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Statistical in Sights in to Anti-Money Laundering: Analyzing Large-Scale Financial Transactions

Balaji Ramanujam
Credit Risk Control, Standard Chartered Bank
New York Metropolitan Area, USA

***Abstract*—The Study motive is to inspect money laundering transactions through the "Anti Money Laundering Transaction Data" (SAML-D) dataset for understanding fraud detection patterns and fundamental patterns. The study uses SPSS (Statistical Packages for Social Sciences) for statistical analysis while applying descriptive statistics and frequency analysis together with T-tests along with correlation analysis and regression modeling. The research design incorporates hypothesis testing in combination with predictive modeling to evaluate the transaction characteristics of sender accounts and receiver accounts as well as transaction amount and payment types. The evaluated cases show that money laundering operations process transactions with substantially larger values. Statistical tests demonstrate significant variations between regular transactions and fraudulent transactions and weak yet substantive relationships exist between banking characteristics and laundering activities. Regression analysis confirms transaction amount as a key predictor, though with limited explanatory power. The study concludes that while traditional statistical approaches effectively identify basic laundering patterns, advanced machine learning techniques should complement these methods for improved fraud detection. Financial institutions must enhance transaction monitoring, enforce stricter regulatory compliance, and adopt real-time fraud detection systems to mitigate risks. Future research should explore deep learning and blockchain integration for more robust anti-money laundering frameworks.**

***Keywords*—Money laundering, fraud detection, SAML-D dataset, SPSS, financial transactions, statistical analysis, risk mitigation, predictive analytics.**

I. INTRODUCTION

There have been new opportunities brought about by the advancement of technology and globalization in the last two decades. The deregulation of capital markets, the efficiency with which fintech facilitates monetary transactions, and economic integration have all been impacted by these issues. But these developments have helped criminal organizations with their money laundering (ML) operations. If you want to escape prosecution and keep the money you made illegally, you can use money laundering to hide where it came from and turn it into regular currency. The goal is to keep the money and make it seem legitimate. The motive of this illegal activity is to cover the origin of capitals and then absorb them into the legitimate financial system [1]. It is now easier than ever to launder money and fund terrorists because of the interconnected web of global financial systems and technologies.

As shown in Figure 1, there are three distinct stages to the process of money laundering: "Placement, Layering, and Integration". Keep in mind that not every money-laundering deal goes through each of these stages. The only way to make sense of this possibly complex procedure is to outline these separate steps. Conventional methods like manual inquiry, transaction monitoring, watchlists, and blacklists often lead to high erroneous rates, inflexibility, problems with managing large amounts of data, an emphasis on particular transactions, and an inability to evolve [2], [3].

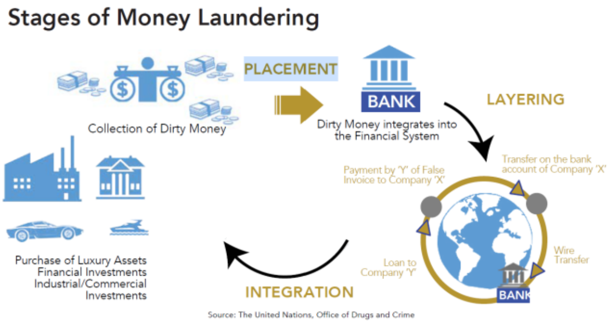

Fig. 1. Money Laundering: a three-stage process [4]

Criminal justice systems aren't the only ones that ML operations could disrupt; financial institutions and the entire financial system are also vulnerable. Consequently, ML is a foremost hazard to the economy of the globe [5]. Using this as a starting point, international organizations have droughted anti-money-laundering legislation, and individual countries have set up agencies to deal with the problem.

