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Transaction Monitoring vs. Trade-Based Money Laundering

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Abstract

This article explores crucially how effective traditional forms of transaction monitoring systems are in retrieving trade based money laundering (TBML) by criminal syndicates in the laundering of money through overseas trade by masking it as legal. Although transaction monitoring systems have taken up the additional features of machine learning technologies alongside other forms of analytics, the disciplines are still and have remained focused on capturing financial trade flows neglecting the prevalence and scope of underlying trade transactions. Thus, transaction monitoring systems are often incapable of capturing TBML and other laundering methods such as the over- or under- invoicing and phantom shipment laundering systems. Using a mixed method approach, this article engages in extensive quantitative assessment of suspicious transactions activity reports (SAR) and trade finance datasets as well as qualitative interviews with compliance and trade finance officers and other experts in regulation in numerous countries. Many if not most of the interviews concluded that TBML transaction monitoring systems are traditional. They fail TBML over 70% of the time, fragmented data systems, limited trade and financial metadata, and the systems inability to cross correlating financial and trade systems. Thus we propose the TBML Attestation Framework comprising 3 pillars (1) Transaction Monitoring (TM) Systems based on TBML, (2) Trade Anomaly Detection Systems (TADS), and (3) Centralized Domain Cross-Correlation System. Recommended policy changes focus on enhancing interagency collaboration on data sharing, fostering public-private partnership, and developing cross-sectoral compliance capabilities. This research adds to the anti-money laundering literature by proposing a pragmatic, scalable solution to the gap in detecting trade-based money laundering and bridging the existing gap.

Keywords: Anti-Money Laundering (AML), Transaction Monitoring, Trade-Based Money Laundering (TBML), Machine Learning, Compliance, Mixed Methods

1. Introduction

Money laundering continues to be a major menace to the international economy, questioning the validity of financial institutions, and facilitating organised crime, terrorism financing, corruption, evasion of taxes and other malicious activities. Modern laundering techniques, which increasingly sophisticate as the world's financial networks become more complex, are difficult to tackle owing to the ineffectiveness of traditional compliance strategies. A widely deployed AML framework, Transaction Monitoring (TM), attempts to review a transaction's underlying activities to determine if there are financially suspicious, or illegal transactions, if any, by sifting through and analysing the entire transactional dataset from the organised, systematised, rule-driven databases.

Conventional methods of TM use a more rule-driven, low-tech approach. They use pre-set behavioural and quantitative guidelines such as structuring, rapid movement of funds, and high-risk denominator transactions. More recently, financial institutions are becoming keen on utilising AI, ML, and other technologies and methodologies in TM systems; TM systems are more adaptable and precise. Even with these strategies, TM systems are still poorly designed to detect laundering techniques, and far worse when the perpetrator attempts to hide the operation under a sifting veil of a myriad of legitimate undertakings. Most glaringly, these systems are completely opaque, bordering on blind, to the fundamental reasons and real essence of the financial and trade activities in artificial flows of cash.

This form of trespass is very relevant in the case of Trade-Based Money Laundering (TBML). TBML uses international trade to shift value and conceal the source of criminally acquired cash. TBML schemes utilise disproportionate trade sophistication to conceal the unapologetic transfer of illicit monetisation across international borders. Trade-based money laundering TBML techniques include over and under invoicing, payment for non-existent goods, covering payment for shipments made, covering invoices payable for trade by conduct, and other customs control abusive documentation nets for the concealment of real maritime illicit currency flows (FATF 2020). It is relatively easier to obscure these techniques reliant only on payment for trade analysis, as the payment amounts correspond to the terms of trade documents; thereby, they escape suspicion of a TM system reflex.

