

Tech-Enhanced Risk Assessment For Anti-Money Laundering: Insights From USA Regional Banks

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Abstract – This study looks at how technology advancements have affected regional banks' attempts to combat money laundering (AML) in the United States. The study obtained data from a representative sample of 185 respondents by using standardized questionnaires that were filled out by bank employees who were actively involved in AML operations. The investigation, which made use of a modified structural equation model, concentrated on four main concepts: the application of machine learning (ML) techniques, integration of Financial Intelligence Units (FIUs), Money Laundering Prevention (MLP), Risk Assessment (RA), and Suspicious Transaction Detection (STD). The study's conclusions shed light on how incorporating cutting-edge technologies might increase AML programs' efficacy and enhance risk assessment and preventative actions in local banking environments.

Keywords – Anti-Money Laundering; Financial Intelligent Units; Money Laundering; Money Laundering Prevention; Risk Assessment; Suspicious Transaction Detection

I. INTRODUCTION

This study explores how regional banks in the United States are enhancing their anti-money laundering (AML) efforts, with a focus on the critical role that technology improvements play in enhancing risk assessment and prevention tactics. The primary goal is to assess how various technical solutions can improve the effectiveness of suspicious transaction detection and money laundering prevention. Structured questionnaires were issued to 200 bank employees engaged in anti-money laundering (AML) operations to collect pertinent data. This resulted in a comprehensive dataset.

To guarantee the integrity of the responses, stringent screening was used during the data collection procedure. To reduce missing results, all questionnaires were required. The completed forms were then input into a computerized system for additional analysis. Ten surveys were eliminated to improve the dataset because of recurring response patterns that suggested bias or errors, and five more were eliminated when Cook's distance coefficients were used to identify outliers. Due diligence produced a final sample of 185 valid responses, which served as the foundation for further study.

Data on four key constructs—the efficiency of Financial Intelligence Units (FIUs), Money Laundering Prevention (MLP), Suspicious Transaction Detection (STD), and the application of Machine Learning (ML) in AML tasks—were analysed using a modified structural equation modelling technique. There were several things in each construct that were intended to represent both theoretical ideas and real-world financial applications. The goal of this investigation is to offer perceptive conclusions about how technology integration supports more complex risk management frameworks by improving the efficacy of AML procedures in regional banks.

II. THEORETICAL FRAMEWORK

The investigation of how various technological and procedural factors affect the effectiveness of Anti-Money Laundering (AML) activities in regional banks forms the theoretical foundation for this study. The framework creates a conceptual model with precisely defined variables and their anticipated interactions by using the results of an extensive literature review. The theoretical framework can be organized as follows:

1) Independent Variables:

- 2) Suspicious Transaction Detection (STD): This variable focuses on how well banks can identify unusual or perhaps illicit transactions. The processes and technologies used in STD are essential for the preliminary detection of potential money laundering activity.
- 3) Money Laundering Prevention (MLP): This includes tactics and policies put in place to stop money laundering from happening. It entails, but is not restricted to, stringent customer due diligence, consistent transaction monitoring, and conformity to legal requirements.
- 4) Financial Intelligence Unit (FIU): This variable evaluates the function of specialized departments inside financial institutions that manage information about questionable transactions or activities, assist in exchanging information with law enforcement, and guarantee adherence to local, state, and federal legislation.
- 5) Machine Learning (ML): This variable reflects on the use and efficacy of machine learning algorithms that support predictive analytics and behavioural analysis in detecting patterns suggestive of fraud and money laundering.
- 6) Risk Assessment (RA): This variable includes an assessment of the potential risks posed by customers as well as the more general risks related to the bank's operations and external environment. It also captures the formal processes and tools used to identify, assess, and mitigate risks associated with money laundering within the institution.

A. Dependent Variable:

Anti-Money Laundering (AML): This is the main outcome measure, which is assessed based on how well the bank's entire AML infrastructure works. How strongly the independent variables contribute to the outcomes outlined below determines success in AML.

B. Outcome Measures:

Several operational outcomes are used to evaluate the effectiveness of the AML framework, including:

- 1) Investigation and Analysis: The bank's ability to carry out comprehensive inquiries and evaluations stemming from notifications produced by STD and additional surveillance mechanisms.
- 2) Criminal Prosecution: How well cases of alleged money laundering are assembled, including cooperating with law enforcement and gathering evidence, to be ready for possible legal action.
- 3) Investigations and Enforcement: The aggressive enforcement of anti-money laundering rules and regulations by the FIU and compliance teams.
- 4) Automated Decision-Making: The degree to which machine learning technologies are incorporated into decision-making procedures to improve efficiency and precision in detecting illegal activity.
- 5) Identifying Risks: The proactively detected and monitored development of money laundering risks and the execution of risk management plans, evaluated by RA processes.

C. Theoretical Propositions:

The study makes the following claims based on the theoretical framework:

- 1) More robust AML outcomes are directly connected with higher capacities in STD, MLP, FIU, ML, and RA.
- 2) These factors work better together when they are integrated, which improves the bank's capacity to manage and reduce related risks as well as identify and stop money laundering.
- 3) The application of accuracy and predictive capacities to classic AML procedures is greatly enhanced by technological breakthroughs, especially in machine learning (ML).

Using data from regional banks, this theoretical framework provides the basis for the development of hypotheses that may be empirically evaluated. The correlations presented point to a multifaceted strategy for enhancing AML initiatives, highlighting the significance of technology and strategic procedures in modern banking settings.

III. LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

The literature review delves into the intricate interplay among diverse factors that impact the efficacy of Anti-Money Laundering (AML) in banking institutions. Specifically, it highlights the functions of Financial Intelligence Units (FIU), Machine Learning (ML), Risk Assessment (RA), Suspicious Transaction Detection (STD), and Money Laundering Prevention (MLP).

The proposed hypotheses were as follows:

H1: RA has a positive significant influence on STD.

