# Tookitaki Typology Repository Management



Tookitaki

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# Executive Summary

Anti-Money Laundering is a significant burden for large and small banks, irrespective of their line of business. Money laundering techniques are evolving faster than we could think. Legacy systems with static rules are good as long as money launderers do not develop a workaround. Further, individual banks have built their AML programs with limited data to cater to specific products, customer types, location and do not have the knowledge of suspicious patterns observed across peer banks. The rules of the game change often as customers behaviour change. New patterns emerge. Result: Financial Institutions need to incorporate new rules or change thresholds of existing rules to suit the market dynamics. Despite huge investments in resources and technology, FIs continue to be plagued with high false positive volumes and poor detection of true suspicious cases, increasing the risk profile and fear of non-compliance.

This paper begins with analysing the current state of the AML Transaction Monitoring (TM) ecosystem, highlighting the challenges across legacy systems and traditional machine learning applications. In the next segment, the paper highlights Tookitaki's innovation in TM through Typology Repository Management (TRM), a new way of detecting money laundering through collective intelligence and continuous learning. At Tookitaki, we envision that this advanced machine learning approach will enable financial institutions capture changing customer behaviour and stop the bad actors with high accuracy and speed, improving returns and risk coverage.

Tookitaki TRM concept was awarded the Monetary Authority of Singapore's Financial Sector Technology and Innovation (FSTI) Proof of Concept (POC) grant on 12th December 2019. The FSTI POC grant provides funding support for experimentation, development and dissemination of nascent innovative technologies in the financial services sector.

## Current Transaction Monitoring (TM) Ecosystem and Challenges

Today's transaction monitoring (TM) solutions fail to provide financial institutions a comprehensive AML risk coverage. The solutions are fragmented and mostly rely on rules or are augmented by traditional machine learning approaches that are not enough to keep pace with changing customer behaviour and detect complex money laundering activities. The 'Fear of Unknown' prevails largely and at the same time the current solutions generate ultra-high false positives, making the AML programs ineffective and inefficient with increasing cost.

The challenges across current TM solutions are elaborated under three broad points:

1. Static and granular rules-based approach
    a. They are oblivious of the holistic trend and network of money laundering activities as the focus is narrow and uni-dimensional. Even money launderers are aware of the rules and adjust their transactions accordingly to stay under the radar
    b. They are not self-sustainable i.e. require manual tuning which is expensive and considerably time consuming. By the time a new rule reaches production, it becomes obsolete
2. Siloed AML programs with no or limited knowledge from peer banks
    a. Absence of a mechanism of sharing insights and patterns across banks, geographies (even in different business units within the same bank) leads to insufficient and ineffective coverage of AML risks globally
    b. Even with relaxed regulations on data sharing, the bank's adoption rate on sharing and management of AML policies and dynamics is limited
3. Traditional machine learning approaches built with inspiration from rules
    a. They are heavily dependent on static rules logic which neither capture money laundering risk holistically nor remain valid for long. Thus, the resulting machine learning based models become quickly obsolete when the rules change or rule-based systems change
    b. Model development life cycle is costly from both time and resource perspective.
    c. The rate of shift in data is usually faster than the rate of change of existing machine learning based models being deployed in production which results in models being ineffective in capturing suspicious behaviour

# Introducing Tookitaki Typology Repository Management

Uncertain economic conditions, digitization of banking, changing regulatory landscape and operational constraints continues to challenge financial institutions (FIs) to build effective AML programs. For FIs, the crisis has reached such an inflection point that they have moved beyond the experimental stage with AI adoption and making significant investment to adopt next-generation technologies in production environment. However, current AI solutions are unable to help FIs address the root cause of weak AML programs, which is substandard detection mechanism.

Legacy systems need frequent changes in thresholds and rules to keep to the changing environments. Custom machine learning models involve massive human effort in model development and face significant implementation challenges in production environment. It usually follows the rules and create attributes that mimic them to differentiate between a fine and a malicious activity. Sophisticated systems using graph analytics can visually represent intricate relationships within datasets and present powerful insights behind a particular money movement, complementing as a great tool for investigation. But it does not do a great job in detecting suspicious cases and prioritizing alerts in three risk levels – High, Medium and Low. The reason being it is a technique to uncover all possible relationships, which can be fine activities, thereby failing to detect true cases and generating false positives. Only when the 'discovered' relationships are automatically overlaid with specific typologies and associate itself with historical customer risk, it is truly able to differentiate between a normal and a suspicious activity.

