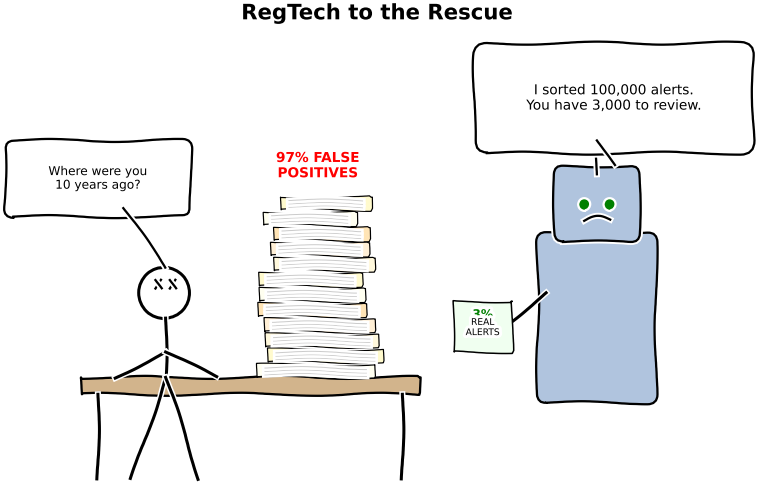
Lesson 7.2: RegTech — Automating Compliance at Scale

Module 7: The Compliance Problem

Prof. Dr. Joerg Osterrieder

Digital Finance — BSc Course



The compliance officer was last seen smiling in 2014.

Learning Objectives

After this lesson you will be able to:

1. **Explain** why manual compliance does not scale for modern financial institutions [Understand]
2. **Compare** rule-based and ML-based transaction monitoring approaches [Analyze]
3. **Design** an alert triage pipeline that reduces false positive rates [Create]
4. **Describe** the eXtensible Business Reporting Language (XBRL) regulatory reporting framework and its automation benefits [Understand]
5. **Analyze** how biometric and document-based identity verification systems work [Analyze]
6. **Evaluate** privacy-preserving techniques (differential privacy, federated learning, secure MPC) for compliance use cases [Evaluate]
7. **Map** the RegTech vendor landscape by functional category [Understand]

Bloom's levels: Understand (1,4,7), Analyze (2,5), Evaluate (6), Create (3).

From Rules to Automation

Lesson 7.1 — The compliance landscape:

- Regulatory requirements: AML, KYC, CFT
- Cost of compliance for banks and FinTechs
- Consequences of non-compliance (fines, license loss)
- Manual processes and their limitations

Lesson 7.2 — Automating compliance:

- Transaction monitoring: rules vs. ML
- Alert optimization and false positive reduction
- Regulatory reporting automation (XBRL)
- Identity verification technology
- Privacy-preserving compliance techniques
- The RegTech vendor ecosystem

We understand the rules. Now: how do we automate compliance?

RegTech applies technology to regulatory challenges — the same way FinTech applies technology to financial services.

Can Technology Cut Compliance Costs by 60%?

Definition: RegTech (Regulatory Technology) refers to technology solutions that help financial institutions comply with regulations more efficiently, accurately, and cost-effectively than manual processes.

- The term was coined around 2015 by the UK Financial Conduct Authority (FCA)
- Global compliance spending by financial institutions exceeds $200 billion annually (conceptual industry estimate)
- Manual compliance teams at large banks: 10,000–30,000 employees
- Key driver: regulations have grown in volume and complexity since the 2008 financial crisis
- RegTech is to compliance what FinTech is to banking: automation of costly manual processes

Core promise: Same or better compliance outcomes at a fraction of the cost and time.

The FCA Innovation Hub and the Bank of England were early champions of RegTech as a distinct sector.

RegTech: Five Functional Categories

Category	What It Does	Example Technology
Transaction Monitoring	Detect suspicious patterns in payment flows	ML anomaly detection
Regulatory Reporting	Automate submission of mandated reports	XBRL, natural language processing
Identity Verification	Verify customer identity (KYC)	Biometrics, document AI
Risk Management	Monitor and quantify compliance risk	Real-time dashboards
Regulatory Change	Track and interpret new regulations	NLP on legal text

This lesson covers the first three categories in depth, plus privacy-preserving techniques that cut across all five.

Each category addresses a different pain point in the compliance value chain. Most large banks use vendors from multiple categories.

