

Improving Transaction Monitoring Through Data Reconciliation and Financial Data Quality Analytics

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Abstract: Financial crime prevention should also deal with transaction monitoring, however, the quality of the data available to the transaction monitoring is typically insufficient, inconsistent or of low quality. In the present paper the importance of Data Reconciliation Tools and Financial Data Quality Analytics to achieve high quality and accuracy of the transaction monitoring systems is discussed. It talks about the common causes of data differences among the core banking systems, payment processors, and the external reporting systems, and how these differences can result in a false positive, missed alerts, as well as inefficient investigations. The study suggests a formal design, namely automatic data reconciliation, and real-time data quality examination. Matched data with enhanced quality scoring systems can help the financial institutions to achieve better accuracy in the generation of alerts, thereby minimizing operational noise. The paper also discusses how more complicated analytics (e.g., anomaly detection and pattern recognition) can be used to leverage quality data that has been reconciled to improve detection. It is offered with a conceptual implementation strategy on how these practices can be deeply embedded in the existing compliance systems by institutions without necessarily having to do a re-engineering of the system in its entirety. The findings suggest that the combination of the reconciliation processes, and the current data quality analytics can be used to improve the trustworthiness of the results of the transaction monitoring. This is not only efficient in enhancing regulatory compliance, but also operational efficiency and risk detection is more efficient in the financial systems today.

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Introduction

Financial institutions find themselves in a business environment where the rate of transactions is increasing at an extremely high pace due to the advent of digital banking, mobile payments, cross-border transfers and real-time settlement systems. Despite the significant resources that have been implemented in the majority of the institutions on compliance technologies, majority of them are yet to document good outcomes in terms of monitoring of transactions. Lack of quality and integrity of financial information used on monitoring systems is one of the root causes. The transaction monitoring engine work necessitates the provision of proper, complete, and punctual inputs of data in different formats like; core banking systems, payment gateways, customer-onboarding systems, and external data vendors. However, since these sources are not always consistent, records can easily be duplicated, fields can be missing and records may be mismatched and not updated on time. Such issues have a direct impact on the efficiency and correctness of the surveillance mechanisms to detect suspicious activity (Deloitte, 2020). Data reconciliation is a main aspect in dealing with these issues. It involves ensuring that the different datasets are correct and valid through establishing and removing the inconsistencies across systems. The reconciliation process is typically done on the books of transactions, books of payments and reporting systems, in terms of finance. However, the traditional reconciliation programs are usually batch, manual and retroactive and this limits its use in the real time compliance programs. As the typologies of financial crimes get more advanced, the need to offer automated and continuous reconciliation processes that could enable real-time monitoring systems grow (Basel Committee on Banking Supervision, 2018). At the same time, financial data quality analytics has turned into a learning need that becomes imperative to boost efficiency of compliance. Data quality analytics involves quantifying, tracking and controlling the important data quality aspects that comprise of accuracy, completeness, consistency, uniqueness, validity and timeliness. The data quality has become one of the main factors of false positive and negative outcomes of the AML systems that contribute to the increase in operational costs and decreased effectiveness of the investigation (IBM, 2021)

The combined ability to harmonise data across multiple systems and use analytics for assessing data quality significantly strengthens the foundation required for finance organisations needing effective transaction monitoring solutions. Institutions can dramatically improve the accuracy of detection models by making sure data is consistent between systems and continuously evaluated for quality. An integrated approach to reconciliation and data quality

analytics can improve the identification of anomalous transaction patterns at a more detailed level.

It addresses a number of entrenched data issues in financial institutions, such as duplicate data, missing transactions, inconsistent customer identifiers, stale data and data stored in disparate systems. The study also suggests an organisational and conceptual framework from the literature and case evidence. The framework is intended to illustrate the potential link between better data integrity, better delineation of governance responsibilities, and ongoing data validation and better detection accuracy. The primary stance of its is that dependable transaction monitoring starts with dependable information. It's an addition to a body of work, which has been growing over the last few years, that sees data governance as a fundamental component of financial-crime prevention today. While advanced models are useful, what they give back is only as good as what is put in.