As an emerging Regtech company, Tookitaki's innovations in the AML space has been applauded by some of the most esteemed organizations such as the World Economic Forum and tested and proven across reputed global financial institutions and risk consultants like Deloitte. Following the market needs, Tookitaki has developed a Typology Repository Management (TRM), the world's first decentralized machine learning-powered AML system. TRM is a revolution in the AML/CFT space as it can capture changing customer behavior and detect suspicious cases, besides prioritizing alerts with high accuracy, without the need to apply any personally identifiable information (PII), rules and thresholds.

TRM has been developed on the following two guiding principles:

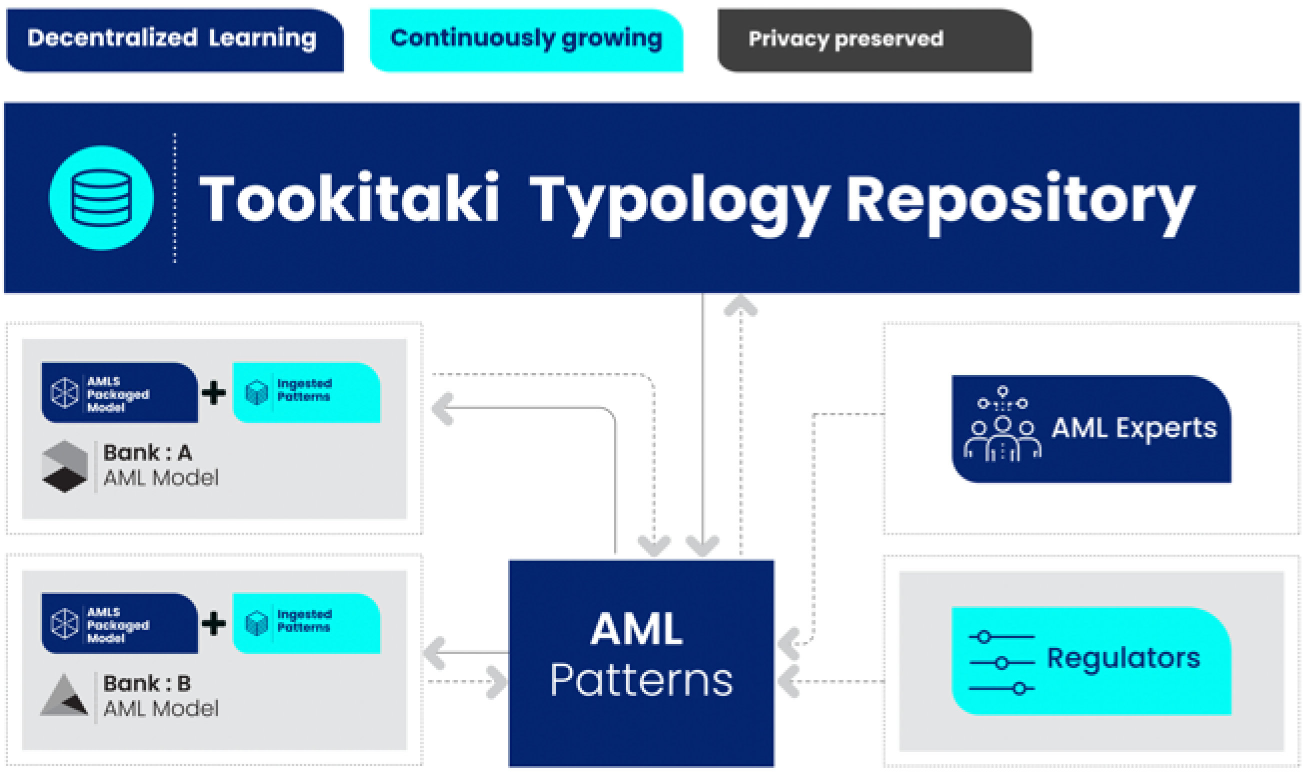
- It is a growing centralized repository of money laundering typologies sourced from financial institutions, AML experts and regulators. Typologies refer to patterns that are used to finance or launder money for illicit activities like drug trafficking, forced labor, forgery, terrorism etc. A money laundering pattern is defined as a technique to aggregate varied customer activities that represents a suspicious behavior. Each money laundering pattern in TRM comprises of four key components – Customer, Counterparty, Network and Transactions. None of the components hold any PII data or any finite value

- It gives an ability to ingest specific money laundering patterns and automatically create thousands of relevant risk indicators, when overlaid on a bank's dataset. These risk indicators are then auto-picked by pre-defined machine learning models to detect suspicious cases.

