WORLD COMET RESEARCH GROUP

International Journal of Data Engineering and Intelligent Computing
Vol. 8, No. 1, 2025
Doi: 10.67228/30715717/IJDEIC-2025PI4G2D
PP. 01-18

Original Article

Real-Time Intelligent Data Engineering for Automated Cross-Border Payments and Regulatory Compliance

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Received: 12-06-2024 Revised: 12-26-2024 Accepted: 01-04-2025 Published: 01-06-2025

ABSTRACT

Real-time processing, AI-driven data engineering, and autonomous integration of payment and compliance functions are critical requirements for improving the efficiency and effectiveness of cross-border payments. Despite recent innovations, the achievement of truly autonomous cross-border payments remains out of reach. Many systems still depend on human intervention as real-time capability is limited to the payment, while compliance processes remain force-fitted thereafter which reduces the efficiency and increases the risk of the overall system. Formal principles of real-time data processing are outlined, together with a formalization of a real-time data engineering pipeline capable of processing the data required to support autonomous cross-border payments. Central to this is the definition of latency requirements for streams of financial data and the steps needed to ensure that these are met. Specific attention is given to the different dimensions of data quality, the notion of streaming data fusion, and the supporting role of regarded components.

KEYWORDS

Real-Time Payment Processing, Cross-Border Payment Systems, AI-Driven Data Engineering, Autonomous Payment Integration, Financial Data Streaming, Payment Compliance Automation, Low-Latency Data Pipelines, Streaming Data Fusion, Payment Data Quality, Real-Time Financial Analytics.

ISSN: 3071-5717
PP: 01-18.

1. INTRODUCTION

Definition of the scope and significance of the research topic, presentation of the main research question, and justification of the assertion that real-time Augmented Intelligence-based financial and business data engineering (processing and analysis of incoming events and data streams) is a prerequisite for the effective deployment and functioning of autonomous cross-border payment and compliance systems, integrating payment, settlement and compliance decision-making into a single system of real-time data engineering for cross-border payments and compliance.

The deployment and functioning of an autonomous systems of cross-border payments, which handles payment initiation, payment clearing, payment processing, payment settlement, and payment- and compliance-related supervision and decision-making, in real-time, let alone into a single system, would be little more than a dream if Augmented Intelligence-based Financial Data Engineering, capable of processing incoming data streams and events, associated with a bank (or banks, payment service providers (PSPs) or platforms), in real-time were not possible. For such a capability to be achieved, three questions must be answered. What are the latency requirements and expectations, originating from the Deployment of Real-Time Payments Systems, for the Continuous Operation of Autonomous Cross-Border Payment Systems? What data requirements for cross-border payment transactions must be satisfied in order for the continuous operation of an autonomous cross-border payment system to meet national regulations and comply with international obligations? Which operational principles constitute a foundation on which Augmented Intelligence-based financial data engineering, capable of processing data and events streams in real-time, can be constructed?

1.1. Mathematical Formulation

This performance and operational metrics governing the AI-driven autonomous cross-border payment pipeline. Equations are derived from the real-time data engineering principles, latency models, compliance accuracy requirements, and resource optimisation objectives discussed throughout the system architecture.

1.1.1. Composite Payment System Quality

The overall system quality of the autonomous cross-border payment pipeline is expressed as the weighted sum of four complementary quality dimensions:

$$\mathbf{Q\_total = Q\_ingest + Q\_process + Q\_latency + Q\_comply} \quad \text{(Eq. 1)}$$

where Q_ingest denotes payment data ingestion quality (freshness × completeness), Q_process represents AI-driven payment classification accuracy, Q_latency captures real-time latency compliance, and Q_comply reflects regulatory compliance assurance. This composite index drives architectural trade-off decisions across all pipeline tiers.

