Transforming AML Compliance with AI
From rule-based to risk-based approach

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Introduction: Exploring AI Trends and their impact on AML Compliance

In the ever-evolving landscape of financial crime, traditional rules-based transaction monitoring is under challenge. As financial institutions grapple with the necessity to remain both compliant and agile, there is a clear need for a paradigm shift.

The trends are showing a tectonic shift from static, one-size-fits-all rules, to the adaptive and flexible terrain of a risk-based approach. Regulators and international standard setters like the Financial Action Task Force (FATF) have promoted a risk-based approach for nearly ten years[1]. Yet in practice many programs remain focused on check-box compliance rather than ensuring a genuine understanding of threats and a targeted risk-driven approach.

The ability to make this change has transformed thanks to powerful new technologies in the form of AI and machine learning. Compliance is no longer confined to rule sets, but rather draws on the intelligence, precision and dynamic adaptability of risk-based systems to achieve better results in identifying and preventing money laundering, terrorist financing and other criminal activity.

This white paper examines the ways AI and machine learning powered transaction monitoring is helping financial institutions of every scale shift to a risk-based approach. We examine the implications, benefits and transformative potential of utilizing AI technology and machine learning algorithms to foster efficiency and effectiveness, ensuring a secure and robust anti-money laundering (AML) program.

Shifting Paradigms in Transaction Monitoring: Embracing a Risk-based Approach

Rules-based transaction monitoring has two major problems

1 Vast amounts of suspicious behavior goes undetected as it does not align with a predefined typology

2 What is detected is not actually suspicious at all (an estimated 95% false positive rate, according to industry research[2]).

Rules-based systems skew heavily towards false positives (needless alerts on unsuspicious activity, which pose a significant resource strain), and false negatives (actual risks going undetected).

AI and machine learning solutions generate highly accurate results, enhancing both efficiency and effectiveness. They dramatically reduce the number of false positives by up to 95%[3], creating a smaller volume of alerts for analysts to investigate.

False negative Bad outcome No alert for suspicious activity	**True negative** Good outcome No alert for non-suspicious activity
True positive Good outcome Alert for suspicious activity	**False positive** Bad outcome Alert for non-suspicious activity

Given they are not constrained by binary rules, machine learning solutions are able to detect more anomalous behavior and identify more risk patterns, leading to better coverage of real risks. This creates what seems like a paradox - better risk coverage and more detected instances of financial crime, through fewer alerts.

A major hindrance to a traditional rules-based approach is its inability to detect new typologies or threats. Criminals adapt quickly, circumventing standard rules and thresholds by devising new methods for laundering illicit funds. Harnessing technology, nefarious actors innovate to evade detection or outsource to technology-savvy professional criminals, who offer what is essentially money-laundering-as-a-service[4].

Because rules-based systems aren't agile enough to contend with the fast evolving nature of criminality, firms become vulnerable to bad actors who learn to bypass and outsmart existing controls.

Conversely, AI can leverage supervised and unsupervised machine learning to identify previously unidentified risk indicators – the 'unknown unknowns' - thus offering better protection from illicit activity.

Supervised vs unsupervised machine learning

Supervised machine learning requires labeling input data and actively teaching the algorithm, which then informs all future predictions based on predefined criteria.

Unsupervised learning is when a machine learning system learns the normal behavior of an institution's database using historical unlabelled data. The algorithm infers its own rules and structure by creating different segments using 'clustering' or 'association'. Once a baseline of normality is established, the system is able to detect patterns and anomalies without guidance or instruction.

Semi-supervised learning is a combined proposition, using both labeled and unlabeled data to train AI models for classification and regression tasks.

The limitations of traditional AI supervised learning

Relying solely on a supervised learning approach presents several disadvantages, including;

- **The extensive time required for data labeling and model training, and**
- **the reinforcement of pre-existing biases and blindspots.**

Because the model is trained on labeled data, any trends in historical decisions or institutional norms will be replicated, creating a feedback loop.

For instance, if analysts historically made unfounded assumptions about certain customers based on their nationality or occupation, and disproportionately labeled their activities as suspicious, the system will learn from this and apply the same bias going forward.

Equally if analysts over-report transactions in sectors they are unfamiliar with, such as complex trade finance transactions, the system will learn this pattern of behavior too.

The problem with labeled data in financial crime is that programmers do not know if historic transactions represented financial crime or not - merely that they were deemed suspicious by human actors prone to error, working with a very limited set of information.

Similar to the drawbacks of rules-based systems, supervised learning may also struggle to detect novel or 'unknown' typologies. If certain patterns are not identified as suspicious in the past, the system is not taught to identify them going forward.

Fundamentally, supervised learning approaches only optimize alerts but don't address the root problems with traditional transaction monitoring approaches. Similarly, a semi-supervised approach still draws on labeled datasets, which reinforces existing errors and biases.

This approach greatly improves the quality and accuracy of transaction monitoring alerts, deepening the level of detection to go beyond predefined factors. Additionally, unsupervised machine learning can reduce false positives to only 1% of alerts[5], offering vast operational benefits for compliance teams.

