VIEW POINT

DYNAMIC AML RISK SCORING: ADAPTING TO EVOLVING FINANCIAL CRIME THREATS WITH AI

Abstract

Between $800 billion and $2 trillion is laundered through the global financial system every year. This amounts to roughly 2 to 5% of global GDP, according to the United Nations Office on Drugs and Crime. Of that, law enforcement seizes less than 1%. The infrastructure detecting and mitigating the remainder is, in most institutions, a patchwork of static rules, periodic reviews, and manual alerts. To counter these threats, AML risk scoring must evolve from a static perimeter check into a dynamic, real-time assessment tool. This article examines what a genuinely dynamic AML risk scoring model looks like, why the risk-based approach demands it, and how AI is beginning to close the gap between compliance volume and compliance quality.

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The data on compliance failure builds a strong case for an imminent restructuring. Global AML compliance costs now exceed $274 billion annually, with a large share consumed by investigating alerts that turn out to be false. More than 90% of transaction monitoring alerts at most banks are false positives, according to McKinsey. Research found that only 2 to 4% of those alerts are ever serious enough to require a Suspicious Activity Report filing.[v]

The US Department of the Treasury published its 2024 National Risk Assessment on Money Laundering, documenting how increasingly complex layering schemes and cross-border structures are outpacing institutions' detection capacity.

The legacy systems

Most legacy AML systems operate on static rule sets and periodic scoring cycles. A customer is assessed at onboarding, assigned a risk tier, and reviewed again at a fixed interval. The reviews are scheduled every 3-5 years for low-risk clients and annually for high-risk ones. Between those reviews, the customer might change. Institutions that update scores only annually create 12-month windows in which customer behaviour can deteriorate undetected.

Research from July 2025 suggests that many compliance programs remain "risk-based in name only." A risk-based approach, as FATF and regulators worldwide require, means directing enhanced scrutiny to customers who actually pose elevated risk, not spreading uniform oversight equally across the entire customer base. Static scoring cannot do that. It can only sort customers into static tiers.

What AML risk scoring is — and what it must be

AML risk scoring assigns a numerical or categorical value to each customer reflecting their likelihood of involvement in money laundering or financial crime. That score informs due diligence intensity, monitoring frequency, and escalation thresholds.

Every strong model distinguishes two types of risk.

- **Inherent risk:** This is the raw exposure before any controls are applied. It is determined by who the customer is, where they operate, and what they do.
- **Residual risk:** This is what remains after the controls are applied.

Regulators expect both to be documented and explainable at every scoring step.

The critical principle is that scores must be dynamic. It is codified across FinCEN, FATF, and EU AML regulatory frameworks. Criminals change methods, structures, and behaviour over time. An effective risk model tracks that change.

The three core factors: customers, products, and geography

Under the Bank Secrecy Act's risk-based framework, inherent AML risk is determined by three primary factors: the products and services offered, the customers served, and geographic exposure. These three appear in some form across virtually every jurisdiction's AML framework.

Customer risk

Customer risk is the most complex. A corporate entity structured through multiple offshore holding companies poses fundamentally different risks from a domestic individual with documented employment income. There is no "one size fits all" approach. The risk factors for an individual (source of funds, residential address, occupation) differ from those for a corporation (ownership chains, beneficial control structure, jurisdiction of incorporation). A model that applies the same parameters to both will systematically under-weigh risk in one category while over-flagging the other.

Geographic risk

Geographic risk is equally time-sensitive. FATF identified 23 countries under high-risk or increased monitoring for AML/CFT deficiencies in 2026. A customer's country of residence may have been low-risk at onboarding and high-risk six months later.

Geographic risk must be assessed across multiple dimensions simultaneously: jurisdiction of incorporation, source of wealth location, custodian and intermediary jurisdictions, and counterparty domicile. When more than one dimension poses elevated risk, those risks should compound, not average.

Product and service risk

Product and service risk is the third leg. A savings account holder who begins actively using prepaid cards and digital wallets has shifted product exposure in a way that is itself a risk signal. It is separate from any individual transaction they make.

Dynamic risk factors: the behavioural change dimension

Static risk labelling has its limitations: it tells you where a customer started, not where they are now.