Transaction Monitoring: The Core Compliance Engine

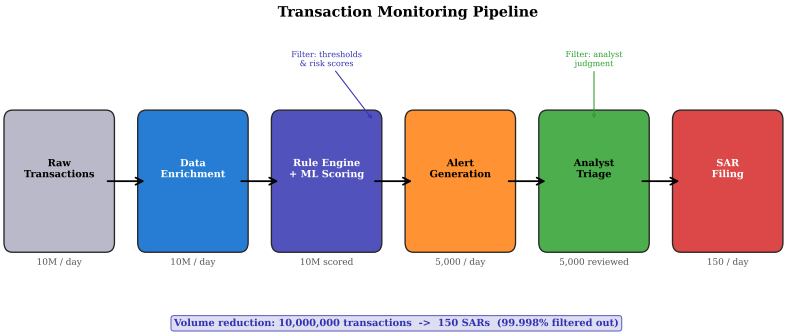
Definition: Transaction monitoring is the automated process of reviewing customer transactions to detect patterns indicative of money laundering, terrorist financing, fraud, or sanctions violations.

- Required by AML regulations in every major jurisdiction
- Processes millions of transactions per day at large banks
- Generates **alerts** when transactions match suspicious patterns
- Alerts are reviewed by human analysts who decide: *escalate* or *dismiss*
- Escalated cases become **Suspicious Activity Reports (SARs)** filed with regulators

The fundamental tension: too few alerts $\rightarrow$ missed laundering (regulatory risk); too many alerts $\rightarrow$ analyst overload (operational risk).

A typical large bank generates 50,000–200,000 alerts per month but files only 1–5% as SARs.

Transaction Monitoring Pipeline



- **What you see:** 10M daily transactions funnel down through rule engines and ML scoring to 150 SARs
- **Key pattern:** 99.998% of volume is filtered out — only 0.002% reaches SAR filing
- **Takeaway:** Each stage (enrichment, scoring, triage) must balance catching true positives with analyst capacity

Each stage filters out legitimate activity. The goal is high recall (catch all true positives) with manageable volume for human review.

Rule-Based Transaction Monitoring

Traditional approach: Hard-coded rules ("scenarios") flag transactions that exceed predefined thresholds.

Common rule examples:

- Cash deposits above $10,000 (Bank Secrecy Act threshold)
- Multiple deposits just below the reporting threshold ("structuring")
- Rapid movement of funds through multiple accounts within 24 hours
- Transactions with sanctioned countries or entities
- Sudden increase in transaction volume relative to customer history

Advantages: Transparent, auditable, easy to explain to regulators.

Limitations:

- Criminals adapt to known thresholds $\rightarrow$ rules become stale
- Static thresholds produce excessive false positives (often $>95\%$)
- Cannot detect novel patterns not anticipated by rule designers

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Most legacy transaction monitoring systems use 100–500 pre-configured rules. Tuning these rules is a full-time job.

ML-Based Transaction Monitoring

Modern approach: Machine learning models learn patterns from historical data to score transactions by suspicion level.

Supervised models:

- Trained on labeled SARs (positive) and cleared alerts (negative)
- Random Forest, Gradient Boosting, Neural Networks
- Output: probability score per transaction
- Strength: high precision on known patterns

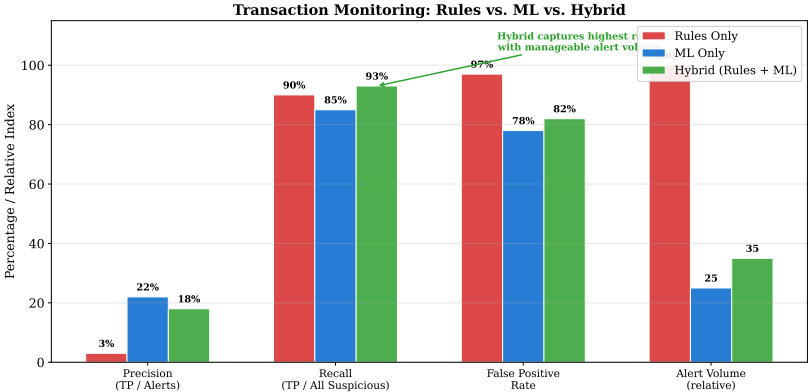
Unsupervised models:

- Detect anomalies without labeled training data
- Isolation Forest, Autoencoders, Clustering
- Output: anomaly score per transaction or customer
- Strength: can find novel, previously unseen patterns

Hybrid approach (most common): Rules for regulatory mandates (e.g., the $10,000 threshold) + ML for everything else.