In its initial recommendation from 1988, the Basel Committee on Financial Supervision (BCBS) sought to combat money laundering by stopping criminals from misusing the financial system. The primary goal of this document was to lay out the ground rules for preventing money laundering, identifying or knowing the client, ensuring legal compliance, working with law enforcement, and complying with declarations. In light of the seriousness of the threat and the weight that this phenomenon deserves, BCBS has, in close conjunction with other relevant authorities, released regulations designed to combat it. Updated the safe handling of ML/FT hazards on July 20, 2020 [6].

Giving people and companies access to banking services has been an important part of the world economy for a long duration. On the other hand, fraud, money laundering, and terrorism funding have all targeted the banking sector [6]. Nevertheless, financial crimes, including money laundering, illicit financing, and fraud, have also targeted the banking system. Laundering allows criminal proceeds to be legalized. A big problem for banks nowadays is money laundering, which is becoming more complex as criminals get smarter [6], [7]. Compliance with

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regulations meant to prevent money laundering is rapidly becoming an area where big data analytics are indispensable, according to the ever-increasing data output by the banking sector. The banking industry's anti-money-laundering efforts could benefit from big data analysis.

The volume of financial data has surged due to the swift expansion of financial transactions enabled by digital banking, online payments, and cryptocurrency. Complex statistical approaches are required to analyze large-scale financial transactions in order to detect abnormalities, discover suspect patterns, or improve regulatory compliance [8], [9]. This contrasts sharply with rule-based systems, which have a high false alarm rate, since statistical-based solutions have the ability to reduce false alarms while enhancing detection accuracy.

Numerous studies demonstrate the effectiveness of statistical techniques in AML applications. K-means and Hierarchical Clustering are two examples of clustering technologies that are used to identify anomalous transaction behavior. Time series analysis has been used in an effort to identify departures from typical financial activity [10]. Additionally, probabilistic techniques and regression models were applied to the classification and prediction of high-risk transactions [11], [12]. The study's current procedures will be expanded upon by enhancing AML frameworks and analyzing financial transaction evidence using empirical statistical techniques [13].

A. Objective of the Paper

This study aims to identify transaction patterns linked to money laundering using statistical analysis. It examines differences in normal and illicit transactions based on amount, payment type, and account details. By assessing correlations and predictive models, the research enhances financial fraud detection and supports regulatory compliance in anti-money laundering efforts.

B. Structure of the Paper

The structure begins with the heading of Introduction, which defines the general background of the topic. Section II: Literature Review explores existing research on money laundering detection. Section III: Methodology outlines data sources, statistical techniques, and analytical methods used. Section IV: Results presents descriptive statistics, hypothesis testing, and regression analysis. Section V: Conclusion summarizes findings, implications, and future research directions.

II. LITERATURE REVIEW

This section provides the existing work on anti-money laundering in the finance sector. Table I provides a summary of this related work.

Jiang (2024) centered on the obstacles and opportunities presented by big data analytics for use in combating financial fraud and money laundering. Financial crimes have changed over time, and this study starts by describing those changes and drawing attention to the new features of the big data age. After that, it takes a methodical look at how this industry is using big data analytics tools including real-time stream processing, machine learning, and network analysis. This study finds that these technologies improve the efficiency and accuracy of unusual financial deal identification through case studies. Big data analytics has many advantages, but the study also highlights some of its disadvantages, including problems with data integrity, bias in algorithms, and safeguarding personal information. Applying privacy-preserving technologies like “federated learning” is one of the technological and administrative methods proposed in the research to tackle these difficulties. The report concludes with a discussion of the future of regulatory technology, highlighting the need for cooperation between new technologies and government regulations [14].

Jiao (2023) Big data approaches were studied to enhance Anti-Money Laundering security measures focusing on reporting suspicious conduct and customer risk evaluations along with trade-based money laundering detection. Applications of big data tools enable more successful fund laundering detection due to improved compliance procedures and regulatory-interfinancial institution collaboration and accurate timely insights according to studies. The management of data privacy, along with ongoing money laundering threats, persist despite constant technological development. The study demonstrates how big data tools used in AML operations represent crucial tools that help battle money laundering activities. The international monetary system benefits from crucial information and solutions delivered through this research for its safety assurance[15].