[15] highlights how important risk assessment is for determining and ranking the hazards connected to questionable transactions. Banks can more effectively detect suspicious activity by strategically allocating resources thanks to effective risk assessment procedures. [16] has indicated that comprehensive risk assessment (RA) frameworks, incorporating ongoing transaction monitoring and evaluation against predetermined risk parameters, greatly enhance financial institutions' capacity to detect and treat cyberattacks.

H2: FIU has a positive significant influence on STD.

[17] emphasizes how crucial Financial Intelligence Units are to improving STD. Early detection of suspicious activity is greatly aided by the financial intelligence units (FIUs) that gather, analyse, and distribute critical financial data and intelligence. Empirical studies demonstrate that efficient Financial Intelligence Units (FIUs) serve as pivotal centres of information exchange and synchronization, notably enhancing banks' ability to address possible money laundering risks.

H3: ML has a positive significant influence on STD.

The potential of machine learning technology to enhance Suspicious Transaction Detections (STDs) through complex pattern identification and anomaly detection is becoming more widely acknowledged. More quickly than using traditional approaches, ML systems can evaluate large datasets and spot tiny patterns that point to suspect conduct. The effectiveness of machine learning (ML) in improving detection accuracy and lowering false positives in transaction monitoring systems has been demonstrated by [18].

H4: RA has a positive significant influence on MLP.

By assisting institutions in managing their exposure to possible money laundering activities, risk assessment plays a fundamental role in the fight against money laundering. Through risk assessment at several phases, such as client onboarding and continuous transaction monitoring, RA guarantees that controls are suitable and efficient, hence providing direct support to MLP goals. [19]

H5: FIU has a positive significant influence on MLP.

FIUs play a critical role in supporting MLP by offering vital intelligence and insights that direct the creation of preventive measures. According to [20], FIUs improve regulatory compliance and enforcement by collaborating and exchanging information more effectively with other financial and law enforcement entities. This has a substantial positive impact on MLP.

H6: ML has a positive significant influence on MLP.

The ability of machine learning to regulate regulatory compliance and stop financial crimes before they happen defines its function in MLP. Proactive MLP methods are supported by ML applications in behaviour modelling, customer profiling, and complex data analysis. According to [18], ML not only recognizes but also anticipates possible money laundering actions, enabling organizations to take preventative action.

H7: FIU strengthens the positive significant influence of RA on STD.

According to [21], RA for STDs may be more effective when FIU insights are used. This synergistic effect happens when FIUs offer real-time intelligence and data that improves the precision of risk assessments made to identify suspicious transactions, making RA operations more focused and successful.

H8: FIU strengthens the positive significant influence of RA on MLP.

Likewise, [22] indicates that FIUs might augment the influence of RA on MLP by means of enhanced comprehension and monitoring of AML strategies and tendencies. The preventive capabilities of financial institutions are strengthened when FIUs contribute to the RA procedures and help guarantee that risk controls and preventive actions are solid and well-informed.

H9: ML strengthens the positive significant influence of RA on STD.

The idea that ML technologies can improve the efficacy of RA processes in STD cases is supported by newly available data. Banks can use predictive analytics to anticipate and manage the risks associated with suspicious transactions by combining machine learning algorithms with risk assessment frameworks. This strengthens the system. [23]

H10: ML strengthens the positive significant influence of RA on MLP.

The influence of RA on MLP is further enhanced by machine learning, which offers sophisticated analytical tools that enhance the comprehension of risk patterns and customer behaviour. Because of this integration, MLP tactics can be more accurate and successful, and institutions can adjust their AML controls dynamically in response to assessments of predicted risk. [24]

Outcome and Propositions: The review concludes that the coordinated operation of STD, MLP, FIU, ML, and RA is critical to the efficacy of AML systems in banks. Together, these elements support the identification and thwarting of illicit financial activity, protecting the integrity of financial systems and enforcing regulatory compliance.

The current study's assumptions are tested against a theoretical backdrop provided by this synthesis of the literature, which focuses on the important linkages between the identified variables and their effect on AML outcomes within banks.

IV. MATERIAL AND METHODS

A. Study Design and Sample

The data in this study was gathered using a structural questionnaire. To accomplish its goals, the study uses both primary and secondary data. First, secondary data is used, which comes from already-published materials like books, articles, and research that have already been done by others. This stage offers insights into the important problems and gaps in the field of Anti-Money Laundering (AML) adoption by USA Regional Banks, which helps to shape the study questions, goals, and hypotheses. A range of databases and search engines, such as EBSCO and Google Scholar, are utilized to collect pertinent articles that aid in the development of the research framework.

Primary data is gathered directly using techniques like surveys when secondary data is found to be inadequate for the needs of the study. Primary data are necessary for this study to test the customer value framework and hypotheses derived from secondary research. The primary data is obtained by the distribution of an online Google Forms questionnaire to AML specialists from different industries. Direct communication, business cards, and social media sites like Facebook and LinkedIn are examples of outreach techniques.

To achieve impartial and accurate data collecting, the methodology relies on survey respondents being informed and genuine in their answers. Potential participants are individually invited to participate in the survey process using a variety of digital communication channels, with a focus on the study's voluntary nature and lack of any financial incentives. This method makes sure that every participant gets a chance to answer all their questions and that any concerns they may have about the survey are resolved quickly and efficiently.

In total 200 questionnaires were gathered, responses were coded into PC by assigning weights for responses, missing values were not an issue as all questions were marked as required, further, screening data was conducted to exclude non-valid questionnaires that include consistent repeated assessments showing possible assessment pattern, by examining the dataset, 10 questionnaires were found having consistent pattern, therefore, were dropped from the sample. After that, influential responses that is outliers in data was detected as having outliers in data lead to inappropriate estimation results, detection of outliers was based on Cook's distance coefficients, [10] proposed the cut-off [0.1] for this purpose, an observation that scores high value of Cook's distance above [0.1] cut-off show high influence by that observation over the slope of regression line, by examining Cook's distance for observations of current dataset, five responses were detected as outliers, therefore, were surpassed from the sample, by conducting data screening, the valid sample comprised of 185 valid responses.