ML models can reduce false positives by 40–70% while maintaining the same true positive detection rate (conceptual benchmark).

Rule-Based vs. ML-Based Detection



- **What you see:** Hybrid approach achieves highest recall (93%) with only 35% alert volume
- **Key pattern:** Pure rules generate 100x alert volume with only 3% precision; ML alone reduces volume but sacrifices recall
- **Takeaway:** Hybrid systems leverage rules for regulatory mandates and ML for noise reduction

ML models trade some interpretability for substantially better precision. Hybrid systems combine the strengths of both.

Why Do Banks Review 100,000 Alerts to Find 2,000 Real Cases?

The #1 operational challenge in transaction monitoring: false positives.

Scale of the problem:

- Rule-based systems: 95–99% false positive rate
- Each alert requires 30–60 minutes of analyst review
- Cost per alert investigation: \$20–\$50 (*LexisNexis True Cost of Financial Crime Compliance*, 2023)
- A bank with 100,000 monthly alerts and 97% false positives wastes resources on 97,000 non-suspicious cases

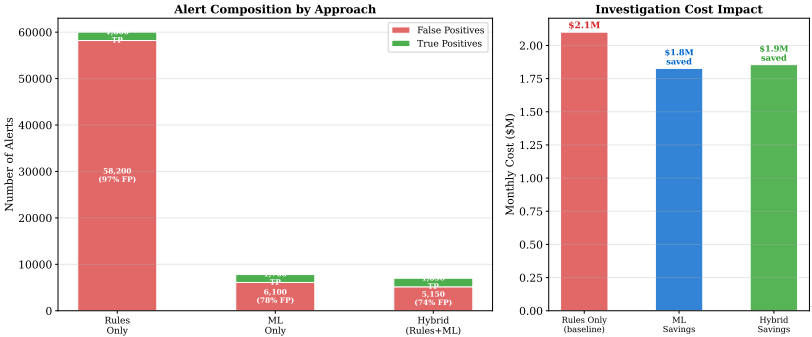
Consequences:

- Analyst fatigue $\rightarrow$ true positives are missed
- Compliance teams are understaffed relative to volume
- Regulatory expectation: every alert must be reviewed
- Banks cannot simply raise thresholds without regulatory approval

Key insight: Reducing false positives is not just about efficiency — it directly improves the detection of real financial crime.

"Alert fatigue" is a recognized risk factor. Regulators increasingly accept ML-based prioritization to address it.

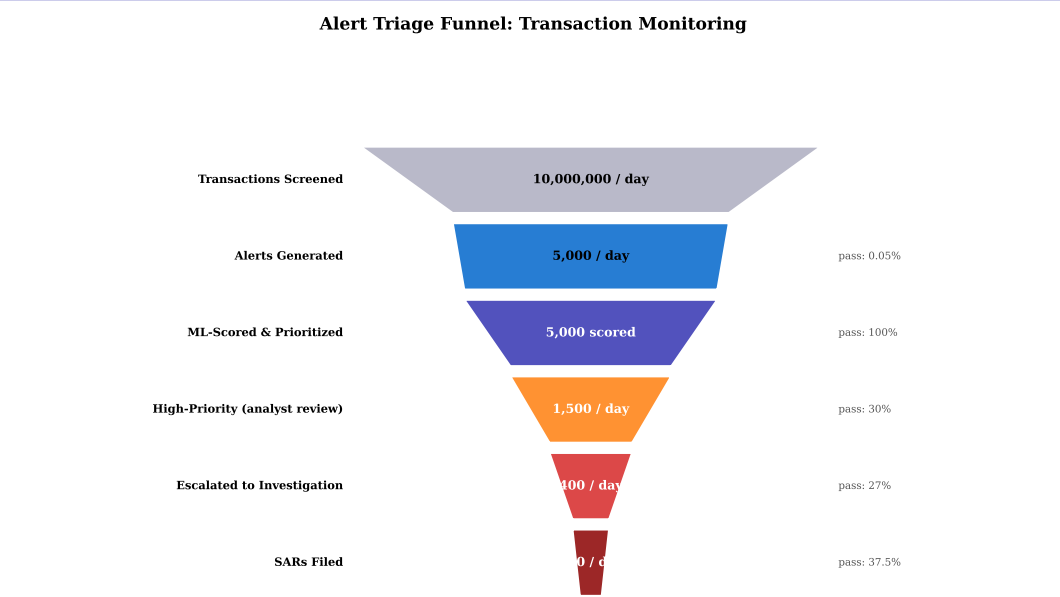
False Positive Reduction: Rules vs. ML vs. Hybrid



- **What you see:** Rules-only generates 58,200 false positives vs 5,150 for hybrid (91% reduction)
- **Cost impact:** At $35 per alert, hybrid saves $1.8M monthly vs rules-only baseline
- **Takeaway:** True positive count remains stable (1,700–1,850) while investigation burden drops dramatically

Even modest false positive reduction translates to millions of dollars in annual savings for large institutions.