Ogbeide et al. (2023) shed light on the process by which professionals evaluate potential threats to combating money laundering. This work objective to discourse a common issue in the risk assessment literature by investigating if experts in the field are less likely to be influenced by cognitive biases when assessing risks: the priority placed on completing checklists instead of making personalized decisions. They discovered that both the expert and novice groups were overconfident in their distribution judgements, with the expert group displaying a slightly more pronounced effect. False positives were preferred over false negatives in both groups as a result of the overconfidence effect. The percentage of right outcomes was somewhat higher for novice participants than for expert individuals. Professionals in this field might benefit from a feedback system that reduces biases, enhances procedures, and leads to more accurate judgments[16].

Parathi Tasan et al. (2023) pinpointed the factors that lead to Malaysian commercial banks engaging in money laundering. Given the paucity of research on the topic, to address. The study's accepted independent variables include technological advancements, regulatory frameworks, income levels, and ethical behavior. Commercial bank workers were surveyed using a convenience sample technique, with 102 questionnaires distributed. The outcome of the data analysis represents that the alternative hypotheses put forth for this study are all correct, but the null hypothesis was rejected. Furthermore, it is asserted that this study can teach commercial banks to detect and avoid money laundering within their own institutions, as well as address existing issues related to money laundering [17].

Lokanan (2019) performed research with the intention of mining and analyzing suspicious transactions using statistical methods. The capacity to identify such transactions is rapidly improving in response to the rising concern of money laundering in some of the world's most advanced democracies. There has been a need for a method that can sift through the mountains of unstructured data pertaining to questionable money laundering activities in order to influence public policy, both from regulators and practitioners. The paper presented a summary of

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data mining approaches for questionable transaction identification through research conclusions about ML detection methods. The text starts by explaining data mining concepts before investigating statistical procedures used to differentiate between legitimate and suspect money laundering activities. The paper thoroughly explains every data mining phase and its relevance to AML compliance rules. Statistical data mining techniques prove to be both beneficial and time-effective for identifying suspicious financial activities[18].

TABLE I. LITERATURE REVIEW SUMMARY

Ref	Aim	Methods	Findings	Conclusion
Jiang (2024)	Look into anti-money-laundering and fraud detection using big data analytics	Case Study Analysis	Big data analytics improves transaction anomaly detection but faces challenges like concerns related to data quality, algorithmic bias, and issues related to security.	Proposes solutions, including federated learning, and emphasizes RegTech innovation and regulatory synergy.
Jiao (2023)	Investigate big data techniques in AML, focusing on suspicious activity reporting and trade-based money laundering.	Analysis of big data applications in AML measures.	Big data techniques enhance AML effectiveness through accurate insights, compliance streamlining, and cross-border collaboration. Challenges include data privacy and evolving fraud tactics.	Highlights the need for continuous improvement in big data techniques to combat financial crimes.
Ogbeide et al. (2023)	Assess cognitive biases in AML risk assessments by experts and novices.	Risk assessment experiments comparing experts and novices.	Both groups showed overconfidence, favoring false positives. Novices slightly outperformed experts in correct outcomes.	Suggests implementing feedback mechanisms to reduce biases and enhance decision-making in AML risk assessments.
Parathi Tasan et al. (2023)	Identify determinants of money laundering in Malaysian commercial banks.	Survey of 102 bank employees, analyzed using SPSS.	"Innovation, the legal structure of income, and moral behavior associated with money laundering risks" appear to have a positive link.	Findings provide insights for banks to better detect and prevent money laundering.
Lokanan (2019)	Use statistical techniques for detecting suspicious transactions.	Examination of financial transactions by data mining and statistical methods.	Data mining effectively differentiates legitimate and suspicious transactions.	Advocates for the application of data mining in AML compliance to enhance detection.

III. RESEARCH METHODOLOGY

A. Research Design

A quantitative research design enables this work to study patterns in AML transactions. The research utilized a secondary dataset to generate statistical findings that provided objective data about transaction monitoring methods.

