this study.

- **Study Area and Population**

The geographic region of the study was Rajasthan. The target population was the banking personnel directly or indirectly associated with AML compliance, KYC/CDD, transaction monitoring, internal audit, forensic accounting, risk management, fraud investigation, vigilance, and regulatory reporting.

- **Sampling and Sample Size**

Purposeful and proportional sampling methods were used. The field sample size was chosen to be around 300 respondents, and after screening the data, 298 completed questionnaires were kept. The sample included ten selected banks from the public, private, and cooperative sectors.

- **Research Instrument**

A structured questionnaire was used. Section A collected demographic and institutional details. Section C contained ten statements measuring AML technology adoption, including:

- AI/ML-based transaction monitoring;
- automated e-KYC and CDD;
- false-positive reduction;
- real-time alert review;
- integration of multiple data sources;
- automated STR generation;
- updating of machine-learning models;
- AML dashboards;
- customer-risk scoring; and
- investment in upgrading AML tools.

Responses were measured on a five-point Likert scale: Strongly Disagree = 1, Disagree = 2, Neutral = 3, Agree = 4, and Strongly Agree = 5.

AML Technology Adoption was constructed from AMLT1–AMLT10. Transaction-Monitoring Efficiency was derived from AMLT3, AMLT4, AMLT6, and AMLT9, relating to false-positive reduction, timely review of alerts, automated STR generation, and customer-risk scoring.

- **Data-Analysis Techniques**

Coding and analysis of data were done using SPSS. Methods such as frequency, percentages, means, standard deviation, Cronbach's alpha, and linear regression were utilized. Regression analysis involved AML Technology Adoption as an independent variable and Transaction-Monitoring Efficiency as a dependent variable. Level of significance was set to 5 percent.

Data Analysis and Interpretation

- **Respondent Profile**

Table 1: Distribution of Respondents by Type of Bank

Type of bank	Frequency	Percent
Public Sector	210	70.5
Private Sector	60	20.1
Cooperative Bank	28	9.4
Total	**298**	**100.0**

Public sector banks dominated the respondent pool, followed by private and cooperative banks respectively. This is representative of the broad operation range of public sector banks without leaving out the views of other technologically heterogeneous banks.

Table 2: Distribution of Respondents by Role or Designation

Role/Designation	Frequency	Percent
AML/Compliance Officer	40	13.4
Risk Manager	62	20.8
Auditor	88	29.5
Forensic Accountant/FAFD	48	16.1
Other relevant banking professionals	60	20.1
Total	**298**	**100.0**

The respondents covered individuals from various control and surveillance departments. The largest group comprised auditors, but AML officers, risk management specialists, forensic specialists, and other staff members were also included in the sample. The majority of the respondents had more than five years' experience working at a bank.

- **Reliability Analysis**

Table 3: Case Processing Summary

Cases	N	Percent
Valid	298	100.0
Excluded	0	0.0
Total	**298**	**100.0**

Table 4: Reliability Statistics

Cronbach's Alpha	Number of Items
.910	40

All 298 responses were used in reliability calculations, and no response was deleted from the calculation. The Cronbach Alpha score of 0.910 reflects high internal consistency. The questionnaire was hence regarded as highly reliable for descriptive and regression analysis.

- **Descriptive Statistics of AML Technology Adoption**

Table 5: Descriptive Statistics

AML Technology Statement	N	Minimum	Maximum	Mean	Std. Deviation
AI/ML algorithms are used in transaction monitoring	298	1.00	5.00	3.9060	1.24637
Automated e-KYC and CDD systems are implemented	298	1.00	5.00	3.7752	1.32057
Technology reduces false positives	298	1.00	5.00	3.7181	1.31082
Real-time alerts are reviewed within 24 hours	298	1.00	5.00	3.8221	1.07868
Multiple data sources are integrated for AML analytics	298	1.00	5.00	3.6409	1.14383
Automated STR generation improves timeliness	298	1.00	5.00	3.7752	1.11605
ML models are regularly updated for accuracy	298	1.00	5.00	3.7248	1.01742
AML dashboards are accessible to compliance teams	298	1.00	5.00	3.5403	.94640
Technology improves customer-risk scoring	298	1.00	5.00	4.0268	1.04412
Bank regularly invests in upgrading AML tools	298	1.00	5.00	4.2953	.92480

The greatest mean value of 4.2953 was observed for continuous investment in AML technology upgrades. This implies that participants fully understood the need for continuous technological upgrade. The mean value of 4.0268 was also observed for customer-risk scoring, implying that technology is very important for sorting out customers based on their risk levels.

For the application of artificial intelligence/machine learning in transaction monitoring, a mean value of 3.9060 was observed while a mean of 3.8221 was recorded for real-time alerts review. This shows overall positive perception of intelligent and timely monitoring. The lowest mean was observed for accessibility of AML dashboards followed by the integration of multiple data sources. However, both mean values were greater than the neutral point, meaning that accessibility and integration were relatively weak aspects of AML technology implementation.