Alert Triage Funnel



Alert Optimization Strategies

How to reduce false positives without missing true positives:

1. **Customer risk segmentation:** Apply different thresholds to high-risk vs. low-risk customer segments
2. **Contextual scoring:** Enrich alerts with customer history, peer group behavior, and external data
3. **Network analysis:** Examine transaction counterparties, not just individual transactions
4. **Above-the-line / below-the-line:** ML scores prioritize the alert queue; low-scoring alerts get expedited review
5. **Feedback loops:** Analyst decisions on past alerts retrain the ML model continuously
6. **Scenario tuning:** Periodically review rule thresholds using historical true/false positive data

Regulatory requirement: Any optimization must be documented and justified. Regulators expect evidence that true positive rates are maintained.

"Model risk management" (the Federal Reserve's supervisory guidance on model risk management (SR 11-7) in the US) applies to ML models used in compliance just as it does to credit models.

Regulatory Reporting: The Reporting Burden

Definition: Regulatory reporting is the mandatory submission of structured financial data to supervisory authorities on a periodic or event-driven basis.

- Banks submit hundreds of distinct reports per jurisdiction per year
- Report types: capital adequacy (Basel III), liquidity (LCR), transaction reporting (Markets in Financial Instruments Directive II (MiFID II) / EMIR), tax (Foreign Account Tax Compliance Act (FATCA) / CRS)
- Manual reporting involves data extraction, transformation, validation, and submission
- Error rates in manual reporting: commonly 5–15% of submissions require restatement (Source: Thomson Reuters Cost of Compliance Annual Survey; Deloitte Global FS Regulatory Outlook)
- A single reporting error can trigger regulatory investigation and fines

Cost: Large banks spend $50–100 million annually on regulatory reporting infrastructure.

The EU alone introduced over 50,000 pages of financial regulation between 2009 and 2020 (approximate industry estimate).

Can Machines Read Financial Reports?

Definition: XBRL (eXtensible Business Reporting Language) is an open, XML-based standard for tagging financial data so it can be read, validated, and analyzed by machines.

How XBRL works:

- Each financial fact (e.g., "Total Assets") is tagged with a machine-readable label from a taxonomy
- Taxonomies define the allowed tags, their relationships, and validation rules
- Reports are submitted as structured XBRL documents, not PDFs or spreadsheets

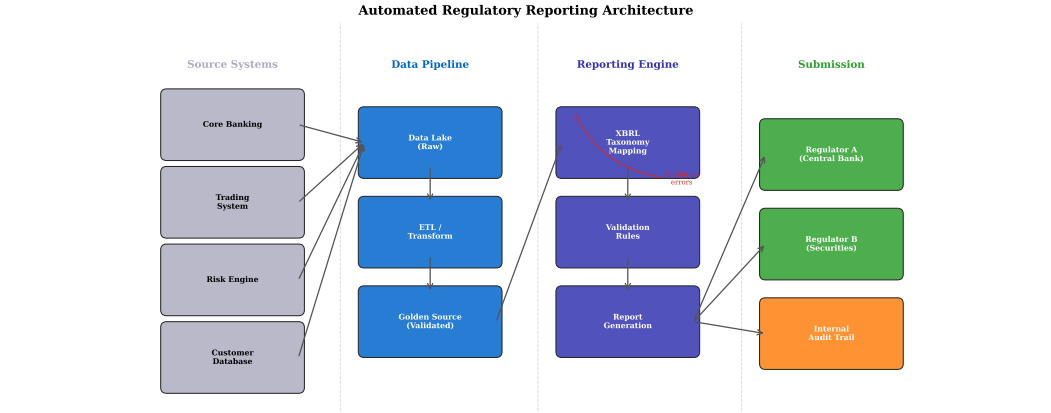
Benefits:

- Automated validation at submission time
- Machine-comparable data across institutions
- Reduced manual data entry errors
- Faster regulatory analysis and response

Adoption: Mandated by the US SEC (since 2009), European Banking Authority (EBA), Bank of England, and 60+ regulators worldwide.