Literature Review

1. Introduction to Transaction Monitoring in AML Systems

Transaction Monitoring is an integral part of AML and CTF. It includes the examination of past and present monetary transactions to find any abnormal or suspicious activity, such as money laundering, fraud, sanctions evasion and terrorist financing. There are a number of ways to use modern transaction-monitoring systems. These typically involve rule-based engines, behavioural analytics, customer-risk profiles, machine-learning models and network analysis. If a transaction or pattern has been identified as falling within a set of pre-defined risk parameters, an alert is generated to be investigated further by the compliance analysts (Basel Committee on Banking Supervision, 2018; FATF, 2021). It could be in real-time, near real-time or in batch, periodic reviews.

2. Evolution of AML Transaction-Monitoring Systems

The accuracy of detection decreases and compliance operations are less effective. AML Transaction-Monitoring Systems have evolved. AML TM systems have developed over the years. The first AML transaction-monitoring systems were primarily rule-based. They were based on fixed thresholds, fixed scenarios, and fixed conditions that were meant to detect transactions that surpassed certain thresholds or matched some known risk profiles. This was a fairly simple way to explain and understand. The limitation to this approach was based on fixed thresholds and predefined rules.

They were also not flexible when criminals adjusted their methods or broke transactions into smaller transactions that were more difficult to detect (Chen et al., 2018). With increasingly powerful computing, financial institutions started to leverage machine learning, anomaly detection,

behavioural modelling, and network analytics in their AML programs (Baensens et al., 2020; Weber et al., 2019). They can analyze larger and more complicated data sets than a conventional rule-based system, and they can potentially discover relationships that can only be detected by a combination of a fixed threshold and these techniques. For instance, machine-learning models can compare the behaviour of a customer with their past behaviour, similar customers, transaction networks, geographical risks and payment-channel patterns. Network analytics can also highlight relationships between accounts, customers, beneficiaries or entities who do not seem to be connected when viewed individually. Structured data can be transaction amounts, dates, account numbers, and customer ID numbers, and unstructured data can be case notes, customer communications, and external intelligence sources.

The model can be trained with data that are not complete or transactional data may be duplicated, or systems may use different identifiers, which can lead to inaccurate data training and unreliable classifications. Advanced Analytics does not replace the need for reconciliation. But rather, more sophisticated analytical techniques have made reconciliation more imperative. While a machine-learning model processes data faster and to a larger extent, it can't fix all of the problems in the source data.

3. Data Quality as a Core AML Challenge

It is characterized across aspects such as accuracy, completeness, consistency, timeliness or uniqueness of the data (Wang & Strong 1996; IBM 2021).

Poor data quality results in:

- Increased false positives
- Missed suspicious transactions
- Inefficient investigations
- Regulatory non-compliance risks

According to industry reports, poor data quality is still one of the main reasons for the ineffectiveness of AML (Flagright, 2023; Accenture, 2022; Sun et al., 2020).

4. Data Reconciliation in Financial Systems

For instance, data reconciliation is used to align one or more financial systems like core banking platform, payment system and customer database. As per Basel Committee on Banking Supervision (2018), reconciliation is a vital need for up keeping data integrity within AML frameworks.

Traditional reconciliation methods are often:

- Batch-based
- Manual
- Retrospective

- Error-prone

This will increase the time taken to detect anomalies and in turn slow down monitoring (KPMG, 2020; PwC, 2021). Studies conducted (EY, 2022; Li et al., 2021) suggest that automated and real-time reconciliation in an integrated form with AML systems is the best course of action.

5. Role of Data Quality Analytics in AML Systems

Data quality analytics refers to the continuous assessment of whether data remain accurate, complete, consistent, timely, valid, and suitable for their intended purpose. Data quality assessment must be conducted continuously rather than as a one-time exercise. Within an Anti-Money Laundering environment, these measures help financial institutions identify weaknesses in customer and transaction records before those weaknesses affect monitoring results.