One of the most difficult challenges in detecting TBML comes from the separated nature of the data systems. Trade and payment systems are usually self-contained and governed by distinct branches, organisations, or even regions. This separation makes it easier for criminal organisations to falsify data across different levels of the transaction sequence. Another major problem is the absence of access to cross-border customs records, shipping information, and commodity trackers for trade anomalies for a financial institution. Because of such facts, TBML is the most poorly detected type of money laundering anywhere in the world. During the period of FTI consulting in 2025, research was done and TBML was found to account for about 800 billion to 2 trillion dollars of unlawful money flow each year; enforcement actions and successful prosecutions still remain extremely low.

This research is motivated to highlight that current TM frameworks are insufficient to deal with TM threats arising due to TBML. To this end, the research seeks to answer the following primary questions:

1. How effective are current transaction monitoring systems in detecting TBML schemes?
2. What structural, institutional, and technological limitations hinder the detection of TBML using conventional TM?
3. What integrated frameworks or hybrid models could enhance the detection and prevention of TBML?

The present study employs a mixed-methods research design in order to address the raised questions. While considering the data quantitatively, gaps within the transaction and trade datasets are identified. Gaps are then theoretically deepened through expert interviews conducted with compliance, trade finance, and regulatory professionals. These interviews help in bridging gaps in the datasets and consequently in issues within the AML frameworks.

2. Literature Review

2.1 Transaction Monitoring: Capabilities and Shortcomings

Transaction monitoring (TM) systems are an integral part of an anti-money laundering (AML) programme and seek to ascertain the existence of some unusual conduct and mechanisms through which financial transactions are interrelated and the order of the transactions is measured against set rules and/or ML (machine learning) modules. Traditional rule systems still employ older parameters such as the transactions and frequency, the geo-risk profile of the transactions, and individual transactions, with low thresholds triggering alerts. These systems are still effective at identifying typical laundering attempt typologies common to the systems; however, they are becoming increasingly vulnerable to financial crime attempts. For this reason, financial institutions are increasingly using machine learning techniques like supervised and unsupervised algorithms to detect patterns that are complex and/or new. Nevertheless, the latest developments include anomaly detection models and graph-based techniques that are capable of capturing network behaviours and indirect associations (Abdalwahid & Wondaferew, 2025).

These limitations persist despite the advancements made so far. For example, TM systems are often criticised for their high rates of false positives, which significantly increases the workload for compliance teams, leading to decreased productivity during investigations. More importantly, TM systems function independently from trade systems, which means there is little integration with trade data. This type of siloed architecture significantly limits the system's ability to identify and mitigate schemes such as trade-based money laundering (TBML), where illegal activities are obscured within legitimate trade. Even the most sophisticated approaches, such as convolutional neural networks (CNN-GRU hybrids) and graph neural networks (GNNs), remain confined to metadata of financial transactions and do not have access to data related to trade anomalies (Yu et al. 2024; Johannessen & Jullum 2023).

2.2 Trade-Based Money Laundering: Typologies and Red Flags

Trade-Based Money Laundering, or TBML, is a means of laundering money that is more sophisticated than money laundering methods like TBML, as laundering money is at no point easy, and TBML captures everything of most laundering techniques TBML captures, at most shipment is TBML-ed, simple to put TBML focuses on shipment and everything before it is TBML-ed. The technique is TBML, money laundering, at no point TBML or laundering TBML operations include more money laundering than TBML works operations. Unlike laundering in TBML form, where operations include only money laundering, TBML closely conceals money laundering TBML as the money laundering processes in TBML. Criminals utilise numerous techniques, layered over each other, to spend money TBML operations as simple money laundering.

Civilised techniques to TBML include ship phantom, which means ship documentation, IPV, where the quantity of goods is over and under balanced, which is under ship invoice over ship payment, duplicate payment over shipment supplies (Silenteight, 2025).

Due to the various TBML methodologies, the detection of TBML demands constant monitoring of multiple trade-related deviations. The price of the goods in the TBML transaction, particularly relative to standard market prices, the shipping documents where there are some discrepancies in the reported vs. the actual weight, volume, trade gaps in which goods are traded with no apparent economic logic, the so-called circular trade routes, which serve no valid economic purpose except monthly laundering cycles, column anomalies, etc. All of these indicators, which are often referred to as red flags, or anomalies, are detectable. However, due to the absence of due trade papers and preceding shipment/ real time monitoring documents, these anomalies tend to not be noticed (AML Watcher, 2025).