1.1.2. Latency Dynamics Model for Payment Streams

End-to-end payment pipeline latency evolves according to data arrival and processing service rates:

$$\partial L/\partial t = \lambda\_pay - \mu\_pipeline \quad \text{(Eq. 2)}$$

ISSN: 3071-5717
PP: 01-18.

where L is the end-to-end ingestion-to-settlement latency, λ_pay is the payment event arrival rate into Apache Kafka / Azure Event Hubs, and μ_pipeline is the throughput rate of the downstream processing engine (Databricks / Flink). When λ_pay > μ_pipeline, backpressure accumulates and horizontal autoscaling is triggered to maintain SLA bounds.

1.1.3. AML / Compliance Detection F1-Score

Predictive accuracy of the AI-driven AML and sanctions screening module is measured using the standard F1 metric:

$$\mathbf{F1\_AML = (2 \cdot Precision \cdot Recall) / (Precision + Recall)} \quad \text{(Eq. 3)}$$

where Precision = TP / (TP + FP) and Recall = TP / (TP + FN), computed from the confusion matrix of the real-time sanctions screening and AML anomaly detection engine operating over streaming transaction windows. F1_AML is the primary accuracy criterion for regulatory compliance sign-off.

1.1.4. Streaming Data Fusion Score

The unified AI inference module fuses streaming payment anomaly scores, batch KYC risk signals, and sanctions residual errors into a single compliance decision score:

$$\mathbf{s'(t) = s(t) + \alpha \cdot k(t) + \beta \cdot r(t)} \quad \text{(Eq. 4)}$$

where s(t) is the real-time streaming anomaly score from the payment stream, k(t) is the KYC/beneficial ownership risk signal from the batch enrichment layer, r(t) is the residual sanctions screening error from the watchlist matching engine, and a, β are empirically tuned cross-domain coupling coefficients. The fused score s'(t) drives the autonomous payment approval or rejection decision.

1.1.5. Weighted Multi-Source Compliance Decision Fusion

To support adaptive decision fusion across payment, KYC, and sanctions data streams, the combined compliance score is modelled as:

$$\mathbf{s'(t) = w_1 \cdot s(t) + w_2 \cdot k(t) + w_3 \cdot r(t) + w_4 \cdot s(t) \cdot k(t)} \quad \text{(Eq. 5)}$$

Here w_1, w_2, w_3, w_4 are learnable weighting coefficients optimised via federated gradient descent across geographically distributed compliance nodes. The interaction term s(t)·k(t) explicitly models the nonlinear coupling between real-time transaction risk and static KYC risk level.

1.1.6. Data Auditability and Provenance Score

Regulatory auditability of the payment data pipeline is quantified by the fraction of data transformations for which complete provenance is captured:

$$\mathbf{S\_audit = 1 - (D\_untraced / D\_total)} \quad \text{(Eq. 6)}$$

where D_untraced is the volume of payment data records for which provenance metadata (timestamp, source, transformation function, lineage ID) is absent, and D_total is the total volume processed per audit epoch. S_audit approaches 1.0 when end-to-end provenance capture is implemented across all Kafka topics and Delta Lake partitions.

1.1.7. Infrastructure Resource Utilisation

Compute resource utilisation across the payment pipeline infrastructure stack is given by:

$$\mathbf{U = R\_used / R\_available} \quad \text{(Eq. 7)}$$

where R_used is the aggregate CPU/memory/GPU capacity consumed by Databricks clusters, Flink stream processing jobs, and AML inference engines, and R_available is the total provisioned capacity. U is monitored continuously via Azure Monitor and drives autoscale policies to maintain latency SLAs.

1.1.8. Pipeline Scalability Efficiency (PSE)

Federated compliance learning across geographically distributed payment nodes introduces convergence overhead. Pipeline scalability efficiency is modelled as:

$$\mathbf{E\_PSE = (F1\_AML \cdot S\_audit) / T\_round} \quad \text{(Eq. 8)}$$

where T_round denotes the duration of one federated model aggregation round in seconds. Higher E_PSE indicates the pipeline delivers strong AML detection accuracy with high regulatory auditability at low synchronisation cost a key objective for cross-border payment networks.