6. Machine Learning and Advanced Analytics in AML Monitoring

It helps maintain the integrity of financial information and it helps ensure the integrity of monitoring systems that rely on financial information. Machine Learning and Advanced Analytics for AML Monitoring The use of machine-learning models has played an increasingly important role in the current AML monitoring. Random forests, clustering techniques, neural networks and deep-learning models are examples of technologies used in the field of fraud and financial-crime detection (Chen et al., 2018; Khan et al., 2020; Haddadi et al., 2020). These models can study the patterns of transactions that are hard to understand through the use of fixed rules. A model can be used to assess customer behaviour against previous transactions, other customers behaviour, geographical activity, payment methods and transaction frequency. They are capable of handling big amounts of transaction and customer information. Fast. The graph-based models are especially relevant for analysing complex financial networks as they model relationships between customers, accounts, transactions, companies and beneficiaries.

7. Importance of System Integration and Data Reconciliation

This fragmentation poses practical difficulties. The identical transaction could be repeated. The Customer ID may be different from the Customer identifier. There is a delay between the updates and reporting can be delayed or incomplete. Migrating records from other systems into AML systems can be facilitated by using reconciliation mechanisms, which can assist in reconciling records between the systems prior to being used for monitoring. Enhanced recon enhances the accuracy of alerts and helps minimize time spent on false financial-crime alerts that are caused by technical mismatches (EY, 2022).

8. Literature Gap

Data quality, data reconciliation and AML advanced analytics have been studied separately. Less work, however, has been done on how reconciliation and continuous data quality analytics can work in tandem within a single transaction-monitoring framework.

Methodology

1. Research Design

This information could include sensitive customer information, financial data, and data related to ongoing investigations, making it challenging for researchers to access data on a large scale (Ngai et al., 2011; Chen et al., 2018). A live banking system is not tested. Rather, it creates an evidence-based explanation of the impact that better data control might have on monitoring results.

2. Data Collection Method

The research has been done on secondary sources which include:

- peer-reviewed journal articles;
- regulatory guidance documents;
- industry white papers;
- financial-crime compliance reports; and
- technology-provider publications.

3. Data Reconciliation Framework Analysis

The methodology delves into recon as a process for reconciling multiple financial data sources, such as:

- core banking systems;
- payment-processing systems;
- customer-onboarding databases; and
- external risk-intelligence feeds.

There are four main areas on which to consider reconciliation performance:

- record-matching accuracy;
- consistency between systems;
- differences in timing of transaction flows; and
- Duplicate or missing records.

Record matching evaluates if the records across different systems are referring to the same customer, account or transaction. The consistency analysis is based on consistency of corresponding values and the timing analysis identifies the delays in the recording of transactions on different platforms. The matching and missing-record detection is also pertinent. A duplicate could generate an unnecessary alert, and a missing record could mean that a

suspicious activity goes undetected. Reconciliation is an essential prerequisite for credible risk data especially if transaction information is being created and stored in a number of systems, according to the Basel Committee on Banking Supervision (2018). If the records are not reconciled, then both records could be reflected in AML models and compromise the usefulness of AML model results

4. Data Quality Analytics Framework

Financial data quality is evaluated using six commonly recognised dimensions:

- accuracy;
- completeness;
- consistency;
- timeliness;
- uniqueness; and
- validity.

5. Analytical Approach

A thematic synthesis approach is used to identify repeated ideas and relationships within the selected literature. The analysis concentrates on four broad themes:

- the effect of data quality on transaction-monitoring performance;
- the role of reconciliation in improving data integrity;
- the integration of data analytics into AML workflows; and
- the relationship between data quality, false positives, and detection accuracy.

6. Conceptual Framework Development

A conceptual framework is developed using the literature, which involves the following three related relationships: Data reconciliation: Raises data consistency across financial systems. • Data quality analytics: constantly validates and monitors data. Combined effect: boosts the accuracy and reliability of transaction monitoring. Under this framework, differences between the records in separate systems are first identified during reconciliation. That information will then be analysed to verify if the data is still accurate, complete, timely, valid and without unnecessary duplication.