B. Data Collection

The study employed the Anti-Mooney Laundering Transaction Data (SAML-D) dataset, sourced from Kaggle. The dataset was developed by [19] and comprises 9,504,852 transactions, with 0.1039% labeled as doubtful. The dataset was generated to enhance AML monitoring, addressing data access limitations and typological diversity.

The “SAML-D dataset” includes 12 key features and 28 typologies, split into 11 normal and 17 suspicious categories. The dataset structure is detailed in Table II.

TABLE II. KEY FEATURES OF SAML-D DATASET

Feature	Description
Time and Date	Chronological tracking of transactions
Sender & Receiver Accounts	Behavioral analysis of transaction flow
Transaction Amount	Detection of high-value transactions
Payment Type	Various methods (credit card, debit card, ACH, etc.)
Sender & Receiver Bank Location	Identification of high-risk regions
Currency Type	Detection of anomalies in currency usage
Is Suspicious	Binary classification (normal/suspicious)
Typology	Categorization of money laundering typologies

C. Data Analysis

Statistics conducted using SPSS, or the Statistical Package for the Social Sciences, allowed for the discovery of trends and outliers. The following tests were performed:

- Descriptive Statistics: The analysis included descriptive statistics that provided summarized transaction details including mean values and standard deviation measurements.
- Frequency Analysis: Examined the distribution of normal vs. suspicious transactions.
- Chi-Square Test: Chi-Square Test evaluated payment type relationships with laundering status results.
- T-Test: T-Test analyzed the transaction amounts and account characteristics between laundering statuses.
- Correlation Analysis: The analysis used Correlation Analysis to evaluate how laundering status related to important characteristics.
- Regression Analysis: Evaluated predictors of suspicious transactions.

IV. RESULT AND DISCUSSION

This segment presents the analysis results from the dataset which includes “Descriptive statistics, Frequency distribution, Chi-Square statistics, Correlation analysis alongside Regression analysis”.

A. Descriptive Statistics

The descriptive statistics for the sender account, receiver account, and transaction amount are summarized in Table III.

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TABLE III. DESCRIPTIVE STATISTICS

	Minimum	Maximum	Mean		Std. Deviation
			Statistic	*Std. Error*	
Sender_account	92172	9999913136	5007746848.03	2822208.253	2889939872.919
Receiver_account	48238	9999971095	5032773667.01	2814983.613	2882541845.691
Amount	5	6213932	8707.65	23.873	24445.817

The above Table III presents the descriptive statistics for sender account, receiver account, and transaction amounts. The mean sender and receiver account values are approximately 5.01 billion and 5.03 billion, respectively, with large standard deviations indicating significant variations. The transaction amount averages $8,707.65, ranging from $5 to $6.2 million.

B. Frequency Analysis of Money Laundering Transactions

This section gives a synopsis of the dataset's distribution of both legitimate and illicit transactions.

TABLE IV. FREQUENCY OF MONEY LAUNDERING TRANSACTIONS

	Frequency	Percent
Normal	1047619	99.9
Money Laundering	956	.1
Total	1048575	100.0

The frequency analysis in Table IV reveals that 99.9% of the transactions in the dataset are classified as normal, while only 0.1% are identified as money laundering cases.

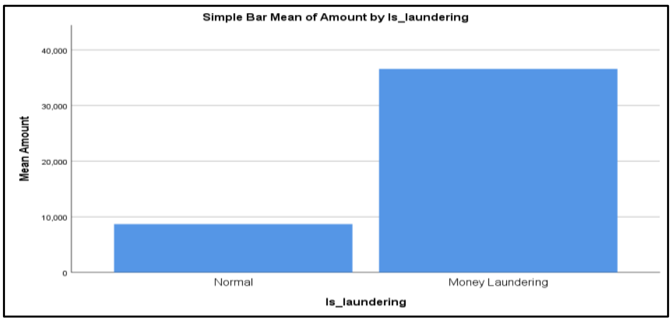

Fig. 2. Simple Bar Mean of Amount by Is Laundering

The above Figure 2 illustrates the mean transaction amount for normal and ML transactions. On average, the money laundering transactions are much higher than the normal transactions suggesting that illicit financial activities involve considerable sums. This distinction suggests the possibility of using transaction values as an important feature in detecting money laundering activities.