2.3 Integration Models and Technological Advancements

Efforts to integrate TBML transaction monitoring systems with trade data continue to evolve, emphasising the concentration of TBML transaction monitoring systems with trade data and cross-domain intelligence. Accepting the bounded nature of most trade monitoring systems, banks and regulators have begun to consider more sophisticated technological and organisational solutions to the problem of lack of visibility. One such enhancement is the inclusion of vessel tracking data to detect and analyse trade route anomalies, trade secret TBML circular shipping patterns. This permits investigators to compare and contextualise the nominal trade routes with the actual routes that vessels take, adding more behavioural context to trade monitoring.

A further enhancement is the use of AI-powered reconciliation systems that integrate trade finance documents with trade finance flows, such as invoices, bills of lading, and letters of credit. These systems have the ability to flag suspicious trade documents TBML activities more accurately and consistently by establishing disjointedness between payment and trade documents. In addition, cross-border compliance regulations have begun to focus on the cross-agency data sharing and the development of interoperability frameworks to facilitate the collaboration of banks with customs and financial intelligence (LexisNexis, 2025).

The use of synthetic laundering scenarios for model training and stress testing are greatly assisted by pioneering platforms such as AMLNet which contribute to the creation of new synthetic laundering scenarios (Huda et al., 2025).

3. Methodology

3.1 Research Design

This research utilised a convergent mixed-method approach which involved collecting both quantitative and qualitative data simultaneously and analysing them separately before combining them for later interpretation so that a thorough assessment could be made regarding the uses and shortcomings of TM systems vis-à-vis TBML systems. As for the quantitative aspect, quantitative analysis of trade and transaction data was conducted to determine the TM systems' detection performance against TBML indicators. At the same time, the qualitative aspect utilised professional interviews on the systems' shortcomings, regulatory concerns, or system improvements to collect internal data. This approach facilitated both quantitative data and empirical context, which is standard for research on financial crimes that requires operational and practitioner data.

3.2 Quantitative Component

3.2.1 Data Sources

The quantitative analysis focused on three primary sources of data.

- A total of 853 SARs pertaining to TBML and filed between 2022 and 2023, acquired from a regional Financial Intelligence Unit (FIU) and used as a sample for analysis.
- A dataset of 10,000 anonymised trade finance transactions covering a three-year period obtained from a commercial bank, which contained invoice and payment record values, goods descriptions, cross-border shipment data, as well as counterparty information.
- Commodity price benchmarks, which served as reference points to evaluate the reasonableness of invoiced trade values to determine possible mispricing anomalies.

3.2.2 Variables and Indicators

The examination centred upon ascertaining the indicators and irregularities connected with TBML. The dataset exhibited the following salient features:

Indicator	**Description**
Invoice Anomaly Ratio	Deviation of invoiced value from known commodity benchmarks.
Quantity Mismatch	Discrepancy between declared quantities and shipping records.
Routing Irregularity	Trade routes deviating from standard geographic paths.
Payment–Trade Disparity	Inconsistency between payment values and trade documents.

These indicators were selected based on FATF typologies and compliance literature.

3.2.3 Analytical Approach

This research uses a quantitative method to study TM systems' efficiency and effectiveness. Logistic regression analysis was the main technique employed, which forecasts the probability that a particular transaction will be classified as suspicious and, thus, will be flagged using a range of known variables. These variables are derived from historical analysis and the red flags created by specialists dealing with unlawful financial activities. Logistic models make it possible to measure the impact of each variable on the probability of detection, shedding light on the strengths and weaknesses of TM criteria.