Unsupervised machine learning has the potential to completely transform transaction monitoring. By analyzing a staggering amount of information within huge and complex datasets (Big data), this system determines a baseline for normality without predetermined human-made rules, thresholds or assumptions. The data analysis of these types of algorithms can detect irregularities and hidden patterns, identifying emerging threats.

Features of an unsupervised machine learning system

- Operates independently of rules and models, analyzing Big data to establish a baseline of normal behavior and identify patterns and anomalies.
- Continuously improves and adapts to changing realities, enhancing accuracy through ongoing learning from the data sets.
- Seamless integration without the need for constant rule programming and reprograming makes onboarding faster, easer and cost-effective.
- Enhances detection accuracy and minimizes false alerts, reducing resources required for monitoring and management.
- Detects 'unknown unknowns' by deriving conclusions directly from the data rather than predefined rules programmed by developers.
- Provides a comprehensive audit trail on alerts for transparent reporting to regulators.

How data fuels Transaction Monitoring

Data is an integral part of effective transaction monitoring. If there are limited data points to enable intelligent and quality alert generation or to properly contextualize a transaction during an investigation, then an institution's transaction monitoring suffers as a result.

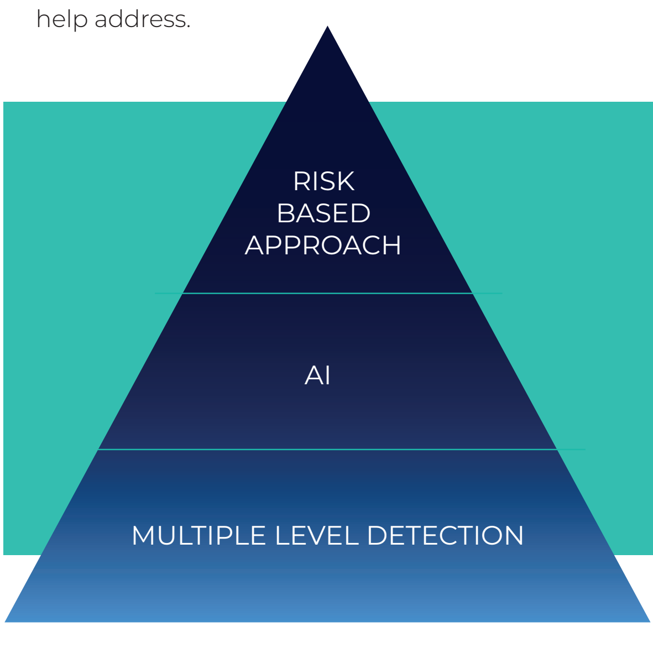
Poor data analysis leads to slow processes and redundant investigations. Sophisticated machine learning solutions draw on multiple data points to identify patterns and connections, producing alerts with a deeper level of detection and accuracy.

Network visualization, which involves showcasing different data points in a clean and easily digestible manner, is an essential component of an effective machine learning tool. These data points include risk indicators such as high-risk jurisdictions, flagged counterparties, and historical activities of a client, which help analysts form links to find suspicious connections that are maybe indicative of financial crime.

Date Range: 03/02/2021 - 13/07/2021
Graph Depth: 1
Transaction Value: All USD
Number of Transactions: All
Display On/Off:
☑ Transaction value
☑ Alerted transaction
☑ Country
☑ Legend
☑ Number of transactions
☑ Show transaction flow to / from alerted entity
☐ Timeline

While different financial institutions have different datasets, a good machine learning will be able to cater to all needs, including working with startups or early stage firms until they have enough data to deploy unsupervised machine learning.

Conversely, for large financial institutions that might have different operating models spanning various countries, machine learning solutions can segment localized data to draw out patterns in specific subsets. There are also a number of jurisdictional challenges or nuances that machine learning tools can help address.



For example, institutions operating in emerging markets may be challenged by a lack of digitized databases or unavailable official data records, such as corporate or property records. Remittance firms often have sparse Know Your Customer (KYC) data and infrequent transactions to draw on, making it difficult to determine the baseline of normality for an individual client. Because machine learning solutions enhance detection by analyzing patterns across datasets, they can provide more accurate results in use cases such as these.

Case study

Travelex Bank is Brazil's largest foreign exchange provider, offering a range of international money transfer products including import/export, remittances, and mass payments. The bank contends with stringent Brazilian regulation and as it operates in mass payments, generates huge volumes of transactions every day. Travelex Bank implemented ThetaRay Transaction Monitoring anti-money laundering solution for both domestic and international transaction monitoring, as well as real-time sanctions screening for its international payments.

Results of adopting a Machine Learning solution:

In the proof of concept (POC), completed in only 3 days, Travelex Bank was able to process 30,000 transactions per minute.

Full integration was completed in only 2 months.

Travelex Bank reported a 10X reduction in false positives.

Increased efficiencies by deploying the Machine Learning solution allowed for a 30-40% predicted business growth.