XBRL eliminates "PDF to spreadsheet" manual transcription, which is the largest source of reporting errors.

Automated Regulatory Reporting Architecture



- **What you see:** Four-layer pipeline from source systems through data lake, XBRL mapping, to regulator submission
- **Key component:** Golden Source (validated layer) ensures one-version-of-truth before XBRL taxonomy mapping
- **Takeaway:** Validation errors loop back to data pipeline instead of reaching regulators — preventing restatements

Automation replaces manual extract-transform-load (ETL) with continuous, validated data pipelines.

Identity Verification: The KYC Technology Stack

Definition: Digital identity verification is the process of confirming a person's identity remotely using technology rather than in-person document inspection.

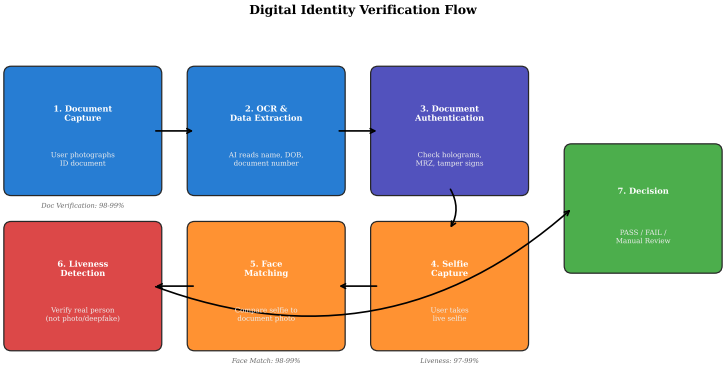
Three pillars of modern KYC verification:

1. **Document verification:** AI-powered extraction and authentication of identity documents (passport, national ID, driving license)
2. **Biometric verification:** Matching a live selfie or fingerprint to the photo on the verified document
3. **Liveness detection:** Confirming the person is physically present (not a photo, video replay, or deepfake)

Method	Speed	Fraud Resistance
Manual document review	1–3 days	Low–Medium
Automated document + biometric	30–90 seconds	Medium–High
Document + biometric + liveness	60–120 seconds	High

Automated KYC can reduce onboarding time from days to minutes while improving fraud detection accuracy.

Biometric Verification Flow



- **What you see:** Seven-step flow from document capture through OCR, authentication, face match, liveness to final decision
- **Accuracy stack:** Each step achieves 97–99% accuracy; combined probability of fraud passing all checks $< 0.001\%$
- **Takeaway:** Liveness detection (step 6) is the critical defense against photo/video replay and deepfake attacks

Each step reduces the probability of a fraudulent identity passing through. Liveness detection is critical against deepfakes.

How Do You Prove You're Not a Deepfake?

Problem: Fraudsters attempt to bypass biometric checks using photos, pre-recorded videos, or AI-generated deepfakes.

Two types of liveness detection:

Active liveness:

- User performs a challenge: blink, turn head, smile, read a number
- Verifies real-time responsiveness
- Higher friction (takes 5–10 seconds)
- Harder to spoof with static images

Passive liveness:

- Analyzes a single selfie for micro-textures, depth cues, reflection patterns
- No user action required (frictionless)
- Uses convolutional neural networks (CNNs)
- Vulnerable to advanced deepfakes without additional signals

Current best practice: Combine passive liveness (for low-risk onboarding) with active liveness (for high-risk transactions or step-up verification).

The ISO/IEC 30107-3 standard defines Presentation Attack Detection (PAD) levels for biometric liveness testing.

The Privacy Paradox in Compliance

Tension: Effective compliance requires analyzing customer data. Privacy regulations (GDPR, CCPA) restrict how that data is collected, stored, and shared.

Compliance needs data for:

- Transaction monitoring across accounts
- Cross-institutional information sharing (e.g., typology networks)
- Customer risk profiling
- Regulatory reporting of individual transactions

Privacy regulations restrict:

- Data minimization (collect only what is necessary)
- Purpose limitation (use data only for stated purposes)
- Cross-border data transfers
- Profiling without explicit consent

Solution direction: Privacy-preserving computation techniques allow compliance analysis without exposing raw personal data.