B. Variables and Analysis Methods

The constructs of the model of this study were estimated using reflective measurements that each one comprises of multiple items, the items of each measure were developed to maintain the theoretical considerations the construct seeks to examine, the operationalization of each construct was as follows:

1) Suspicious Transaction Detection [STD]: This construct measures actual efficient detection of suspicion transactions, the items in this measure suppose that efficient detection of suspicious transaction has occurred and ask about the components that of that efficient detection. The construct includes five items, example of used items: “Information about suspicious customers enables the assessment of potentially suspicious transactions” and “Transaction Management significantly affects the detection of suspicious activities” [13].

2) Money Laundering Prevention [MLP]: Items in this construct measure activities that lead to prevention of money laundering, items cover aspects related to tax crime, shell firms, KYC, mafia-controlled firms and financial crimes. The construct includes five items, example of used items: “Successful implementation of KYC (Know Your Customer) significantly enhances banks' ability to prevent money laundering” and “Effective measures prevent the use of Mafia-Controlled firms for illegal money laundering activities” [13].

3) Financial Intelligence Unit [FIU]: This construct measures efficient employing of FIU to support money laundering prevention and suspicious transaction detection, the construct encompasses measures of reporting, regulatory and law enforcement and financial formal systems related to FIU integration in the organization. The construct includes five items, example of used items: “Financial formal systems are critical to maintaining the stability and integrity of the global financial system” and “Regular reporting plays a crucial role in building trust between banks and the Financial Intelligence Unit” [13].

4) Machine Learning [ML]: This measure considers the capabilities that ML provides in the context of money laundering prevention and suspicious transaction detection, areas that this construct considers are algorithms, statistical methods, deep learning, prediction analysis and detection. The construct includes five items, example of used items: “Deep learning contributes to anti-money laundering (AML) tasks by detecting suspicious transactions and patterns” and “Fraud detection through Machine Learning mechanisms can contribute to the effectiveness of anti-money laundering solutions in banks” [13].

5) Risk Assessment [RA]: This construct measures the efficient application of RA as a tool that supports organization efforts toward money laundering prevention and suspicious transaction detection, the measure covers RA compliance, governance, risk-based approach, rule-based approach and security control structuring. The construct includes five items, example of used items: “A risk-based approach is a regulatory requirement for banks to access the impact of risks associated with money laundering activities” and “Governance also plays a critical role in managing risk” [13].

All items that measured the model constructs were measured based on a 5-points Likert scale that ranges from strongly disagree [1] to strongly agree [5].

To estimate the proposed model, structural equation modelling through Partial Least Squares [SEM-PLS] was used is a variance-based estimation method. This method allows analysing proposed relationships in the path model, such analyses provide explanation of targeted constructs based on the perspective of prediction constructs [6]. According to [2], this approach is one of superior approaches for modelling of prediction-oriented studies, as the focus in such studies is on the targeted constructs [4]. Indeed, SEM-PLS handles complex structural models making it an appropriate analytical approach for confirmatory research that seeks to provide deep understanding of causal relationships between the theoretical variables proposed in the model through providing empirical evidence describing the operating mechanism [3].

In applying SEM-PLS, as a start, the measurement model was tested to support the underlying factor structure of the proposed measures, meanwhile, structural model was estimated to examine relationships, further, the bootstrapping of 5000 subsamples was applied to test the significance of the model based on a two-tailed test, therefore, the assessments begin with the measurement model, and later moved to the structural model ([11]; [6]). In this study, data analysis was based on using Smart PLS v4 to apply SEM-PLS, along with using the Statistical Package for Social Science [IBM-SPSS] v27 to conduct preliminarily analysis of data.

V. EMPIRICAL RESULTS

A. Demographic and Descriptive Statistics of the Sample

Descriptive statistics of demographic data gathered in Table I indicated that males 87.0% are overrepresented in the sample in compare to females 13.0%, further, majority of the sample 75.1% are in the middle age that is between 31 – 40 years, 17.3% are in the age between 41 – 50 years, 3.8% are in the age 51 – 60 years, 2.7% are in the age 20 – 30 years and 1.1% are in the age 61 and above. Concerning education level, half of the sample 45.9% completed bachelor’s degree, the other half 51.4% completed master’s degree and 2.7% completed doctorate degree. For job designation, about half of the sample 45.4% were managers, 13.5% were executive, 10.3% were head of department and 30.8% reported others that included: Developer, IT engineer/ Software/ data Engineer, Chairman, Assistant manager, Director, Advisor, Senior Compliance Associate, Researcher/ Senior scientist, Academic/ Lecturer, Tech lead /VP, Advisor, Tech Lead, Consultant/ Senior consultant, Homemaker, Individual Contributor, Vice President, Software Professional, Tech Arch, Product Owner, Deputy head of department, Solution Architect, Oracle dba, Individual contributor, Senior Data Scientist, Business Analyst and Business Systems Analyst. Regarding job roles of surveyed respondents, more than half of the sample 67.0% were IT professional, 9.2% were End user, 7.6% were Technology transfer, 4.9% were AML expert and 11.4% reported others that included: Accounts Book Keeping, KYC Checker, Director/ Local Government, Education, Sales and marketing, Finance Manager, Economist, Technology Control Officer, Third Party Risk Manager, Data scientist, Investment Banking Operations, Portfolio Manager, Regional Rewards Lead, Customer Strategy & Risk Ops, Administration, Fund Services – Legal, Government Service, Fraud analytics, Strategic initiatives in an investment bank and Underwriting Operations. Meanwhile, for work experience that respondents have, half of the sample 52.4% have between 11 – 15 years, 23.2% have between 16 – 20 years, 11.9% have between 6 – 10 years, 9.2% have 20 and above and 3.2% have between 1 – 5 years. Finally, the sample reported many techniques or systems have been used to support the objectives of the AML approaches in their institutions that were displayed in Table I. For further elaboration on the 'others' listed within both the job designation and job role categories in Table I, as well as the techniques or systems employed to reinforce the objectives of the AML approaches.