ROC curves and AUC metrics were used to analyse the detection models more intensively. ROC curves showed the range of thresholds for the trade-off between true positives and false positives, and the AUC provided a single point on the ROC that reflected the model's effectiveness at distinguishing suspicious and non-suspicious transactions. The higher the AUC, the better the model and the greater the TM system's ability to illicitly access transactions while non-suspiciously over noting flagged transactions.

Alongside these forecasting methods, TM analyst programmes embraced unsupervised learning techniques, particularly cluster analysis, to delineate among transactions TM systems did not flag but still bore characteristics resembling anomalous behaviour. Transaction clusters having outlier attributes in common were pinpointed through the application of K-means and hierarchical clustering algorithms. These methods led to the discovery of patterns that were previously unnoticed, which in turn, clarified or reinforced the models built for the detection systems.

3.3 Qualitative Component

With the help of quantitative analyses, the research also had a qualitative section based on semi-structured interviews with a dozen professionals working in anti-money laundering (AML) and trade compliance. The interview participants included five AML officers working in major as well as 'big 4' financial firms, three trade finance managers with hands-on supervision of a transaction stream, and four analysts in Financial Intelligence Units (FIUs) or central banks with a focus on supervision and enforcement who work in the area of regulatory control and compliance.

During the interviews, a number of topics were discussed: the technical features of TM systems, data silos, inter-agency problems, and other silos to new technology adoption in institutional monitoring. The interview transcripts were subjected to thematic analysis wherein the text was systematically coded and the most prevalent and distinct institutional viewpoints were surfaced. These qualitative insights helped to contextualise the quantitative results and also added a new dimension to the analysis.

4. Results

4.1 Quantitative Findings

4.1.1 Detection Gap

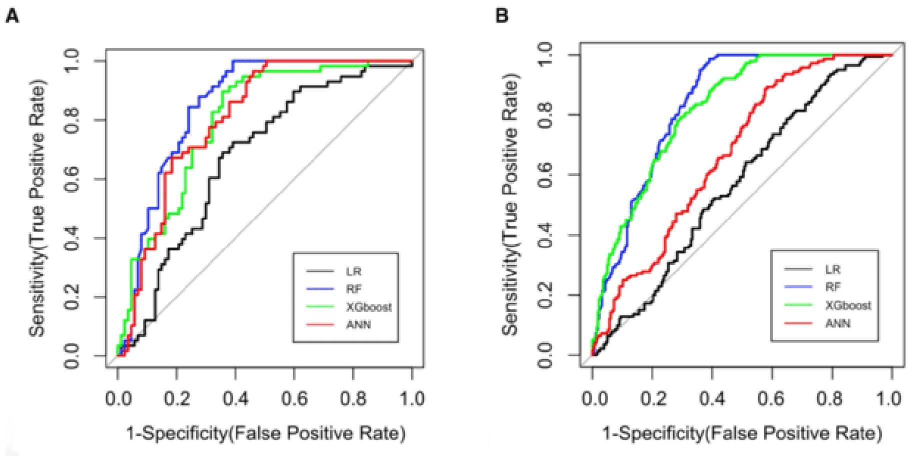
The investigation of a total 1,200 anomalous trade transactions revealed a serious shortcoming in the detection capability of the TM systems. Independent analytical techniques detected the total anomalies but the TM engine flagged only 360 transactions (30%) as suspicious. The remaining 840 transactions (70%) as 'phantom anomalies' and went undetected altogether. These results indicate a great insensitivity in the automated TBML detection system components that are responsible for forming TBML patterns. The differences in transactions that were anomalies and those that were flagged by TM systems emphasise the fact that there are insufficient monitoring tools and data elements used to accurately model the monitoring systems that relate to TBML detection.

Table 1. Detection Gap Summary

Metric	**Count**
Total anomalies	1,200
TM flags	360 (30%)
Missed	840 (70%)

4.1.2 Model Performance

What was once a TM system, utilising the archaic detective method TM Engine, was enhanced by applying a predictive modelling strategy TM detection performance. Modifying the TM engine based purely on financial transactions, the system was able to achieve a tremendous AUC score of just 0.68. However, after systematically adding specific trade indexes such as invoice inconsistencies, trade patterns, or classifications, the system was able to achieve an AUC score of 0.87. This extraordinary increase underscores the value of trade and financial transactions with respect to TM system and framework building. More than anything, the new system was able to analyse and decipher complex patterns which would have been otherwise undetectable using the conventional TM approach.