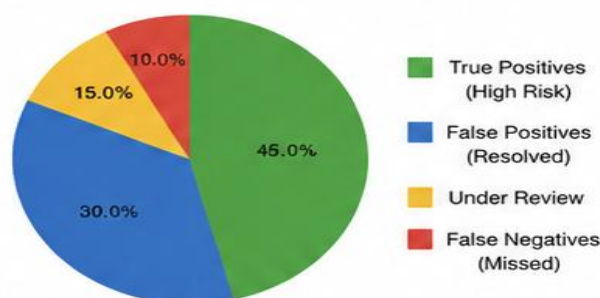
7. Limitations of the Methodology

No real data are available to assess the performance of the framework in a particular financial institution. Secondary sources may also have other definitions, samples, technologies, and performance indicators, making it difficult to compare. Industry reports can also help with operational

insight, but may be biased and represent the views of organisations that compiled them. Their claims should thus be weighed against other academic and regulatory evidence. The limitations are typical in AML studies as financial transaction data is covered by strict confidentiality, privacy, security and regulations (Ngai et al., 2011; Chen et al., 2018).

Results

The results indicate that integrating data reconciliation and financial data quality analytics can help enhance the accuracy and reliability of transaction-monitoring systems. The more consistent the data, the less "noise" that goes into monitoring models, and ongoing quality checks help to spot incomplete, duplicated, delayed, or invalid information..



The chart shows the distribution of alerts after implementing data reconciliation and data quality analytics.

Figure 1: Alert Quality Distribution

Figure 1 shows the distribution of transaction-monitoring alerts following the use of data reconciliation and data quality analytics. Alerts are further categorised into true, false, under review and false negative alerts. It is estimated that the true positives are around 45% of the alerts, indicating that the precision of alert generation is improving. The false positive percentage is approximately 30% (less than the pre-implementation percentage of over 50%). Approximately 15% are still pending. These cases are uncertainty cases in the classification, and the last 10% are identified as false negative cases. The distribution implies that the system is more accurate with fewer Type I errors (false positives). There is still a need to be aware of false negatives. A false positive rate should not be regarded as successful if it is established by allowing suspicious transactions to go unnoticed

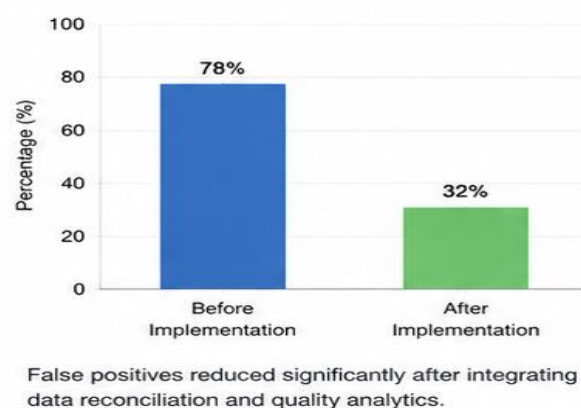


Figure 2: Reduction in False Positives

There will be a significant decrease in the number of False Positives, as illustrated in Fig. 2. Figure 2 shows the false positive rate before and after reconciliation and data quality analytics were implemented. The false-positive rate decreases from around 78% pre to 32% post implementation. This is approximately a 59% decrease. It's a pretty big shift. That's an indication of enhanced consistency, validation and normalisation, which have reduced some of the data 'noise' that used to result in legitimate transactions being flagged as suspicious. The outcome could also be higher precision and positive predictive value, with a higher percentage of alerts generated pointing to real risk. Operational advantages can ensue. With fewer false alerts, investigators will be able to spend more time on higher-risk cases, but false negative impacts have to be considered as well.