TRM provides comprehensive AML risk coverage. Financial institutions of any type (retail banks, corporate banks, private banks, correspondent banks, asset managers, institutional investors) can ingest any type of typologies, including graph-based typologies. FIs can use its interactive GUI to search and select typologies using single or combined parameters across the following lines

# TRM Components and Workflow

## TRM Workflow: A Visual Representation

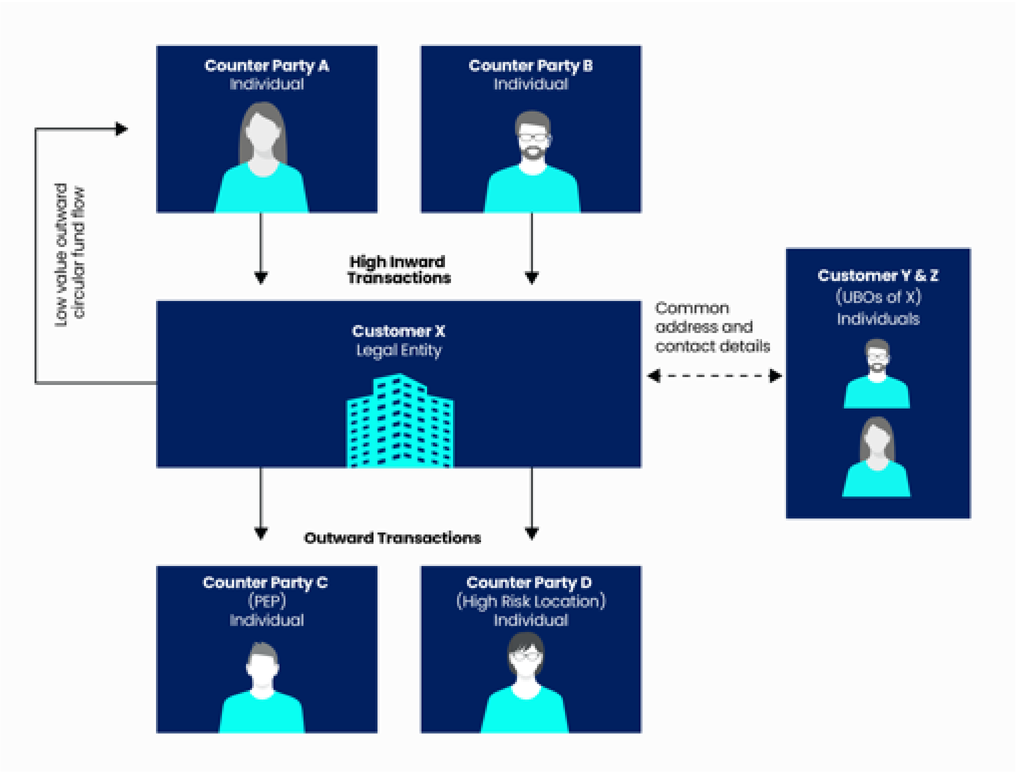



| | Sharing workflow | Ingestion workflow |
|---|---|---|
| Process | AML experts and regulators can share new typologies through an interactive GUI. The sharing process starts with defining the typology and then configuring the same using properties like Customer, Counterparty, Network and Transactions linked to either individual or legal entity customer type or a combination of both, without divulging any PII data and thresholds. The typology can then be submitted for validation and approval. On the other hand, Financial Institutions can share typologies or true cases through the auto-extraction engine, without trading any customer info | Financial institutions can view and select the typologies relevant to them by applying single or combined parameters across customer type, product type, predicate offence, location and technique. The selected typologies are automatically converted into machine readable format and creates thousands of risk indicators, once applied on the bank's dataset. These risk indicators are consumed by pre-defined machine learning algorithms to detect suspicious cases, matching the select typologies. This specific typology-powered new model is combined with the pre-trained machine learning model (that comes with a |