- **Regression Analysis**

Linear regression analysis using the Enter approach was performed. The AML Technology Adoption variable was entered as the predictor, whereas Transaction Monitoring Efficiency was entered as the dependent variable.

Table 6: Variables Entered/Removed

Model	Variables Entered	Variables Removed	Method
1	AML Technology Adoption	—	Enter

  - **Dependent Variable:** Transaction-Monitoring Efficiency
  - **Predictor:** AML Technology Adoption

Table 7: Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.837	.701	.700	.40301

R-value of 0.837 denotes an exceptionally high degree of positive correlation between AML technology implementation and efficiency in monitoring transactions. R^2 value of 0.701 suggests that AML technology implementation accounts for 70.1 percent of variations in monitoring efficiency. The adjusted R^2 of 0.700 is further proof that the explanatory power does not change significantly following adjustments for sample size and number of predictors.

Table 8: ANOVA

Model	Sum of Squares	df	Mean Square	F	Sig.
Regression	112.743	1	112.743	694.165	.000
Residual	48.075	296	.162	—	—
Total	**160.818**	**297**	—	—	—

- **Dependent Variable:** Transaction-Monitoring Efficiency
- **Predictor:** AML Technology Adoption

The output from the ANOVA indicates that the model is statistically significant, $F(1,296) = 694.165$, $p < .001$. It is thus unlikely that this association arose by mere chance.

Table 9: Coefficients

Model	Unstandardised B	Std. Error	Standardised Beta	t	Sig.
Constant	−.150	.153	—	−.981	.328
AML Technology Adoption	1.043	.040	.837	26.347	.000

- **Dependent Variable:** Transaction-Monitoring Efficiency

The estimated regression equation is:

Transaction-Monitoring Efficiency = −0.150 + 1.043 (AML Technology Adoption)

From the unstandardized coefficient value of 1.043, there is a relationship such that a one unit increase in AML technology implementation results in a 1.043 unit increase in the effectiveness of transaction monitoring. From the standardized beta coefficient value of 0.837, it is evident that there is a very strong positive effect. The predictor is statistically significant, $t = 26.347$, $p < 0.001$. The constant is statistically insignificant.

- **Decision Regarding the Hypothesis**

  Since $p < 0.001$, the null hypothesis is rejected. The alternative hypothesis is accepted.

  - **Decision:** AML technology adoption has a statistically significant and positive impact on transaction-monitoring efficiency in selected banking institutions operating in Rajasthan.

Findings of the Study

The study made the following important findings:

- First, there has been an increasing deployment of AML technologies such as artificial intelligence, machine learning, e-KYC, real-time alerts, customer-risk scoring, compliance dashboards and automated reporting at banks in Rajasthan. Continuous updates in the use of AML technologies were rated highly.
- Second, customer-risk scoring proved to be one of the most positively evaluated applications of technologies. Customer risk assessment automation facilitates concentration on customers at high risks, as well as suspicious transactions and enhanced due diligence.
- Thirdly, data integration is relatively low. The relatively low average of multi-data source integration implies that the KYC, transaction, customer-risk, audit, and case management data may not always be available on one single platform.
- Fourthly, the results of regression analysis revealed that adoption of AML technology was a very significant determinant of transaction monitoring effectiveness. It accounted for 70.1 per cent of the variance in the dependent variable and thus was the strongest among the four models analyzed in the parent thesis.

- Finally, the analysis provides evidence that the importance of AI is not only the installation of software. Technology will be more productive if there is accuracy in data, timely updating of models, proper investigative procedures, professional analysts, systems integration, and governance.

Suggestions to Possible Stakeholders

- **Suggestions for Banks and Senior Management**

The AML technologies should be considered as an investment of the organization, which requires continuous expenditure, instead of just the purchase of software. It is important that the bank management budgets sufficiently for system upgrades, model validation, data systems, cybersecurity, and training programs.

A technological platform must integrate rule-based monitoring with machine-learning models. Old-fashioned regulations will continue to serve their purpose in identifying well-known risks, while the machine learning technology will be helpful in uncovering anomalies and hidden correlations.

The bank should set up metrics of performance for AML technologies. These could be number of alerts generated, ratio of false positives, time taken to clear alerts, quality of escalation, time taken for filing STR, re-opening of cases, etc.

- **Suggestions for AML and Compliance Departments**

Transaction-monitoring scenarios and thresholds need to be regularly updated by compliance officers. Thresholds that trigger unimportant alerts continually need to be revised, while new forms of laundering activity need to be integrated into monitoring algorithms.

The alerts need to be prioritized based on customer risk, transaction size, geographic risk, behavioural anomaly, relationships, and past suspicious activities. Most important cases must get to experienced analysts without any delay.

Additionally, AML officers must document the process of closing an alert, escalating it or reporting it to the authorities. Automated risk scores must supplement professional judgment.