1.1.9. Adaptive Freshness Threshold for Payment Data

Payment data freshness requirements vary dynamically with pipeline load and regulatory deadlines. The adaptive freshness threshold is governed by:

$$\boldsymbol{\theta(t) = \theta_0 + \gamma \cdot \sigma\_pay(t) + \delta \cdot drift(t)} \quad \text{(Eq. 9)}$$

where θ_0 is the baseline SLA-defined freshness ceiling (in seconds) for the payment processing tier, σ_pay(t) is the real-time variance in payment message arrival (proxy for burst load), drift(t) captures temporal distribution shift in cross-border payment flows, and γ, δ are scaling parameters tuned during CI/CD pipeline validation.

1.1.10. Resilience and Throughput Efficiency

The payment pipeline resilience efficiency combines AML detection accuracy, auditability, and inference speed:

$$\boldsymbol{\eta = (F1\_AML \cdot S\_audit / T\_infer) \times 100} \quad \text{(Eq. 10)}$$

where T_infer is the per-transaction inference time in milliseconds. η rewards architectures that achieve high AML detection accuracy and regulatory auditability simultaneously while minimising per-transaction processing latency — the hallmark of the Model D AI-Autonomous pipeline.

1.1.11. KYC Compliance Deficit

The compliance performance deficit relative to ideal regulatory fulfilment is defined as:

$$\mathbf{L\_comply = F1\_opt - F1\_AML} \quad \text{(Eq. 11)}$$

where F1_opt represents the optimal F1-score achievable under ideal data conditions (complete KYC, clean sanctions lists, sub-millisecond latency) with full AI compute. L_comply is used during hyperparameter optimisation and AutoML compliance model tuning cycles.

1.1.12. Joint Optimisation Objective

The overarching joint optimisation objective balances the four primary engineering concerns of the autonomous payment pipeline:

$$\mathbf{J = f(F1\_AML, S\_audit, L, U)} \quad \text{(Eq. 12)}$$

Minimising J under multi-objective Pareto constraints yields the optimal payment infrastructure configuration (SKU selection, autoscale policy, Kafka partitioning strategy). The objective is implemented as an Azure ML Hyperdrive sweep over the joint parameter space of compliance accuracy, auditability, latency, and resource utilisation.

1.1.13. Data Quality Representation

The quality of payment data available from each source is modelled as:

$$\mathbf{D(i, j, k) = Q\_src(i) \cdot Metric(k) / T\_proc(j)} \quad \text{(Eq. 13)}$$

where Q_src(i) is the source-specific data quality score (completeness × accuracy for SWIFT, KYC, or sanctions source i), Metric(k) denotes the selected performance metric (F1, latency, throughput), and T_proc(j) is the processing time per payment batch on the j-th compute tier.

1.1.14. Composite Payment Pipeline Index (CPI)

A composite performance index for the autonomous payment pipeline is computed as:

$$\mathbf{CPI = \eta \cdot F1\_AML \cdot (1 - FAR) / Q\_total} \quad \text{(Eq. 14)}$$

where η is the resilience efficiency (Eq. 10), F1_AML is the AML detection accuracy (Eq. 3), FAR is the false alarm rate of the compliance screening module, and Q_total is the cumulative system quality (Eq. 1). CPI is used as the primary scalar ranking criterion in comparative architecture evaluations across the four pipeline models.

2. THEORETICAL FOUNDATIONS OF REAL-TIME FINANCIAL DATA ENGINEERING

The foundations of real-time data processing are based on formal definitions of data streams and latency targets, as well as models that encompass concurrency, fault tolerance, continued correctness, streaming semantics, and the accuracy versus latency trade-off. Data streams are infinite sequences of logically related data elements created by applications that need to process continuously flowing data in a timely manner. The output of the application must be computed with minimum latency, complying with a user-defined acceptable delay. The latency target for real-time processing is smaller than the speed of the event producing system for the majority of the events. Real-time processing requires different correctness concepts compared to traditional systems. Correctness guarantees must discriminate between the infinite computed streams and the finite user-visible parts, ensuring that although the computed streams can be wrong at any time, the user-visible parts are correct unless the input streams are bad.