| | | |
|---|---|---|
| | | set of risk indicators) into a final model and applied on the bank's dataset to prioritize alerts into three risk levels – High, Medium and Low. The ingestion process is powered by automated model management and develops stable, generalized models that can withstand market changes and retain performance over time. |
| Benefits | Provides various industry stakeholders to collaborate and share AML wisdom in a privacy-preserved manner. | Helps FIs to detect suspicious cases accurately and prioritize alerts, with high false positive reduction and true positive classification in High Risk bucket. |

## Real life example of TRM Pattern Implementation

The below example of money laundering pattern explains how TRM enabled sharing of a shell company typology in a privacy preserved manner.
**Typology:** Shell companies used to transact funds involving high risk jurisdictions and multiple counter parties



| Customer | Counterparty | Transaction | Network |
|---|---|---|---|
| • Corporate Account | • Counterparty D is located in High Risk Jurisdiction<br>• Counterparty C Is a PEP | • The ratio of IN/OUT fund flow is high<br>• High value inward transfers<br>• Low value outward transfers<br>• Low value outward transfers through circular fund flow to specific counter parties | • Customers X shares the same address and contact details with two other customers of the same bank – Customer Y and Customer Z |

These properties are ingested into a bank and they automatically convert into thousands of risk indicators, suited for the specific dataset. Some examples of risk indicators are as below:

- watchlist_pep_organization_director
- amount_incoming_transactions_individual_30Days
- amount_outgoing_transactions_individual_30Days
- relationship_individuals_employment
- relationship_individuals_organization

These risk indicators are consumed by pre-defined machine learning algorithms (that comes with Tookitaki AMLS-TM module) to detect shell company scenarios.

# Value Proposition

**Key drivers to introduce patterns in their TM system**


Global and regional regulators have continued to issue guidance and joint statements encouraging Financial Institutions to explore the role of technologies, specifically Artificial Intelligence to enhance AML programs.

- Organizations can capitalize on this guidance and explore the benefits of using collective intelligence and automated evolution approach to develop a comprehensive and smarter AML system.
- TRM significantly strengthens the Financial Institutions risk appetite that arises from various business growth strategies such as geographic expansion and exploring new avenues in digital banking
- Consistent intelligent alert triaging and new cases detection with generalized models that can help Financial Institutions withstand any changes in consumer behavior and regulatory developments, thus achieving operational resilience

# Expected Benefits

**Financial Institutions**

- Faster implementation: TRM will help Financial Institutions implement and update any typology of their interest and this can be applied in production in days and see results. Imagine – with digitization as customers shift to use e-wallets, TRM can help them just select and implement digital payment typology and achieve risk coverage in no time. In traditional way, they had to create rules and test them and would take 4-5 months

- Better Alert Prioritization: Due to the number of typologies coming into the model, the alert dataset may be analyzed along multiple dimensions thus giving precise boundary values and lesser misclassification rates amongst L1 and L3 buckets.
- Detect New Cases: The capability to detect new cases which were previously unknown or were unable to be detected may now be detected because of better feature set availability due to typologies