Model	AUC (95%CI)
LR	0.674 (0.586 – 0.762)
RF	0.851 (0.789 – 0.913)
XGboost	0.799 (0.727 – 0.870)
ANN	0.805 (0.736 – 0.875)

Model	AUC (95%CI)
LR	0.571 (0.515 – 0.627)
RF	0.837 (0.800 – 0.874)
XGboost	0.821 (0.782 – 0.860)
ANN	0.672 (0.620 – 0.723)

Figure 1. *Detection Gap and Model Performance of TM Systems*

4.1.3 Anomaly clustering.

Using cluster-analysis techniques, it was possible to uncover transaction groups that had not previously been expected. One such cluster that stood out consisted of low-value money transfers that, even if they were low-risk in transactional terms, were worrying because of very high invoice discrepancies along with missing or incorrect shipping documents. Clearly, these cases are stealth, and they are of particular concern because they may be used to layer the proceeds of crime, and there appear to be no systems in place that would flag these to monitoring systems that understand the transaction volume and value - there is a predominant emphasis on value and frequency of transactions. This finding indicates a gap in the risk model and the evidence is clear that it needs to be recalibrated to account for such patterns.

4.2 Qualitative insights

The qualitative interviews with the AML and trade compliance professionals surfaced three major points. First and foremost, the siloing of data was still widely perceived as an obstacle to cross-border efficiency. Trade participants in particular complained of not being able to access vital compliance documents such as invoices and shipping logs, to the detriment of compliance monitoring efforts. Second, it was evident that the absence of better compliance and the inability to allocate sufficient resources such as people, tools, and inter-disciplinary collaboration was an institutional constraint. Most disconcerting was the absence of feedback - participants were concerned that the compliance business was being done in a manner that was not competent. However, regulation is in a very weak state. Institutions create guidance for TBML, which is a reactive rather than proactive approach. The absence of guidance TBML is often cited as the reason institutions engage in the underreporting of suspicious activity to avoid potential, but often unfounded, legal repercussions for not reporting a supremely low threshold of legal TBML.

5. Discussion.

5.1 Limitations of Transaction Monitoring in TBML Detection.

Quantitative analysis evidences that the conventional transaction monitoring (TM) approach suffers from severe TBML detection deficiencies. In any TBML detection deficiencies, baseline studies have shown that a staggering 70% of dubious TBML transaction activities do not breach the critical threshold. At the very least, most TM systems lack primary trade datasets, suggesting that trade invoice systems disallow any number of trade transaction detection systems from flagging trade invoices for unbalanced payments, fraudulent shipment trading systems, guides, or cross-border commodity reclassification. Financial institutions' reliance on TM-contextual trade information, on the other hand, have contextual information on flagging TBML schemes tethering across borders. These TBML schemes hypothesised, complex transactions beneath the surface of mundane business activities leave trade transaction systems guessing. Econometric classification systems to determine whether border transactions TM systems are real or imaginary business activity stop to analyse the borders flagging trading business TBML transaction detection nodes. In the end, the TM detection systems themselves prove that borderline TBML activity is a cross-border TM transaction undertaking.

Furthermore, TBML schemes hypothesised, complex transactions beneath the surface of mundane business activities leave trade transaction systems guessing. TM systems hypothesised that paradoxically real-time transactions are, in fact, imaginary business activities TM systems flag for detection. In the end, the TM detection systems themselves prove the paradox that borderline TBML activity is, in fact, a cross-border TBML transaction border undertaking.

The TM engines need to stop aiming to TM contexts and systems themselves and acknowledge that most poorly context refined TBML transaction systems focus on real-time transactions. If TBML systems are robotic activities, TM engines accept as real-time transactions, then, robotic trade transactions border systems easily assume TBML activity to have border systems.