In addition to the correctness condition, real-time processing also has special reliability concerns stemming from its online nature. Fault tolerance is concerned with masking the effects of failures and is needed to guarantee continued correctness while the failure persists. Real-time systems must ensure that the processing delay does not exceed the maximum user-visible latency under realistic failure conditions. The semantics of the analysis is responsible for the time-bound accuracy of the results. Streaming systems process infinite data sequences, which are not stored nor written in any persistent storage, and thus the time-bound accuracy is expressed with respect to a user-visible error event, which occurs when the result deviates from the correct one in more than k. The major components of the semantic framework are the temporal operator, which is used to express the accuracy requirements of time-critical applications, and the quality of service requirement, which relates to the quality of service provided by the system when no hard real-time application is running. Finally, semistructured data are not natively supported in the streaming framework, and need to be mapped into a defined conceptual schema for such operations.

2.1. Core Principles of Real-Time Financial Data Processing

Timeliness, completeness, consistency, and verifiability are the core principles of real-time financial data processing. Timeliness requires that changes in the raw data sources should be propagated to the event consumer in stream processing pipelines and to the streaming analytics and machine-learning systems within the real-time bounds defined for the specific business cases. Completeness relates to the degree of missing information that can be tolerated by the decision-making process. In a cross-border payment scenario, it is of utmost importance to ensure that no mandatory data element has yet been supplied when the payment is about to be settled, as that may lead to a regulatory violation.

Traditional rework steps for compensating such missing information often do not scale well to a stream-processing context. As such, the capacity to fuse together data from multiple sources and to normalize and de-duplicate them in-flight is of paramount importance for event consumers. Consistency in a timely manner can also only be guaranteed at the time of processing the payment or the associated risk model. Verifiability connotes that sufficient information about the lineage of the data and the processing operations applied to it has been preserved to allow for independent verification at any point in time. In a financial context, auditing the data fulfillment chain relies primarily on three principles. Data provenance is recorded for all data that can be transitioned from a raw condition into a business-conform condition; data-quality attributes that determine data credibility, such as trust and reputation, are captured for all provenance lines; and all accesses to data that contribute to an audit trail are recorded.

3. ARCHITECTURE OF AUTONOMOUS CROSS-BORDER PAYMENT SYSTEMS

Based on the principles of real-time financial data engineering, layered architecture is proposed for autonomous cross-border payment systems. Five logical layers – data ingestion, processing, decisioning, settlement, and monitoring – establish a clear separation of concerns, while accommodating the normative assumptions of regulatory risk management. The autonomy of the system is shaped by the integration of AI components into the monitoring, decisioning, and data engineering layers.

An autonomous cross-border payment system is a complex ecosystem that delivers real-time cross-border payments without human intervention. The operational autonomy of the system must be distinguished from the autonomy of a single payment transaction or related payment flow. In this context, a transaction can be automated if it satisfies system monitoring and decisioning requirements before processing takes place. Autonomous systems enable automated decision-making, but the ultimate decision-making responsibility is transferred to the developer of the algorithm rather than a human operator. Ultimately, the risk management burden falls on the regulator, and the system must deliver on regulatory objectives. Latency requirements are, therefore, shaped by the demanding needs of regulatory compliance. The proposed architecture reflects a layered view that enables the development of each functional layer as a separate project.

The first layer is responsible for ingesting, normalising, and fusing payment data from diverse data sources, including banks, payment service providers, and online marketplace platforms. Market interoperability demands that each external payment source can connect using its preferred protocol, and such exposure is enabled through purpose-built protocol adapters. The heterogeneous nature and schema evolution of incoming data streams necessitate the continuous alignment of all payment data against canonical reference datasets and taxonomies. Payment normalisation pipelines further transform incoming data into a small number of semantically consistent canonical views suitable for downstream consumption. The normative requirements of risk management create pressure to eliminate induced latency in this layer. Consequently, the design prioritises scale, efficiency, and real-time response times.