**Regulatory authorities and Enforcement agencies**

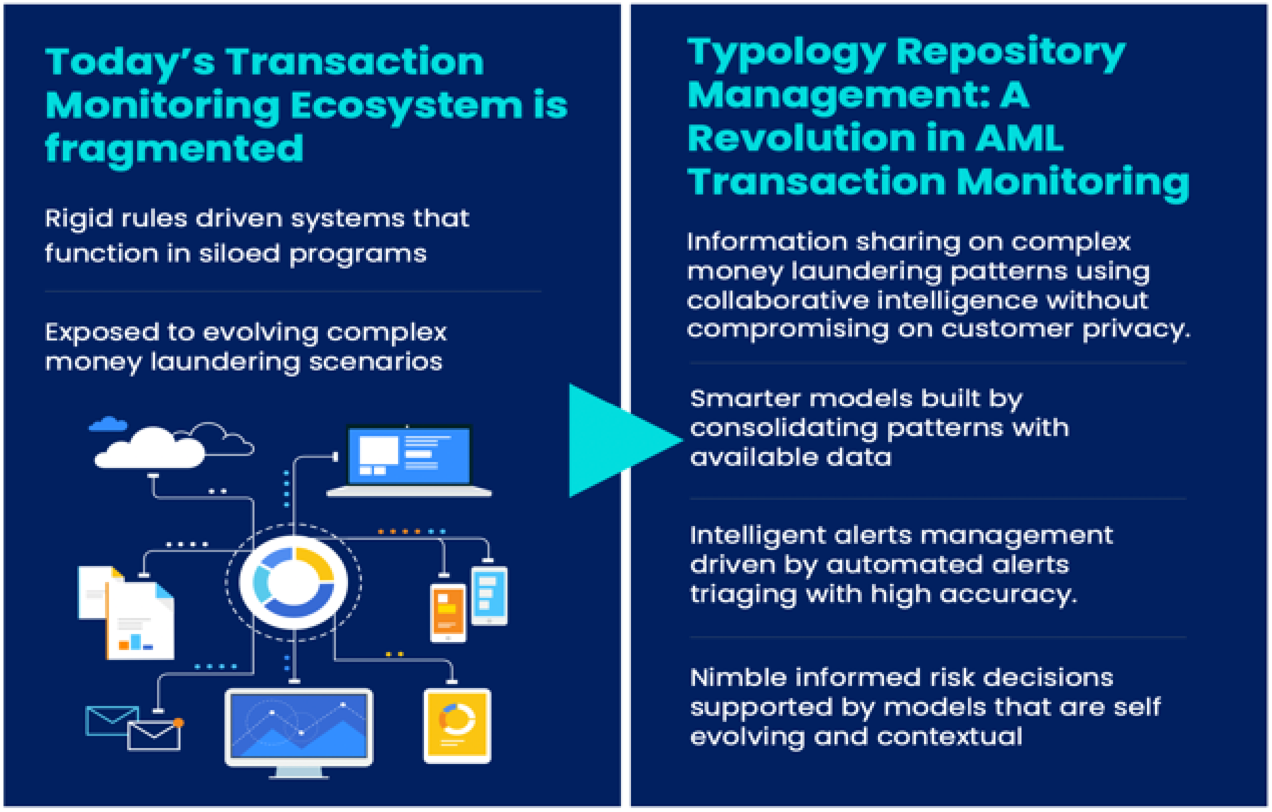
- As global and regional regulators who manage regulatory policies with an objective to curb money laundering, it is essential they have the necessary guidance to strengthen AML policies. With TRM, regulators get a comprehensive view of the TM landscape across all banking segments and regions which not only assists them in tightening the policy measure but also have a sharper focus on emerging risk areas.
- TRM also facilitates Regulators in enhancing their regulatory assessment framework and provide them a holistic view of the concerned bank's AML policy during regulatory reviews and provide stronger recommendations for improvements

**AML experts**

- NPOs: The exhaustive coverage of the risk indicators involved in each money laundering activity provides essential inputs to NPOs, who work collaboratively with numerous organizations to crack criminal activities. In addition, the information they can extract from TRM, can serve as one of the key inputs in sharing best practices with their peers and enforcement agencies
- Risk Consulting companies: With TRM, these organizations can strengthen the various risk assessment tools and frameworks and provide enhanced risk consulting support to help Financial Institutions design optimal AML policies, especially when concerned with specific risk categories

## Concluding Thoughts




AI as a broader concept has witnessed significant hype in recent years, with most vendors claiming AI expertise. However, most innovations in AML compliance is still rules-oriented, and the new-age sophisticated systems that are using graph analytics have not gone beyond improving investigations. These are clear indicators that banks move beyond the current state and seek synergies to adopt AI/ML in an efficient manner if they want to achieve the goal of sustainable compliance. For this it is essential they embark on a journey with next-gen technology partners who present strong technology capabilities to prioritize solutions with demonstrated efficiency and effectiveness improvements with reduced load on human resources and enhanced risk coverage. Next-gen technology companies should enable this without ripping and replacing existing systems; adopt strategies such as augmentation with secondary scoring and most importantly provide transparent models and explainable and documentable predictions to ensure banks are aligned with the Explainability requirements of regulatory authorities.

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