The GDPR (Article 6(1)(c)) provides a legal basis for processing personal data when required by law, but the principle of data minimization still applies.

Differential Privacy for Compliance Analytics

Definition: Differential privacy (DP) is a mathematical framework that adds calibrated noise to data or query results so that the output does not reveal whether any individual's data was included.

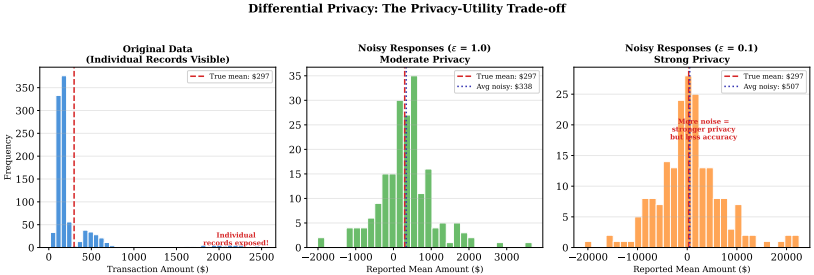
- **Core idea:** The result of an analysis should be approximately the same whether or not any single individual's record is in the dataset
- **Privacy parameter ε (epsilon):** Controls the privacy–utility trade-off. Lower ε = stronger privacy but noisier results
- **Mechanism:** Add random noise (Laplace or Gaussian) calibrated to the query's sensitivity

Compliance application: A bank can share aggregate transaction statistics with regulators or industry utilities without exposing individual customer transactions.

Example: Reporting the average transaction amount per customer segment $\pm$ noise, rather than individual transaction records.

Differential privacy was pioneered by Cynthia Dwork (2006) and is now used by Apple, Google, and the US Census Bureau.

Differential Privacy: How Noise Protects Individuals



- **What you see:** Original data exposes individuals; adding Laplace noise hides them while preserving mean estimate
- **Privacy-utility tradeoff:** $\varepsilon = 1.0$ gives tighter noise distribution; $\varepsilon = 0.1$ gives stronger privacy but wider error bars
- **Takeaway:** Aggregate statistics remain accurate (noisy mean $\approx$ true mean) but reverse-engineering individual records becomes impossible

The noise is calibrated so that aggregate statistics remain useful while individual records cannot be reverse-engineered.

Federated Learning for Cross-Institutional Compliance

Definition: Federated learning (FL) is a machine learning technique where a model is trained across multiple institutions without sharing raw data. Only model updates (gradients) are exchanged.

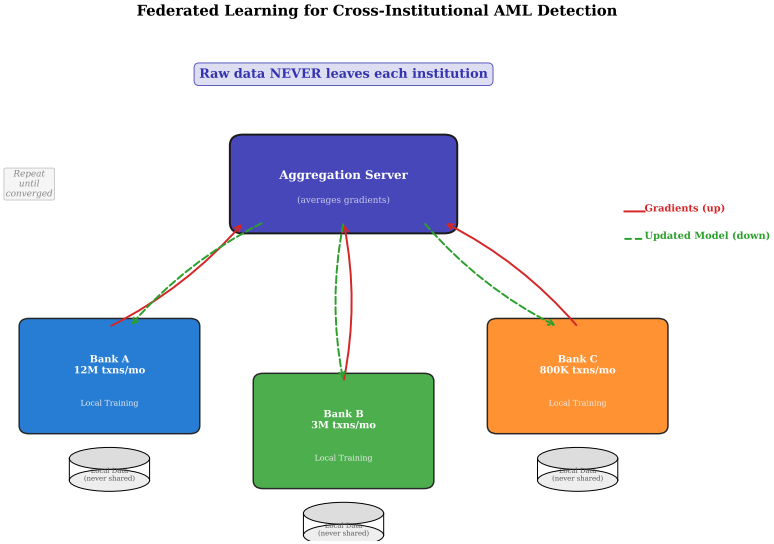
1. A central server distributes a global model to participating banks
2. Each bank trains the model on its local transaction data
3. Banks send only the model weight updates (not data) back to the server
4. The server aggregates updates and distributes an improved global model
5. Repeat until the model converges

Compliance application: Multiple banks collaboratively train an AML detection model that benefits from cross-institutional patterns — without any bank seeing another bank's customer data.

Key benefit: Catches typologies that span multiple institutions (e.g., layering across different banks) without data pooling.

Federated learning was introduced by Google (McMahan et al., 2017) for mobile keyboard prediction and has since been adapted for finance.