Transaction amount and frequency are the most visible signals. An account inactive for months that begins executing multiple large-value transfers in a single week warrants immediate attention, because the account holder's behaviour has diverged from their established baseline. A system with dynamic monitoring tools detects such a pattern, adjusts the risk rating, and generates an investigation trigger in real time.

The baseline matters as much as the deviation. Organisations can establish behavioural norms during the first 90 days of a customer relationship, against which subsequent transactions can be compared. Without that baseline, institutions cannot distinguish genuine anomalies from unusual but entirely lawful activity.

Adverse media and sanctions status are equally time-sensitive. A company classified as low risk at onboarding that subsequently appears in credible reporting linked to a corruption case requires immediate score recalibration. Such a recalibration cannot wait until the next scheduled review. The same applies when PEP status changes, when ownership structures change, or when source of wealth narratives evolve in ways that no longer match documented history.

Dynamic scoring is essential because AML risks are not defined by static labels, but by how customer behaviour evolves over time.

Building the AML risk scoring model

Effective AML risk scoring models share a common architecture regardless of the technology that powers them. There are five essential components:

- Defined risk factors with empirical correlation to money laundering behaviour
- Weighting mechanisms assigning relative importance based on predictive power
- Scoring algorithms aggregating weighted factors into a numerical score
- Threshold definitions demarcating low, medium, and high risk
- Validation processes ensuring accuracy without excessive false positives

A number of factors define different model types.

- Rule-based systems are tansparent and auditable. They apply fixed-point weights to predetermined criteria and produce results that are straightforward to explain to regulators. But they cannot adapt to patterns that were not anticipated when the rules were written.
- Machine learning algorithms detect complex relationships across hundreds of variables simultaneously and continuously improve as new data arrives. Their limitation is explainability: opaque outputs create problems in regulatory examination.
- The strongest approach is a hybrid. It defines mandatory rule sets applied for regulatory compliance, with machine learning identifying emerging typologies that static rules would miss. A PEP designation carries a different weight from a residential postcode. A high-risk source of wealth with limited documentation carries a different weight from either.

For investment advisers preparing for FinCEN's evolving requirements, the recommended framework requires models to be built on four principles:

- Client-centric rather than transaction-centric
- Separating inherent from residual risk
- Event-driven and lifecycle-based rather than calendar-based
- Fully explainable and auditable at every tier assignment.

Why AI makes a difference

Legacy rule-based AML models were not built for today's transaction volumes or for the adaptability of modern criminal methods. AI addresses both problems directly. McKinsey's research finds that AI-driven AML monitoring can reduce false positive rates by 50% while identifying 10 to 20% more alerts related to actual money laundering activity.

The mechanism of continuous learning allows a machine learning model to adjust its understanding of normal customer behaviour as new transactions arrive. Whereas, a rule-based system fires an alert whenever a transaction crosses a static threshold. A transaction anomalous against a static rule may be entirely consistent with a customer's established behavioural pattern, and a well-trained model recognises that.

In institutions still running legacy systems, compliance teams spend 30 to 45 minutes investigating every Level 1 alert. At 1,000 alerts per day, that is up to 750 analyst hours spent on activity that only yields 20 to 40 actionable cases.

AI also enables what is increasingly called perpetual KYC. It is the continuous updating of customer risk profiles as new data arrives, rather than relying on scheduled review cycles. When a new sanctions hit, an adverse media report, or a transaction pattern change appears, an AI-powered system triggers immediate risk recalibration without waiting for a quarterly review. This is the operational expression of what a genuine risk-based approach actually requires, and the standard regulators are moving toward.

Whether AI fully resolves the explainability challenge remains genuinely contested. Some compliance experts argue that hybrid models can satisfy regulatory examination; others maintain that the opacity of deep-learning models creates liability that rule-based logic does not. That debate will not be settled quickly, and institutions building AI-first AML frameworks need to factor explainability into model design from the beginning.

End note

The regulatory direction is set by the changing market. FinCEN's Investment Adviser AML rule, delayed to January 2028, still mandates risk-based customer due diligence and ongoing monitoring as central obligations. The EU's Anti-Money Laundering Authority became fully operational on 1 January 2026, bringing coordinated supervisory pressure across member states. FATF continues to expand its monitored jurisdiction list. The financial institutions that build dynamic, AI-enabled AML risk scoring models now will be compliant, robust, and operationally efficient.

For more information, contact infosysbpm@infosys.com

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