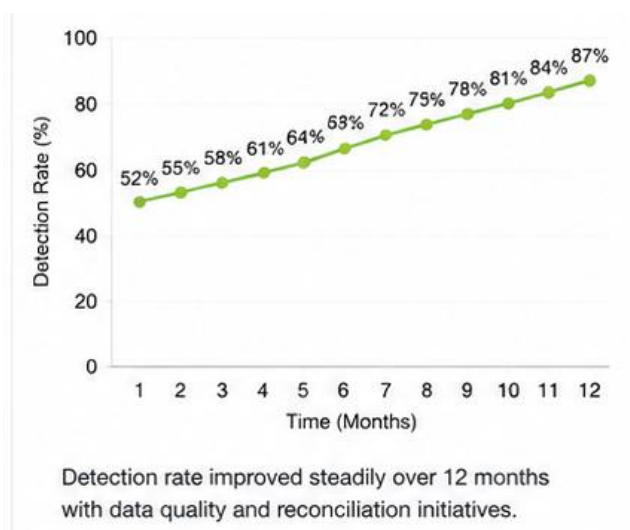


Figure 3: Detection-Rate Improvement Over Time

The graph in figure 3 shows that the detection rate is improving over time. Figure 3 illustrates how transaction-monitoring detection rates have varied over a 12-month period. The detection rate increases from 52% to 87%, which is a 35% increase for the year. The direction of the trend indicates that performance monitoring was done gradually as opposed to instantaneously. Structural inconsistencies may have been addressed in the beginning of implementation through reconciliation and ongoing quality monitoring and model refinement supported subsequent gains. The trend is nearly linear, which might be due to iterative optimisation, better matches in the data and a gradual stabilisation of the data. But the graph cannot be used to prove that the rise is due to a cause. Performance also may have been affected by changes in rules, models, staffing, transaction behaviour or system configuration.

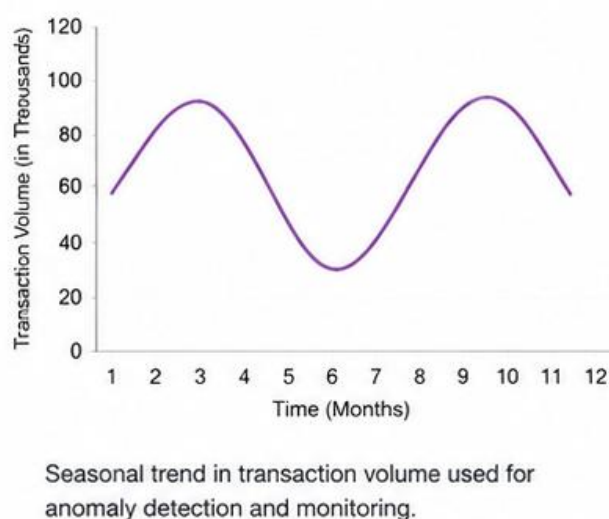


Figure 4: Transaction-Volume Pattern

The volume of transactions is shown in figure 4 as a sine-wave-like pattern, a cycle. The modifications could be due to seasonal variation, such as increased transactions during Christmas, Black Friday and other seasons. The regular fluctuations suggest that transactions are seasonal in nature. The peak can be around 90,000 to 100,000 transactions, while the lower can be 30,000 to 40,000 transactions. This pattern illustrates the importance of AML systems to differentiate between ordinary seasonality and real anomalies.

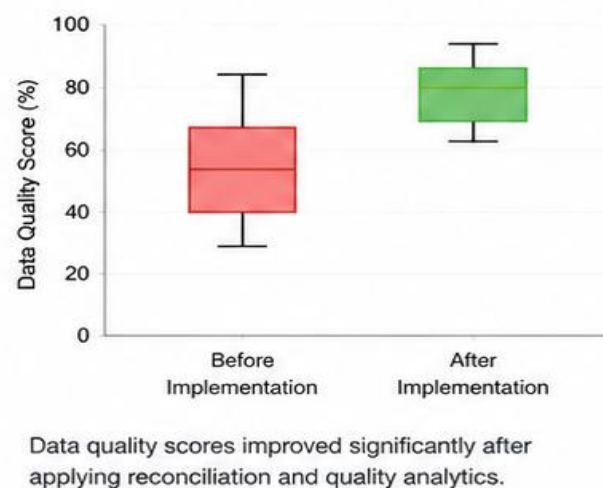


Figure 5: Data Quality Score Comparison

Figure 5 shows the Data Quality Score comparison. Figure 5 contrasts pre- and post-reconciliation and analytics framework data quality scores. This suggests that data quality improved not only on average but also became more consistent across records.