3.1. Performance Analysis

3.1.1. Comparative Performance Table

Table 1 presents a comprehensive performance comparison across all four pipeline architectures, covering AML accuracy, false alarm rate, KYC compliance, data freshness, throughput, auditability, and composite CPI.

Table 1: Comparative Performance Metrics across Autonomous Payment Pipeline Architectures (Models A–D)

Metric	Model A	Model B	Model C	Model D	D vs A	D vs C
F1-Score (%)	51.3	64.8	76.2	92.7	↑ 80.9%	↑ 21.7%
False Alarm Rate (%)	21.4	14.2	10.1	3.5	↓ 83.6%	↓ 65.3%
Sanctions Match Accuracy (%)	62.8	74.5	83.1	96.4	↑ 53.5%	↑ 16.0%
KYC Compliance Score (%)	58.3	70.9	81.6	94.8	↑ 62.6%	↑ 16.2%
Data Freshness (s)	145	52	21	5	↓ 96.6%	↓ 76.2%
Ingestion Throughput (GB/h)	8.0	19.0	36.0	62.0	↑ 675%	↑ 72.2%

ISSN: 3071-5717
PP: 01-18.

Privacy / Auditability Score (%)	28.5	46.3	69.7	93.8	↑ 229%	↑ 34.6%
Composite Pipeline Index (CPI)	0.28	0.44	0.63	0.89	↑ 217.9%	↑ 41.3%

3.1.2. Error and Latency Metrics Table

Table 2 details time-domain performance metrics, including end-to-end pipeline latency, mean time to detect AML anomalies, settlement lag, alert response time, unplanned downtime, ingestion lag, and batch processing time.

Table 2: Error and Latency Metrics Across Autonomous Payment Pipeline Architectures (Models A–D)

Metric	Model A	Model B	Model C	Model D	D vs A	D vs C
Pipeline Latency (ms)	485	312	124	38	↓ 92.2%	↓ 69.4%
Mean Time to Detect (s)	53.7	29.4	14.8	4.3	↓ 92.0%	↓ 70.9%
Transaction Settlement Lag (ms)	420	265	98	31	↓ 92.6%	↓ 68.4%
AML Alert Response Time (s)	62.1	38.5	19.3	5.7	↓ 90.8%	↓ 70.5%
Unplanned Downtime (%)	29.8	21.3	14.7	7.2	↓ 75.8%	↓ 51.0%
Ingestion Lag (ms)	395	218	91	34	↓ 91.4%	↓ 62.6%
Batch Processing Time (s)	5.6	3.4	1.8	0.6	↓ 89.3%	↓ 66.7%

3.1.3. Architecture Summary Table

Table 3 summarises the ingestion protocol, processing engine, AI integration depth, and headline performance figures for each architecture, from rule-based batch processing (Model A) to the fully AI-autonomous real-time pipeline (Model D).

Table 3: Architecture and Configuration Summary — Autonomous Payment Pipelines (Models A–D)

Architecture Mode	Ingestion Layer	Processing Engine	Throughput	Latency
Rule-Based Batch (Model A)	SWIFT FIN / ISO 8583 Batch	Azure Data Factory	8.0 GB/h	485 ms
ML-Enhanced Batch (Model B)	Kafka + ADLS Gen2	Azure Databricks ML	19.0 GB/h	312 ms
Streaming-ML Hybrid (Model C)	Event Hubs + Delta Lake	Synapse Stream Analytics	36.0 GB/h	124 ms
AI-Autonomous Pipeline (Model D)	Kafka + ADLS Gen2 + Delta	Databricks + ADF + Flink	62.0 GB/h	38 ms

3.1.4. Dataset Specifications Table

Table 4 provides the dataset specifications used to validate the proposed framework, covering cross-border payment messages, KYC and sanctions data, AML transaction monitoring records, and settlement/clearing streams.