C. Relationship Between Payment Type and Money Laundering Transactions

The association between payment type and money laundering transactions is analyzed using chi-square tests.

TABLE V. PAYMENT TYPE * IS LAUNDERING CROSSTABULATION

Payment_type	Is_laundering		Pearson Chi-Square	P-Value
	Normal	*Money Laundering*		
ACH	222519	117	1115.802	.000
Cash Deposit	25024	130		
Cash Withdrawal	33455	122		
Cheque	221824	115		
Credit card	222033	133		
Cross-border	101093	229		
Debit card	221671	110		
Total	1047619	956		

The findings of the chi-square test in Table V show that there is a substantial correlation between the kind of payment and transactions involving money laundering ($\chi^2 = 1115.802$, $p < 0.001$). The highest proportion of illicit activities are found in cross-border transactions, the second is credit cards, and another one is cash-based ones. A suspicious transaction also occurs in certain other forms of payment like cheque, debit card, and ACH; however, their relative frequency is lower. This significant p-value indicates that money laundering is not randomly present in different payment methods but occurs more in particular payment methods. However, these findings emphasize the importance of closely examining high-risk payment channels, especially cross-border transactions, where the degree of illicit activities seemed to be greater.

D. T-Test Analysis

T-tests were conducted to compare normal and money laundering transactions.

TABLE VI. T-TEST STATISTICS

	Amount		Receiver_account		Sender_account	
Is_laundering	*Normal*	*Money Laundering*	*Normal*	*Money Laundering*	*Normal*	*Money Laundering*
Mean	8682.22	36571.56	5032942667.28	2882587337.380	5007475929.83	2890008214.859
Std. Deviation	22265.085	334010.9	4847577130.18	2827663791.565	5304628706.01	2799797141.312
t	-35.279		1.987		-3.178	
P-Value	0		0.047		0.001	

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In Table VI the t-test results indicate significant differences between normal and money laundering transactions. The transaction amount shows a substantial difference (t = -35.279, p < 0.001), with money laundering transactions having a much higher mean amount. The receiver account values are slightly lower for illicit transactions (t = 1.987, p = 0.047), indicating a weak but significant difference. Conversely, sender accounts exhibit a significant difference (t = -3.178, p = 0.001), suggesting potential behavioral patterns in fund transfers. These findings highlight key financial

discrepancies between normal and illicit transactions, supporting targeted monitoring efforts.

E. Correlation Analysis

The purpose of the correlation study was to determine the nature and direction of the correlations between the important variables.

TABLE VII. CORRELATION BETWEEN VARIABLES

		Is_laundering	Sender_bank location	Receiver_bank_ location	Payment_type	Laundering_type
Is_laundering	Pearson Correlation	1	-.002*	-.019**	-.002	-.019**
	P value		.026	.000	.064	.000
Sender_bank_location	Pearson Correlation	-.002*	1	.007**	-.119**	.034**
	P value	.026		.000	.000	.000
Receiver_bank_location	Pearson Correlation	-.019**	.007**	1	-.181**	.051**
	P value	.000	.000		.000	.000
Payment_type	Pearson Correlation	-.002	-.119**	-.181**	1	.044**
	P value	.064	.000	.000		.000
Laundering_type	Pearson Correlation	-.019**	.034**	.051**	.044**	1
	P value	.000	.000	.000	.000	
*. Correlation is significant at the 0.05 level (2-tailed).						
**. Correlation is significant at the 0.01 level (2-tailed).						