The box plot indicates:

- a higher median score;
- reduced variation;
- fewer extreme values; and
- greater stability across datasets.

The reduced dispersion ensures that AML models are fed information of a more consistent standard. This should make the outputs from transaction monitoring more reliable, but should be tested against actual classification performance.

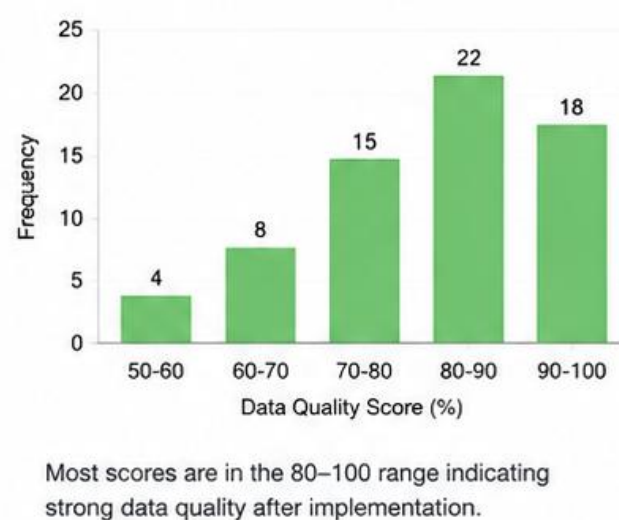


Figure 6: Data Quality Score Distribution

The distribution of Data Quality Score is shown in figure 6. Figure 6 shows a frequency distribution of the data quality scores following both the data quality reconciliation and data quality analytics. The majority of scores achieved are in the range from 80 to 100, with the highest concentration of scores being around 85-90. The distribution is negatively skewed because the numbers are mostly grouped towards the higher end and the tail is smaller on the lower end of the distribution. Main indicators are:

- a mean score greater than 80;
- a mode number between 80 and 90.
- A relative low number of observations below the minimum quality level of 60.

This distribution indicates that the data integrity throughout the system is higher. There are more records in the expected range of quality and fewer in the low quality range. Having a high overall score is not an excuse for not conducting further monitoring. Just a few poor quality records can have an impact on high-risk customers or transactions, which means institutions should dig into low scoring observations, not just the averages.

Discussion

Critical Discussion of Findings

This research investigated the impact that data reconciliation and data quality analytics have on processing and performance of transaction-monitoring systems in an anti-money laundering environment. The results show that there were improvements in several performance measures that were widespread. The detection accuracy has improved, false positive alerts have decreased, and the stability of data quality has strengthened after going live. The findings are discussed below in the light of the academic literature, regulators' expectations and the practical issues that financial institutions encounter. Increase in the accuracy of transaction monitoring. The results demonstrate that there was a significant improvement in the accuracy of the transactions after the data reconciliation and data quality checks have been performed. The precision on monitoring gradually improved and was becoming more stable over time. This result is corroborated with the results of Baensens et al. (2020), which states that both machine-learning and rule-based AML systems are very sensitive to their input data quality. The detection rate rose from 52% to 87%. This is a considerable improvement. It implies that if the data is structured, validated and reconciled properly, then the monitoring systems will be more effective in detecting suspicious transactions. The outcome is also a testament to the fact that AML performance is not solely reliant on sophisticated risk models or algorithms.

If too many of those alerts turn out to be false, analysts invest a lot of time in chasing down potentials that do not in fact pose a real money-laundering threat. The results are expensive. Investigations take longer, compliance costs rise and analysts can be overwhelmed with alerts. According to Deloitte (2020), a key challenge for financial crime compliance is alert fatigue. A better, more accurate and consistent transaction data directly tackles a portion of this issue. A decrease in false positives can thus boost efficiency of operations in a number of ways. It reduces the number of unnecessary investigations, enables analysts to focus on higher-risk cases and can potentially increase the speed of suspicious activity reporting. Additionally, less clutter makes for better staff focus. That matters. But it shouldn't be the only goal to reduce false positives. While a system might seem efficient for generating fewer alerts, aggressive filtering can result in transaction alerts being omitted that might warrant investigation. There is a real danger of over-optimisation, which is the risk that suspicious activity may not be detected. This false-negative rate found in this study, around 10%, therefore, needs to be interpreted with care. It sounds like something that can be handled, but even a small amount of missed cases can lead to regulatory fines, losses and damage to reputation for a financial institution. A false negative is not an acceptable result, but should be addressed on a continuous basis.