Federated Learning Architecture



- **What you see:** Three banks train local models on their data; only gradients (not data) flow up to aggregation server

Secure Multi-Party Computation (MPC)

Definition: Secure MPC is a cryptographic protocol that enables multiple parties to jointly compute a function over their combined inputs without revealing those inputs to each other.

How it works (simplified):

- Each party "secret-shares" its input
- Computation is performed on encrypted shares
- Only the final result is revealed
- No party learns anything beyond the output

Compliance applications:

- Sanctions screening across banks without sharing customer lists
- Joint fraud detection on shared transaction graph
- Privacy-preserving identity deduplication
- Aggregate risk reporting to regulators

Trade-off: MPC provides the strongest privacy guarantees but is computationally expensive. Practical for batch processing, challenging for real-time use.

Secure MPC was first theorized by Andrew Yao (1982). Modern implementations are fast enough for many financial applications.

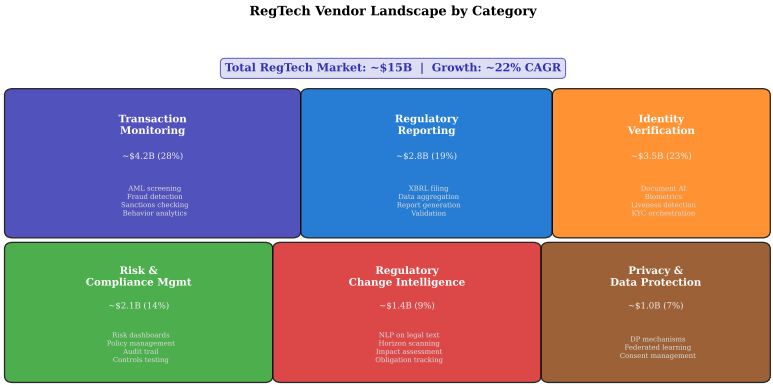
Privacy-Preserving Techniques: Comparison

Property	Differential Privacy	Federated Learning	Secure MPC	Homomorphic Encryption
Data leaves institution?	Noisy aggregates only	No (gradients only)	No (shares only)	No (ciphertext only)
Computational cost	Low	Medium	High	Very High
Accuracy impact	Noise reduces precision	Minimal	None	None
Best use case	Aggregate reporting	Collaborative ML	Joint computation	Cloud computation

Practical reality: Most RegTech deployments combine techniques — for example, federated learning with differential privacy applied to the gradient updates.

Homomorphic encryption (computing on encrypted data) is included for completeness but remains too slow for most real-time compliance workloads.

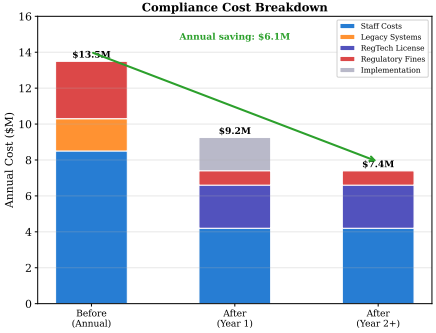
The RegTech Vendor Landscape

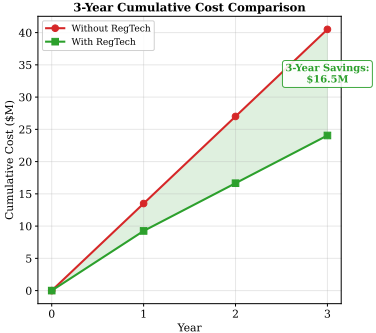


- **What you see:** Six functional categories totaling $15B market; transaction monitoring (28%) and identity (23%) are largest
- **Growth driver:** 22% CAGR reflects rising regulatory complexity plus shift from manual to automated compliance
- **Takeaway:** Privacy & data protection ($1.0B) is smallest but fastest-growing segment as GDPR/AI Act compliance demand increases

The RegTech market is estimated at $10–15 billion globally and growing at 20–25% annually (conceptual industry estimates).

The Business Case: Compliance Automation ROI





- **What you see:** Annual cost drops from $13.5M to $7.4M after Year 2 — $6.1M annual savings
- **Payback period:** Year 1 includes $1.85M implementation cost; cumulative 3-year savings reach $17.4M
- **Takeaway:** Largest savings come from staff cost reduction (50%) and eliminated regulatory fines ($3.2M → $0.8M)

ROI is driven primarily by headcount reduction in alert review and reporting, plus avoided regulatory fines.