The correlation analysis in Table VII reveals weak but statistically significant relationships among key variables. receiver_bank_location has a negative correlation with Is laundering (r = -0.019, p < 0.01) and sender_bank_location (r = -0.002, p < 0.05) a small but significant impact of banks on law breaking. It has been detected that payment type is negatively correlated with sender_bank_location (r = -0.119, p < 0.01, r = -0.181, p < 0.01, in receiver_bank_location), hinting at the existence of particular payment types related to laundering transactions. All other variables except laundering type or the laundering type have weak positive correlations, which implies diverse laundering methods. When correlations are weak, they help detect useful patterns for financial crime detection.

F. Regression Analysis

The effect of critical variables on money laundering transactions was ascertained by a regression analysis.

TABLE VIII. MODEL SUMMARY

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.035a	.001	.001	.030
a. Predictors: (Constant), Amount, Receiver_account, Sender_account				

The model summary Table VIII shows an R-value of 0.035, indicating a very weak correlation between the independent variables (Amount, Receiver account, and Sender account) and the dependent variable (Is laundering). The R-Square value (0.001) suggests that only 0.1% of the variation in money laundering transactions is explained by these predictor variables, indicating that other unexamined factors contribute significantly to money laundering activity. As a measure of how far actual values have strayed from the predicted line, the standard error of the estimate is 0.030.

TABLE IX. ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1.145	3	.382	419.543	.000b
	Residual	953.983	1048571	.001		
	Total	955.128	1048574			
a. Dependent Variable: Is_laundering						
b. Predictors: (Constant), Amount, Receiver_account, Sender_account						

The regression model's statistical significance is assessed in ANOVA Table IX. The model is statistically significant, showing that the individual variables impact the dependent variable's value, according to the F-statistic (419,543, p < 0.001). Nevertheless, with an R-Square value being so low, the model only explains a small people of variance in money laundering transactions, indicating that there are other explanatory factors

TABLE X. COEFFICIENTS

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	*Std. Error*	*Beta*		
1	(Constant)	.000	.000		6.144	.000
	Sender_account	3.205E-14	.000	.003	3.144	.002
	Receiver_account	-2.064E-14	.000	-.002	-2.020	.043
	Amount	4.251E-8	.000	.034	35.279	.000
a. Dependent Variable: Is_laundering						

The above Table X of coefficient presents the relationship between individual predictor variables and money laundering likelihood.

- Sender account (B = 3.205E-14, p = 0.002): A positive but negligible effect on laundering transactions, suggesting that sender account details have a weak influence.
- Receiver account (B = -2.064E-14, p = 0.043): A very weak negative relationship, indicating that receiver account details have minimal impact.
- Amount (B = 4.251E-8, p < 0.001): A significant positive effect, meaning higher transaction amounts are strongly associated with money laundering transactions.

Despite statistical significance, the low coefficients highlight that these variables alone are not strong predictors of money laundering.

V. CONCLUSION

This study analyzed money laundering transactions using statistical techniques to identify key patterns and anomalies. The study found that money laundering transactions have much greater amounts than other transactions, but are only a fraction of the total. Secondly, T-test results showed the significant differences between normal and fraudulent ones with regard to sender and receiver accounts as well as transaction amount. Correlation analysis proved weak but significant correlations between laundered activities and bank location and payment type. Furthermore, regression analysis showed that the transaction amount is very predictive for money laundering. However, the overall explanatory power of the model was low.

In order to enhance money laundering detection, financial institutions will need to implement advanced machine learning models along with the statistical approaches for a better identification of fraudulent transactions. Regulators should also meet strict adherence to compliance measures in cross-border and high-value transactions, as these are more vulnerable to illegal activities. Real time transaction monitoring and Know Your Customer (KYC) as well should be enhanced by the banks for minimizing risk. Future research focusing on deep learning techniques as well as good integration of blockchain towards better fraud detection can be explored. Overall, for effective money laundering combat, a multi-layered approach that combines statistical, machine learning, and regulatory frameworks is needed.

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