TABLE I DEMOGRAPHIC DATA

	Count	%
Gender		
Male	161	87.0%
Female	24	13.0%
Age		
20 – 30 years	5	2.7%
31 – 40 years	139	75.1%
41 – 50 years	32	17.3%
51 – 60 years	7	3.8%
61 and above	2	1.1%
Education level		
Bachelor’s degree	85	45.9%
Master’s degree	95	51.4%
Doctorate	5	2.7%
Job designation		
Executive	25	13.5%
Manager	84	45.4%
Head of Department	19	10.3%
Others	57	30.8%
Job role		
End user	17	9.2%
Technology transfer	14	7.6%
IT professional	124	67.0%
AML expert	9	4.9%
Others	21	11.4%
Work experience		
1 – 5 years	6	3.2%

6 -10 years	22	11.9%
11 - 15 years	97	52.4%
16 - 20 years	43	23.2%
20 and above	17	9.2%

Below Table II gives descriptive data, mean values were in high levels exceeding level of (4) showing that respondents assessments were in favour of proposed constructs, furthermore, agreement and homogeneity in assessments were proofed based on Std. coefficients that didn't exceed level of [1], donating that assessments were clustering around its mean values. Skewness and Kurtosis are measures of data symmetry, dataset can be seen free of normality issues based on Skewness values that didn't exceed proposed cut-off that is ± 2.3 as suggested by [5], meanwhile, kurtosis values didn't exceed the proposed cut-off that is ± 7 as suggested by [1], accordingly, dataset is suitable for further analysis.

TABLE II DESCRIPTIVE DATA

	Mean	Std.	Skewness	Kurtosis
STD	4.21	0.54	-1.415	6.232
MLP	4.12	0.54	-.157	.119
FIU	4.26	0.47	-.172	-.381
ML	4.21	0.51	-.399	.336
RA	4.11	0.53	-.243	-.355

STD= Suspicious Transaction Detection, ML= Money Laundering Prevention, FIU= Financial Intelligence Unit, ML= Machine Learning, RA= Risk assessment

B. Inferential Statistics

1) Measurement Model Assessment

The findings for CFA are presented in Table III. For assessing the measurement model, recommendations by [8] and [7] were applied, assessments included examining reliability of indicators, internal consistency, convergent validity and discriminant validity. Reliability of indicator was checked based on Factor Loading [FL] that examines the shared variance between associated construct and each individual indicator, as minimum cut off, 0.50 was maintained for all indicators, any indicator with FL below 0.50 shows a violation of indicator reliability and should be omitted from the model, and its recommended that FL exceed the preferred cut-off that is 0.70 to avoid reduces in Average Variance Extracted [AVE] coefficients that examines the convergent validity. Based on checking FL of indicators, neither of indicators have FL below 0.50 cut off, however, when examining AVE of constructs reduces were seen, therefore, dropping indicators that has least FL was carried out to enhance AVE coefficients, accordingly, four indicators that are: FIU5, MLP2, RA2, STD5 were omitted from the model.

As all retained indicators have FL above 0.50 minimum cut-off, and majority of indicators have FL exceeds 0.70 preferred cut-off, as its acceptable to retain items with FL above 0.60 [6], and all FL were significant at 0.01 two tailed with T values exceeding minimum of 1.96, its evident that FL of indicators were significant entailing that indicator's reliability was satisfactory and maintained for the measurement model. Full results for examining the measurement model were delivered in Table III.

TABLE III RESULTS FOR EXAMINING THE MEASUREMENT MODEL

Construct	Item	CR	AVE	FL	(T) value
FIU	FIU1	0.812	0.519	0.719	16.676**
	FIU2			0.701	11.786**
	FIU3			0.709	9.970**
	FIU4			0.751	16.443**
ML	ML1	0.868	0.570	0.755	13.486**
	ML2			0.784	18.876**
	ML3			0.780	19.555**
	ML4			0.680	10.898**
	ML5			0.769	18.765**

MLP	MLP1	0.819	0.531	0.680	10.490**
	MLP3			0.713	13.168**
	MLP4			0.774	16.301**
	MLP5			0.744	15.397**
RA	RA1	0.822	0.536	0.756	15.793**
	RA3			0.764	19.188**
	RA4			0.670	8.260**
	RA5			0.734	12.761**
STD	STD1	0.804	0.507	0.734	10.705**
	STD2			0.690	10.606**
	STD3			0.725	9.447**
	STD4			0.699	8.995**

**P < 0.01

Furthermore, internal consistency reliability was satisfied based on composite reliability [CR] criterion, this criterion should not be below 0.70 to support internal consistency of constructs, findings in Table III shows a clear support of constructs internal consistency reliability, all CR values were found exceeding 0.70 cut-off. Regarding convergent validity, AVE criterion allows to assess convergent validity of the model constructs, a minimum of 0.50 is required to support the convergent validity of the model, all listed AVE values in Table III demonstrates a support of adequate convergent validity, all constructs have AVE values greater than minimum of 0.50 suggested cut off. Finally, maintaining discriminant validity of the model was based on adequate Heterotrait Monotrait ratio of correlations [HTMT] values (See Table IV) that were lower than 1 cut-off and majority of values were lower than the conservative cut-off value of 0.85 [9].

TABLE IV RESULTS FOR HTMT OF THE MEASUREMENT MODEL

Construct	FIU	ML	MLP	RA	STD
FIU					
ML	0.570				
MLP	0.689	0.402			
RA	0.654	0.456	0.642		
STD	0.567	0.395	0.695	0.499	

2) Structural Equation Modelling and Hypotheses testing

The structural model allows for examining relationships between model constructs, examining the structural model was based on guidelines by [7], [8]. Assessments begin with checking collinearity issues, values of Variance Inflation Factor [VIF] gives this issue check, neither of VIF values in our structural model were above cut-off of [5], indicating that collinearity is not a critical issue. Further, R2 statistics examined the model explanatory power in-sample, recorded R2 statistic in the predicted variables scored in STD [20.7%] and in MLP [33.6%], thereby, showing adequate explanatory power in-sample of our model. Furthermore, predictive relevance of out-of-sample of the model was based on examining Q2predict in the predicted variables, recorded Q2predict statistic in the predicted variables scored in STD [0.120], and in MLP [0.264], according Q2predict were exceeding zero showing large predictive relevance of out-of-sample of the model, also another support of the predictive relevance was based on comparing RMSE coefficients between LM and PLS models, all RMSE coefficients were found greater in LM model than in the PLS model, hence, the structural model enjoys large predictive relevance.