RegTech Implementation Challenges

Technical challenges:

- Legacy core banking systems resist integration
- Data quality: inconsistent formats, missing fields, duplicate records
- Model validation: regulators require explainability for ML-based decisions
- Real-time processing at scale (millions of transactions per day)
- Cross-border data residency requirements

Organizational challenges:

- Compliance culture favors conservatism over innovation
- Regulator skepticism toward "black box" ML models
- Vendor lock-in concerns with proprietary platforms
- Change management: retraining compliance analysts
- Budget competition with revenue-generating projects

Key insight: Technology is rarely the bottleneck. Organizational readiness and regulatory acceptance are the harder problems.

Successful RegTech adoption requires close collaboration between compliance officers, data scientists, and regulators.

Regulatory Acceptance of ML in Compliance

Question: Will regulators accept ML-based compliance decisions?

Current state by jurisdiction:

- **US (FinCEN / OCC):** Supportive in principle. Joint statement (2018) encourages "innovative approaches" to AML compliance. Requires model risk management (the Federal Reserve's supervisory guidance on model risk management (SR 11-7)).
- **EU (EBA):** Published guidelines on ML use in AML/CFT (2023). Emphasizes explainability, human oversight, and ongoing validation.
- **UK (FCA):** "TechSprints" actively test RegTech solutions. Open to ML if governance is adequate.
- **Singapore (MAS):** Actively promotes RegTech via sandbox programs and industry grants.

Common requirements across jurisdictions:

1. Explainability — regulators must understand why an alert was (or was not) generated
2. Human-in-the-loop — final SAR filing decisions must involve a human
3. Ongoing monitoring — model performance must be tracked and documented

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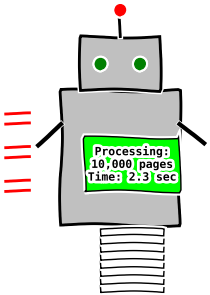
No regulator has banned ML in compliance. The trend is toward cautious acceptance with strong governance requirements.

One Last Thought...



The regulatory compliance race: humans vs. machines. Spoiler: the machines are winning.

Sometimes the best way to remember a concept is to laugh about it.

Key Takeaways

1. **RegTech** automates compliance across transaction monitoring, regulatory reporting, identity verification, risk management, and regulatory change tracking
2. **Transaction monitoring** generates massive alert volumes; ML reduces false positives by 40–70% vs. rule-based systems alone
3. **Alert triage** combines ML scoring with human review to ensure both efficiency and regulatory acceptance
4. **XBRL** standardizes regulatory reporting into machine-readable formats, eliminating manual transcription errors
5. **Biometric verification** with liveness detection enables fast, fraud-resistant KYC that replaces in-person document checks
6. **Privacy-preserving techniques** (differential privacy, federated learning, secure MPC) resolve the tension between compliance data needs and privacy regulations
7. The RegTech market is large and growing, but **organizational change and regulatory acceptance** remain the primary adoption barriers

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RegTech is not optional — it is how compliance will work at scale as transaction volumes and regulatory complexity continue to grow.

Summary / Next Lesson Preview

This lesson:

- Defined RegTech and its five functional categories
- Compared rule-based and ML-based transaction monitoring
- Analyzed the false positive problem and alert optimization strategies
- Explained XBRL-based regulatory reporting automation
- Examined biometric identity verification with liveness detection
- Evaluated privacy-preserving techniques for cross-institutional compliance
- Surveyed the RegTech vendor landscape and implementation challenges

Next lesson — Lesson 7.3:

- Deep dive into AML case studies and typology detection
- Network analysis for uncovering layered laundering schemes
- Real-world SAR filing workflows and regulatory feedback loops

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With the technology toolkit established, we next apply it to real compliance scenarios and measure outcomes.

Self-Check: RegTech

Attempt these before turning the page.

1. [Understand] What does XBRL add that PDF regulatory reports do not? Name two regulators mandating XBRL in 2025.
2. [Apply] A bank switches from 98% FP rate (rule-based) to 85% FP rate (ML-based). If alert volume is 150,000/day and investigation cost is \$10/alert, compute daily savings.
3. [Evaluate] Under EU AI Act, AML screening models are "high-risk" and require documentation + oversight. Is a rule-based system exempt? Argue.

Solutions hidden unless `\solutionstrue` is set before compiling.