Capitalizing on AI-driven Compliance to Enable Business Growth

Deploying an AI-powered solution is viewed as cost prohibitive, and justifying those costs is front and center of decision-making for businesses. However, machine learning compliance solutions can help accelerate business growth in a number of ways:

Enhancing Risk Detection

Machine Learning solutions detect real instances of financial crime as well as previously unidentified typologies, increasing risk coverage. It also enables analysts to focus on value-add activities; identifying opportunities for business growth, highlighting trends, supporting wider stakeholders with reporting and being able to draw more impactful insights from data.

Enabling business scalability keeping compliance cost

Machine learning solutions allow firms to process more transactions without proportionally increasing compliance costs, enabling business expansion and increased client acquisition.

Expanding business scope

Machine Learning transaction monitoring is better at detecting real risk and handling business fluctuations, thus firms can expand their scope of business confidently without necessarily increasing their risk exposure. An institution can thus explore new clients or deals in jurisdictions previously deemed too risky.

Provides the ability to serve the traditionally underbanked and encourage financial inclusion.

Reducing false positives

Machine Learning solutions reduce the need for large teams of analysis investigating unproductive alerts.

Eliminating unnecessary investigation work provides long-term benefits including staff retention. With 87% of organizations having no additional capacity due to staffing issues[6], it's crucial that firms focus their teams on value added contributions.

Ensuring regulatory compliance

Global AML penalties are on the rise, with fines surging more than 50% in 2022[7]. A robust machine learning- powered AML compliance program helps avoid severe fines.

Evolving AML detection

Machine learning solutions don't need constant reconfiguration and are able to continuously learn and adapt based on ongoing data collection and analysis.

Case study

NOW Money is a Dubai Fintech, and the Gulf Cooperation Council's first mobile banking solution focused on financial inclusion. It helps customers excluded from the traditional banking system send remittance payments abroad as quickly and cheaply as possible. NOW Money partnered with ThetaRay to monitor cross-border payments and support the detection of financial crime.

> "Anything to do with cross-border requires the best technologies and the ability to use AI. From NOW Money's perspective, we want to be best-in-breed when it comes to compliance, audit and governance, so we need to work with good parties like ThetaRay".
>
> **Noel Connolly, CEO at NOW Money**

Adopting an AI monitoring solution has helped NOW Money process transactions efficiently so that their customers' families can receive payment without delay. **The number of false positives has dropped dramatically**, and the **centralized investigation dashboard** allows for the quick distribution of work so cases are dealt with faster. The solution also **instantly screens beneficiaries**, which enables teams to deal with flagged individuals and alerts immediately, speeding up the process and retaining customers by preventing unnecessary customer friction.

Most obviously, financial institutions that leverage machine learning tools in their AML compliance program benefit from enhanced risk detection, which helps them remain regulatorily compliant and avoid hefty fines.

Another important benefit is the simple integration and ongoing use of machine learning solutions. Traditional rules-based solutions require regular testing and reprogramming of scenarios and thresholds. Upon discovering a new financial crime typology, it can take 6-12 months to reprogram legacy systems to detect it.

By then, criminals have likely devised new methods rendering the solution out of date again. Conversely, machine learning solutions don't need constant reconfiguration and are able to continuously learn and adapt based on ongoing data ingestion and analysis.

Conclusion: Transforming Compliance from Cost to Profit with AI

As criminals innovate and crimes become more complex, financial institutions must adapt. Rules-based systems are resource-intensive, provide only partial coverage, generate increased false positives, and unintentionally introduce bias. Their inefficiencies strain compliance resources and leave firms vulnerable to bad actors and regulatory fines.

By adopting a risk-based approach with unsupervised machine learning, firms can enhance transaction monitoring, detect previously unknown threats, increase risk coverage, reduce compliance costs, and ensure regulatory compliance. AI-powered solutions transform compliance from a cost center to a profit generator, allowing financial institutions to expand into new markets and customer segments previously deemed too risky all the while maintaining compliance.

Appendix: Overview of ThetaRay & FINTRAIL

About ThetaRay

ThetaRay is a pioneer in the field of anti-money laundering (AML) with AI-powered solutions that deliver trusted transactions and trusted customers for banks, fintechs, and regulators around the world.

Designed to reduce our clients risk exposure through unparalleled detection of financial crime, uncovering 'unknown-unknowns' and delivering insightful alerts, with a precise assessment of customer's risk profiles.

Fast to deploy, fast to update and fast to maintain, our solutions enable cost-efficient AML compliance.

About FINTRAIL

FINTRAIL is a global financial crime consultancy. We've worked with over 100 leading global banks, FinTechs, other regulated financial institutions, RegTechs, venture capital firms and governments to implement industry-leading approaches to combating money laundering and other financial crimes.

With significant hands-on experience, we can help you build, strengthen and assure your transaction monitoring program to meet evolving regulatory requirements, use technology effectively, and stay competitive.

Sources: **1** FATF Risk based approach for the Banking Sector **2** Global Investigation Review, 2020 **3** Per ThetaRay research, 2023 **4** Europol **5** Per ThetaRay research, 2023 **6** Deloitte, 2023 **7** Financial Times, 2022

If you would like to see how ThetaRay can positively impact your AML program and improve your compliance posture, speak to a member of our team.
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