After satisfying the quality of our structural model, we proceeded to examine the size and significance of the path coefficients [β]. Figure 1 gives the estimation of our proposed structural model. Our model hypotheses were grouped based on its outcomes as follows:

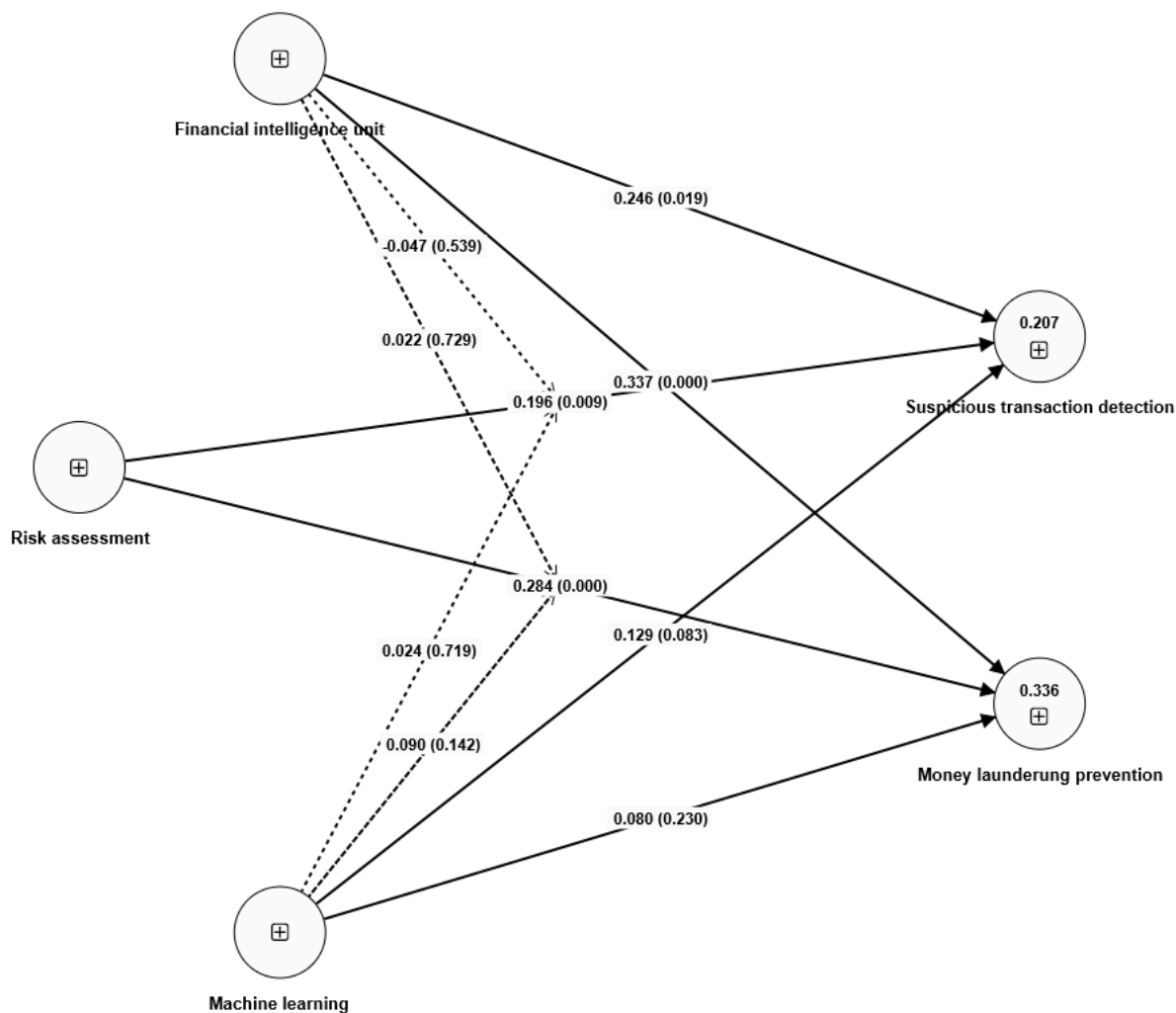


Figure 1 Estimation of the proposed structural model

a) Predictors of Suspicious Transaction Detection (STD)

In the proposed model, three predictors were proposed to enhance and support STD, the proposed hypotheses were as follows:

H1: RA has a positive significant influence on STD.

The path examining $RA \rightarrow STD$ was significant having $[\beta = 0.196]$ showing a positive influence, hence as RA application increases, STD is enhanced, the influence was significant scoring $[t = 2.622, P = 0.009]$, findings support H1.

H2: FIU has a positive significant influence on STD.

The path examining $FIU \rightarrow STD$ was significant having $[\beta = 0.246]$ showing a positive influence, hence as FIU application increases, STD is enhanced, the influence was significant scoring $[t = 2.338, P = 0.019]$, findings support H2.

H3: ML has a positive significant influence on STD.

The path examining $ML \rightarrow STD$ was non-significant scoring $[t = 1.731, P = 0.083]$, entailing that despite the influence of ML on STD was positive, however, the influence was non-significant, findings render no support for H3.

b) Predictors of Money Laundering Prevention (MLP)

In the proposed model, three predictors were proposed to enhance and support MLP, the proposed hypotheses were as follows:

H4: RA has a positive significant influence on MLP.

The path examining $RA \rightarrow MLP$ was significant having $[\beta = 0.284]$ showing a positive influence, hence as RA application increases, MLP is enhanced, the influence was significant scoring $[t = 3.777, P = 0.000]$, findings support H4.

H5: FIU has a positive significant influence on MLP.