- **Suggestions for Information-Technology Departments**

Integration within IT should include customer onboarding, KYC, CDD, transaction monitoring, sanctions screening, fraud monitoring, internal audit, and case-management platforms. Ineffective integration of information leads to the impossibility of building a complete picture of the client's actions.

Measures related to data quality need to be provided within the AML systems framework. Missing information about clients, double data entry, inaccuracy in assessing risks, mismatched identification data, and incomplete description of transactions can negatively impact model accuracy.

It is required to track model performance in terms of deterioration, bias, instability, and changing of transaction behavior. Each material change in models must be registered.

- **Suggestions for Regulators and Supervisory Authorities**

A guide must be provided by the regulator for the right use of AI and machine learning in AML compliance. Such guidance should include topics like explainability, validation, data security, accountability, audit logs, and human supervision.

The evaluation process of the regulator should consider the performance of the monitoring system rather than its presence. It will become incumbent upon the banks to demonstrate how their system detects suspicious transactions, minimizes false alarms and helps report on time.

There could be an information exchange mechanism between the banks, RBI, FIU-IND, and enforcement agencies, which can assist in identifying cross-border transactions. Such a mechanism should ensure confidentiality of data.

- **Suggestions for Technology Vendors**

The providers of the technology need to create systems that can be implemented within the existing banking systems. Standalone technologies would only lead to more fragmentation instead of resolving the problem.

Explainable outputs should be produced by the AML software. The analysts should be able to determine why the system flagged certain customers and transactions as high-risk.

- **Suggestions for Forensic Accountants and Auditors**

The forensic accountant must work in close coordination with the AML and technology teams. The knowledge of the forensic accountant in relation to transaction history, beneficial owner, linking, documentation, and financial evidence might prove useful in understanding the system alerts.

The internal auditor is required to continuously monitor AI governance, model validation, data source, access control, alert resolution, escalation, and implementation of remediation measures. The audit must concentrate on the real improvement of the monitoring process made possible through technology.

- **Suggestions for Academic and Training Institutions**

There must be a development of interdisciplinary training in subjects including but not limited to accounting, banking regulations, data analytics, artificial intelligence, cybersecurity, digital forensics, and financial investigation by universities and professional institutions.

The training programs must include tasks like pattern recognition in transactions, risk scoring, alerts analysis, relationships charting, documentation, and reporting of suspicious transactions.

Conclusion

The research clearly indicates that the application of AML technology is a crucial part of transaction monitoring in today's banking institutions. With the help of artificial intelligence, machine learning, automated electronic know-your-customer (e-KYC) checks, real-time surveillance, risk scoring, automated submission of suspicious transaction reports (STRs), and analytics, banks can manage huge amounts of financial transactions more effectively than through manual processing.

There is substantial evidence provided by the regression analysis in support of this conclusion. The use of AML technology could explain 70.1 per cent of the variance in transaction monitoring efficiency, and the correlation was significant at $p < 0.001$. The null hypothesis was therefore rejected.

This does not mean that the adoption of technology alone could solve all AML issues. It was found from the qualitative findings that some issues remain unresolved even after the implementation of technology and those include too many alerts, false positive alerts, lack of systems integration, absence of trained staff, etc.

The future for banks operating in Rajasthan is neither just more automation nor is it just responsible and intelligent automation. A good AML system should assist in identifying risks, understanding the reasons for raising alerts, linking entities, prioritising alerts, and reporting suspicious activities. Combining technology with knowledge about compliance and forensic skills will make the banking system much more robust and resilient.

Limitations of the Study

This study focuses on selected banks functioning in Rajasthan. It is unclear whether the results can be generalized to banks functioning in other states or countries. The sample had an unusually high percentage of respondents from public sector banks that could affect their responses as a whole.

The study is cross-sectional and provides a view of the perception of respondents at one point in time. There are no data measuring any change before and after implementing AI technology. This study also relies on subjective reporting of information rather than confidential operational measures like false positive rate, STR conversion rates, investigation outcomes, or monetary loss prevention.

Finally, even though regression finds association and impact, a cross-sectional study cannot demonstrate causal relationship. There might be many other variables influencing the efficiency of monitoring such as management support, compliance culture, data quality, budget, system age, and expertise of the staff.

Future Scope of the Study

Further research can distinguish between public banks, private banks, and cooperative banks and see whether there is any difference in the strength of the technology-efficiency connection between these types of banks. Cross-sectional studies conducted in several Indian states will increase the validity of the results.

Future studies might conduct longitudinal studies that assess the performance of monitoring before and after the implementation of AI and machine learning technologies. Future studies may use actual monitoring measures like number of alerts, false positives, case resolution time, STR submission rate, and regulatory observation.

Further research may also look into explainable AI, privacy-preserving analytics, federated learning, graph neural network, generative AI investigation, and information sharing. Other variables like data quality, employee skills, management support, regulatory readiness, technology investment, and organizational culture may be used as moderators or mediators.

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