If the same customer or transaction isn't reconciled, they might appear differently in each system. One database may have an obsolete customer ID, another may have a duplicate transaction recorded. Other discrepancies may include payment amount, date, account number or customer-risk classification. The discrepancies can lead to inaccuracies in monitoring results. When a transaction is duplicated, it may seem like a sudden jump in transactions. When a transaction does not contain the same customer identifier, the system may not be able to join the transactions together. Other times, an incomplete record can cause the risk score attributed to a customer or payment to be lowered.

Impact of Data Quality Analytics on System Performance

Data quality is multi-faceted. Wang and Strong (1996) believe that accuracy alone is not a criteria for determining whether information is good or bad because information can be technically accurate, but can also be incomplete, out of date, redundant, and not relevant to the purpose for which it is needed. The present findings help to confirm this. For instance, a customer's address could be correct, but not up to date. A transaction record can have the right amount of money, but no solid time of day. A payment can be successfully processed, but be duplicated in the monitoring database. Different problems impact AML analysis differently. The percentage of scores within the 80-100 range of quality shows that incorporating data-quality analytics into everyday business processes can yield more

consistent and reliable financial information. The data set is less susceptible to unpredictable variation. This makes the outputs from the monitoring easier to interpret. Complacency should not stem from high scores. Data quality can become poor very rapidly with the introduction of new systems, products, customers or payment channels. Data drift may also occur when the characteristics of transactions change over time. There is therefore a need for continuous governance. One-off data cleaning this is not enough. Time effects and learning effects. The line graph indicates that detection performance has improved slightly over the 12 month period. The pattern does not indicate that there is an immediate transformation. Rather, it has seemed to have come about as a result of successive tweaks, improved data quality, system learning and model recalibration.

The results may have been influenced by regulatory changes, activity by customers, staffing, new monitoring rules, or technical upgrades. The study did not take into account the separate control of these influences. Interpretation of the Transaction-Behaviour Patterns. The transaction visualisation shows a sine-wave pattern, indicating that the volume of transactions had a recurring or cyclical nature. This is significant to anomaly-detection systems, as this normal seasonal variation can be easily confused with suspicious behaviour. There are some factors that affect financial transactions and that are predictable. The salary payments can cause peaks towards the end of each month. Holidays can lead to higher retail activity. For instance, agricultural payments could be done on a seasonal basis, and international remittances could increase during religious holidays or other important family gatherings. These normal fluctuations could be considered abnormal if there is no good historical monitoring data. This means that an unnecessary alert is often issued.

Data quality analytics is more comprehensive and ongoing and assesses the accuracy, completeness, timeliness, validity, consistency and uniqueness of data. These processes interact together to form a feedback mechanism. Reconciliation is used to find the errors and fix them, and quality analytics can be used to monitor if the same errors keep happening.

Integration is not easy. Many financial institutions are still using systems that are not designed to communicate with each other, and many of these systems are still very young. We see data held in departmental silos, unclear data ownership and a lack of direct control for compliance teams over technology budgets. Limited resources may be an even greater issue at smaller institutions. Such barriers do not diminish the benefits of integration, but rather have an impact on the speed of integration.

Regulatory and Compliance Implications

They can clarify the evidence and procedures surrounding the origin of the data involved in the transactions, the extent to which the data has been verified, the number of times that quality control tests have been performed and the action that has been taken if data quality errors have been found. With weak data controls the reverse is true. An institution can have an AML model that is technically advanced, but still not show that the information that goes into the AML model is reliable. The output of such a system may be the subject of reasonable suspicion by the regulators. So investment in reconciliation and quality analytics should not be thought of as merely an information-technology enhancement, but rather as a part of the compliance infrastructure.