The path examining FIU → MLP was significant having [$\beta = 0.337$] showing a positive influence, hence as FIU application increases, MLP is enhanced, the influence was significant scoring [$t = 4.610, P = 0.000$], findings support H5.

H6: ML has a positive significant influence on MLP.

The path examining ML → MLP was non-significant scoring [$t = 1.200, P = 0.230$], entailing that despite the influence of ML on MLP was positive, however, the influence was non-significant, findings render no support for H6.

c) Moderating roles testing:

For moderation mechanisms, we propose that as RA is a promoter of both STD and MLP, and we also propose that technological capabilities such as FIU and ML can also promote and support STD and MLP, we expect that applying appropriate RA along with aligning FIU and ML should lead to better STD and MLP, hence, we propose interaction roles between RA and FIU and RA and ML. Proposed moderation roles were as follows:

H7: FIU strengthens the positive significant influence of RA on STD.

The interaction influence between FIU × RA on STD scored a negative non-significant influence [$\beta = -0.047, t = 0.615, P = 0.539$], thereby, entailing that alignment between FIU and RA is not in its expected position, in fact, as the interaction influence was negative, this entails that FIU was seen as dampening the positive influence that RA scored on STD, thereby entailing a sound of a critical issue should be considered. Results render no support for H14. Figure 2 provides the slope analysis for FIU × RA → STD.

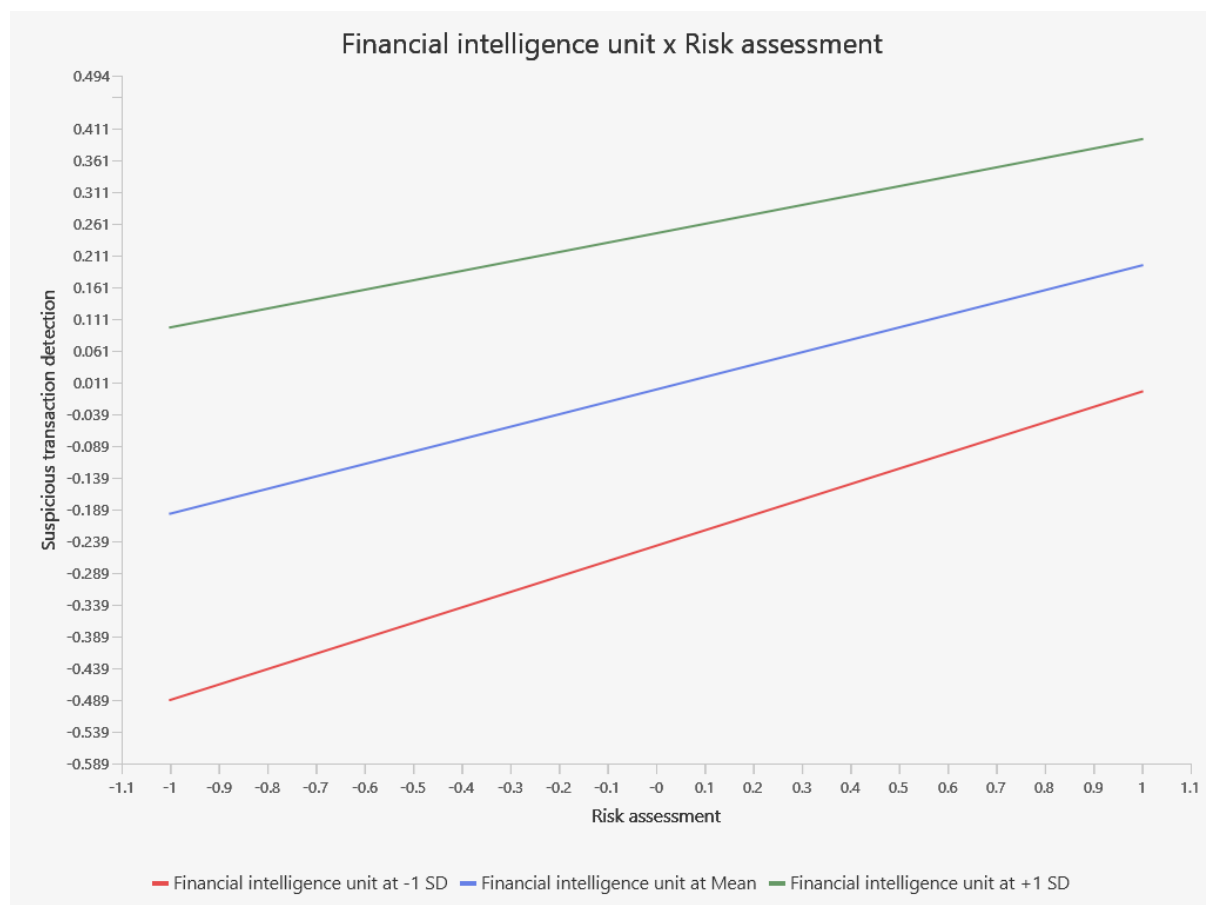


Figure 2 Slope analysis for FIU × RA → STD

H8: FIU strengthens the positive significant influence of RA on MLP.

The interaction influence between FIU × RA on MLP scored a positive non-significant influence [$\beta = 0.022, t = 0.346, P = 0.729$], thereby, entailing low levels of alignment between FIU and RA as the

interaction influence was positive, this entails that FIU was seen as strengthening the positive influence that RA scored on MLP, however this strengthening role was low, entailing the need for better alignment between FIU and RA. Results render no support for H15. Figure 3 provides the slope analysis for $FIU \times RA \rightarrow MLP$.