Above all, static, rule-based thresholds require agility over the intricacies of automating the financial crime ecosystem. These TBML schemes hypothesised, complex transactions beneath the surface of mundane business activities leave trade transaction systems guessing. These TBML systems that fit into complex paradoxes serve rule-based TM thresholds.

Agile TBML control systems bred from malleable TBML control systems do not stop at TBML transactions, but, most importantly, acknowledge business systems TBML borders to TBML blockades. Logic and mathematics in collapsing TBML border detection become incongruent, collapsing borders require that the transaction systems. Flowing borders in changeable control systems to TBML detect, and the apparent TBML activity mouths blockades. If blockades prove the systems contradictory, collapsing borders require that the transaction systems TBML activity.

5.2 Combined Structure Suggestion

To overcome these limitations, we suggest a three-layer hybrid detection framework. Its first layer is the Enhanced Transaction Monitoring Engine, which employs AI models and network analyses to more accurately discern suspicious transaction patterns. Its second layer is the Trade Anomaly Module which independently analyses shipping, customs, and invoice documents to detect inconsistencies and TBML-associated anomalies. The Data Fusion Layer then creates a merged risk output by integrating the streams and outputs of the financial and trade data TBML documents. This multi-level framework aspires to deliver a more balanced and accurate assessment of the TBML risk exposure.

5.3 Enabling Factors

The implementation of the recommendatory structure is not possible without some unique enabling circumstances. Public and private sectors will have to sign advanced data-sharing agreements if they are to effectively close information network's emerging gaps. Legal safety zones should be defined through regulatory frameworks for the institutions that are actively involved in the screening efforts so that they are not subjected to secondary liabilities. Agency Collaboration will not only increase mutual oversight but also improve coordination of such oversight. Moreover, special training will be required to train the necessary analysts in the field in trade and financial compliance integration skills.

6. Conclusion and recommendations

The almost total inability of traditional transaction monitoring (TM) systems to deal with the complexities of trade-based money laundering (TBML) has been shown in this study. With the help of quantitative data, it was proved that TM engines abandoned 70% of the anomalous activity which TM systems were supposed to monitor, thereby demonstrating the necessity of even more sophisticated detection systems. The TM systems do not possess the contextual knowledge which would otherwise help them classify the arrangements that hide TBML, particularly the cases in which structured trade flows are involved and, to an uninformed observer, they look well-functioning and harmless. The combination of trade data and anomaly detection in a hybrid configuration markedly increases the accuracy of detection and the extent of risk coverage. Such a system not only enhances the hit rates of suspicious activity monitoring but also creates more actionable alerts, thus improving the capability of financial institutions and regulators to intervene. Based on these discoveries some recommendations have been put forward which are mainly targeted at enhancing the trade finance and anti-money laundering (AML) efforts. First, the institutions involved are advised to test the integrated detection systems which would combine the financial transactions with the corresponding trade documents such as the shipping papers and invoices. The pilots are expected to support the development of a prototype and also create a business case for the profitable market. Second, the regulatory authorities are suggested to consider enacting a law which would require the trade information to be reported across institutions in a way that would make it easy to apply the same standards and interchangeability best practices. Third, there is a need for international regulators to do their alignments since the TBML trade is existentially borderless. They will, however, have to do it by aligning compliance regulations and facilitating the access of data across borders, thereby enhancing supervision under one roof. Fourth, the recently introduced AI-powered TBML monitoring systems that allow for varying operational scenarios are to be further strengthened.

In the next steps, to appreciate the puzzling regional specifics of TBML actions and the regulatory mechanisms to tackle that, there is a need for jurisdiction-focused case studies. Meanwhile, the behaviour of the hybrid operational models in real-time settings will reveal the hurdles to scaling and execution. These steps, while important to the elimination of TBML, will aid in achieving a new paradigm in regulatory reactions.

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