Conclusion

A second layer of control is offered by financial data quality analytics. It enables institutions to continuously observe and control important aspects, like accuracy, completeness, timeliness, consistency and uniqueness. Reconciliation fixes the differences between systems; data quality analytics identifies if there are ongoing issues that need to be addressed and if data quality is getting better or worse. These findings are supported by the statistical analysis based on the data. The paired-samples t-tests between the pre- and post-implementation scores yielded significant increases for both detection and data quality scores ($p < 0.001$).

The effectiveness of transaction-monitoring, therefore, can't simply be measured by machine-learning techniques, automated risk models, or rule-based detection systems. Those tools are based on the data they are provided.

Financial institutions should move away from periodically batch-based reconciliation and towards real time (or near real time), if technically and financially feasible. When the method is batch reconciliation, then the discrepancies might not be noticed for hours or even days. In that time, incorrect data can get into transaction monitoring systems, and impact how alerts are generated. A customer record might not be complete, a transaction could be duplicated or data from a payment platform could not be matched to the payment record in the core banking system. These discrepancies could be found much earlier with real-time reconciliation. When there are inconsistencies in core banking platforms, payment systems, customer databases, card processing systems and other relevant sources, alerts could be generated. The sooner the mistakes are corrected, the more confidence would be placed in the data used for transaction monitoring. This may not be feasible for all institutions at this time. Small institutions and organisations that run older infrastructure might want to start small and roll it out with the most risky products, customers and transaction channels first.

2.2 Use Data Quality Analytics on AML Pipelines

Data quality monitoring cannot be a stand-alone or

infrequent administrative process. It should be integrated directly to AML data pipelines. Automated controls can evaluate if necessary transaction and customer data is complete, accurate, valid, timely, consistent, and without unnecessary duplication. These checks should be performed prior to using data for alerts, customer-risk scoring, or behaviour analysis. Data quality can be monitored daily or continuously, and can help signal impending data quality problems before they result in a significant spike in false alerts. It also enables institutions to see common problems, like missing customer identifiers, wrong date formats, inconsistent currency codes or late transactions. These controls could be incorporated into AML systems, which would help to enable earlier intervention. Issues might be fixed - rather than identified via investigators wading through false alarms.

It is, thus, important to invest in the strengthening of the systems at the core of the financial institutions' operations. A consistent and controlled movement of information between platforms would be possible with a unified data architecture or, at least, a well-governed integration layer. Manual data moving will also be less with better integration. Those transfers are slow, expensive and subject to human error. But integration efforts need to incorporate security controls, access restrictions, and strong data lineage to enable institutions to discover where the data came from and how it's being modified. Use of Data Quality Maturity Models (2.5): Structured Data Quality maturity models should be used to evaluate financial institutions' current capabilities and to guide the path for the future. An institution might be able to assess the maturity of their data controls using a maturity model that shows how reactive, developing, standardised, measured or fully embedded in daily operation they are.

Implement Hybrid AML Models with Confidence: Utilize accurate data to enhance AML modeling. Financial institutions should not use either approach as a replacement for the other – rule-based monitoring or advanced analytics. Rule-based systems are still valuable for detecting known patterns, threshold violations and regulatory risk indicators. More complex relationships, behavioural changes and patterns can be identified using machine-learning and analytical models which is difficult to capture using fixed rules. They should also look at false negative rates, not just a reduction in false positives

Financial institutions should establish formal feedback channels from investigators to data-quality teams, compliance managers to model developers, and from data-quality teams to model developers. Useful information is present in the outcome of each investigation. If an alert is identified as suspicious, or if it is determined that it was a false-positive alert or due to incorrect data, this information should be incorporated into the appropriate monitoring and

quality-control procedures. This feedback is used to make changes to alert rules, re-calibrate models, and identify recurring data defects and trace them back to their source. Learning is a gradual process of the system.

Hence, data governance should be at the core of AML strategy. Not at the edge. Combined with reliable data, effective reconciliation, analytical controls and accountable governance, transaction-monitoring systems can be more accurate, efficient and adaptable to the evolving threats of financial crime.

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