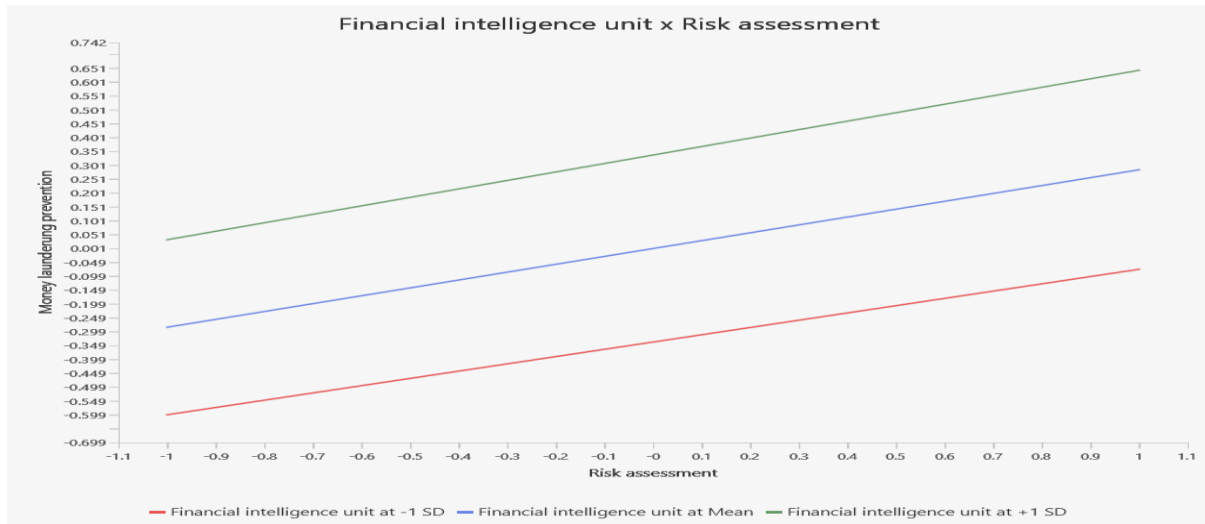


Figure 3 Slope analysis for $FIU \times RA \rightarrow MLP$

H9: ML strengthens the positive significant influence of RA on STD.

The interaction influence between $ML \times RA$ on STD scored a positive non-significant influence [$\beta = 0.024$, $t = 0.359$, $P = 0.719$], thereby, entailing low levels of alignment between ML and RA as the interaction influence was positive, this entails that ML was seen as strengthening the positive influence that RA scored on STD, however this strengthening role was low, entailing the need for better alignment between ML and RA. Results render no support for H16. Figure 4 provides the slope analysis for $ML \times RA \rightarrow STD$.

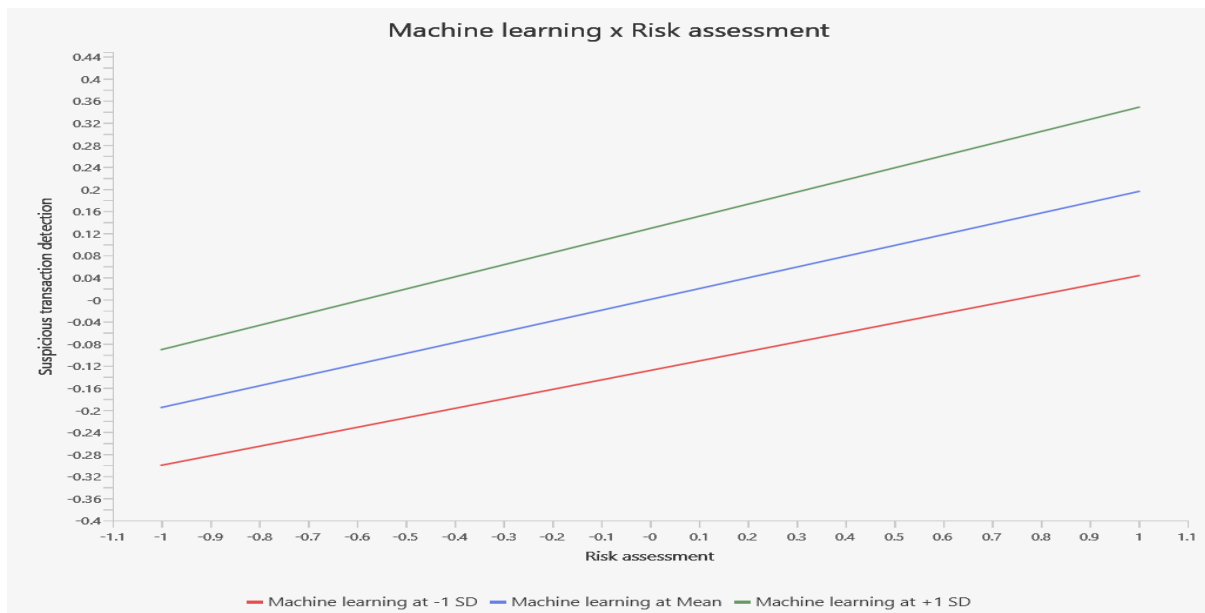


Figure 4 Slope analysis for $ML \times RA \rightarrow STD$

H10: ML strengthens the positive significant influence of RA on MLP.

The interaction influence between $ML \times RA$ on MLP scored a positive non-significant influence [$\beta = 0.090$, $t = 1.468$, $P = 0.142$], thereby, entailing low levels of alignment between ML and RA as the interaction influence was positive, this entails that ML was seen as strengthening the positive influence that RA scored

on MLP, however this strengthening role was low, entailing the need for better alignment between ML and RA. Results render no support for H17. Figure 5 provides the slope analysis for $ML \times RA \rightarrow MLP$.

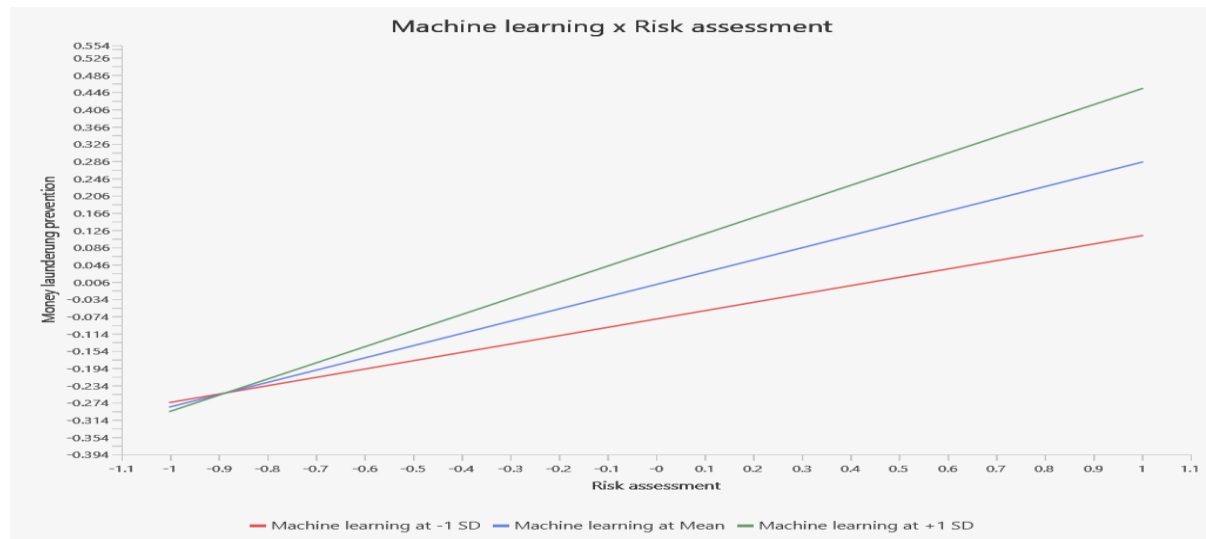


Figure 5 Slope analysis for $ML \times RA \rightarrow MLP$
 Below Table V gives a summary of structural model estimation.

TABLE V
 SUMMARY OF STRUCTURAL MODEL

Path	β	(T) value	(P) value	Decision
Predictors of STD				
RA \rightarrow STD	0.196	2.622	0.009**	Supported
FIU \rightarrow STD	0.246	2.338	0.019*	Supported
ML \rightarrow STD	0.129	1.731	0.083	Not supported
Predictors of MLP				
RA \rightarrow MLP	0.284	3.777	0.000**	Supported
FIU \rightarrow MLP	0.337	4.610	0.000**	Supported
ML \rightarrow MLP	0.080	1.200	0.230	Not supported
Moderating roles				
FIU \times RA \rightarrow STD	-0.047	0.615	0.539	Not supported
FIU \times RA \rightarrow MLP	0.022	0.346	0.729	Not supported
ML \times RA \rightarrow STD	0.024	0.359	0.719	Not supported
ML \times RA \rightarrow MLP	0.090	1.468	0.142	Not supported

*P < 0.05 // **P < 0.01

VI. DISCUSSION

This study sought to investigate predictors of Suspicious Transaction Detection [STD] and Money Laundering Prevention [MLP] in the context of USA's Regional Banks, based on a structured survey that gathered perceptions of employees in the targeted banks, results of this study were delivered. The sample has 185 respondents, SEM-PLS was applied through Smart PLS software. Findings of the study provided insights for the role of Risk assessment [RA] and technological capabilities such as Financial Intelligence Unit [FIU] and Machine Learning [ML] in the Suspicious Transaction Detection and Money Laundering Prevention.

Results of the study emphasized the role of effective RA in promoting and enhancing STD and MLP, in fact, RA was found significantly influencing both constructs, hence, it's vital for banks and financial institutions to apply adequate RA to achieve its desired goals in regard of STD and MLP. Moving on to the role of current technology that can take a role in this vin, FIU was seen as taking its suggested role in promoting STD and MLP, thereby, demonstrating the necessity of adopting such technologies around STD and MLP. On the other hand, disappointing results for ML technology was found, in fact, ML was unable to achieve significant positive influences neither on STD nor MLP, this in fact doesn't

underestimate of ML role, however, entailing possible defect in the current application of ML for these purposes in surveyed banks, accordingly, its vital to consider better application of ML to trigger its capabilities and allow for efficient support for STD and MLP.

Finally, as we are aware that systems and operations within the organization are interdependent on each other, we propose that applying RA should benefit of technological capabilities that the organization adopt such as FIU and ML, so that we argue that adequate alignment between RA and FIU and ML capabilities should achieve better levels in regard of MLP and STD, our moderation roles were non supported, and this also provided disappointing results, however, this can be taken as lessons and issues surveyed banks should consider to resolve, as technological team applying FIU and ML should work together with RA team to support their activities.

CONCLUSION

The results of this study highlight the important role that technology integration plays in fortifying regional banks' anti-money laundering (AML) policies in the United States. Applying cutting-edge technology, especially in the fields of financial intelligence units (FIU) and machine learning (ML), has demonstrated to improve banks' capacity to identify suspicious transactions and successfully stop money laundering operations. The goal of the study was to verify the premise that improvements in technology will lead to better anti-money laundering (AML) practices. However, the data strongly supported this assumption for both money laundering prevention (MLP) and suspicious transaction detection (STD).

Even with the encouraging results, there were several difficulties with the study, especially with the moderating functions of the constructs, which did not produce the desired results. This part of the results shows that although technology is important, it needs to be integrated into AML strategies carefully, considering the organizational environment and current procedures. The statement posits that a universal solution is unattainable and that financial institutions must customize their technology implementations to precisely correspond with distinct operational demands and regulatory mandates.

The practical consequences are as follows: in addition to making technology investments, regional banks also need to make sure that their technological capabilities and the AML rules are strategically aligned. To guarantee that the adoption and integration of new technologies favourably impact the banks' AML initiatives, cooperation between technological teams and AML departments needs to be improved. In addition, it is imperative to establish ongoing training and development initiatives to furnish AML staff with the requisite competencies to proficiently utilize these technologies.

In summary, this study adds to the body of knowledge by presenting actual data on the efficiency of technology integration in AML initiatives throughout the regional banking industry in the United States. Future studies ought to examine the technology kinds that have the biggest effects on AML as well as any possible implementation hurdles. Furthermore, comparative research involving various banking institutions or global settings may offer more profound understanding of the adaptability and scalability of technological solutions in various regulatory environments. This will improve banks' strategic methods to fight money laundering worldwide as well as increased awareness of technology's role in AML.

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