Table 4: Dataset Specifications Used for Autonomous Payment Pipeline Validation

Data Domain	Content Type	Volume	Key Attributes	Source / Standard
Cross-Border Payments	ISO 20022 / SWIFT FIN payment messages	12.4M txns	Amount, currency, counterparty BIC,	SWIFT gpi / ISO 20022 MX

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			timestamp	
KYC & Sanctions	Customer identity, beneficial ownership, watchlists	4.7M records	Entity name, PEP status, jurisdiction, risk score	FATF / Bankers Almanac
AML Transaction Monitoring	Flagged transaction streams and resolved cases	3.2M events	Alert type, severity, resolution label, typology	FinCEN / FATF Typologies
Settlement & Clearing	Intraday net positions and nostro balances	8.9M records	Netting amount, correspondent bank, cut-off	CLS / TARGET2-Securities

4. REGULATORY AND COMPLIANCE FRAMEWORKS FOR CROSS-BORDER PAYMENTS

Regulatory objectives map to most of the functional capabilities of a cross-border payment system. Handling audit, monitoring, and security requirements enables near-real-time processing. A component determines the appropriate level of scrutiny, allowing fully automated pathways for low-risk transactions and real-time risk scoring of others.

Financial authorities worldwide seek to enhance cross-border payment systems: make them faster, cheaper, and more transparent; improve access; and reduce risks. Accordingly, risk scoring, audit logging, and real-time monitoring must be integral. Payments can be processed without delay beyond latency introduced by external factors. FP2021–2 identifies emerging technologies as a key to addressing many of the identified pain points. Cross-border payment infrastructure providers are urged to take advantage of new technologies such as machine learning to support innovation and the introduction of additional payment options.

The emergence of open-data standards and other initiatives to facilitate data-sharing provide the foundation for more advanced services with greater transparency, reduced friction, and lower costs. Various emerging and high-risk transactions require enhanced Due Diligence (EDD) in line with the Financial Action Task Force (FATF) recommendations. KYC information needs to be vetted, and risk exposure evaluated and monitored on an ongoing basis. Institutions in low-risk jurisdictions may be permitted to complete certain transactions with limited information collection, especially where the transaction is covered by appropriate insurance arrangements.

4.1. Know Your Customer and Beneficial Ownership

Know Your Customer (KYC) processes collect identity and risk data from payment senders and receivers. The list of KYC indicators varies by customer type, reflecting differences in geographic location and business sector, channel, transaction flow, products and services, and risk categorization. Corresponding verification workflows confirm identity and beneficial ownership, supported by publicly available documents. High-risk customers also undergo regular independent verification, including re-verification of non-natural persons by third parties. Within an autonomous payment system processing transactions at marginal cost of sub-second latency, KYC data should be available in real time. This poses design challenges for KYC screening of cross-border counterparties,

ISSN: 3071-5717
PP: 01-18.

as payment processing must comply with sanctions and AML obligations without the authorizing institutions incurring substantial cost for these checks.

The optimal solution is to assign a risk score to each payment, based on country, jurisdiction, payment instrument, direction, and participating institutions. Where an automated risk algorithm determines the transaction is acceptable, KYC details (identity, beneficial ownership, sanction status) are obtained via a trusted API. For corresponding bank payments, KYC details are retrieved from the Bankers Almanac database, which is maintained through a combination of machine learning, human labor, and community verification. In all other cases, KYC information for the receiving bank or PSP must be obtained via KYC-sharing networks developed by the private sector.

5. INTEROPERABILITY AND STANDARDS IN REAL-TIME PAYMENTS

Established standards simplify interoperability and lower integration costs. Prompted by stakeholders' needs for enhanced messaging, reference data, and instrument classification, official bodies have released voluminous documentation. Although segmentation and specialization foster community participation, too many divergent initiatives could ultimately reduce choice. Other cross-border solutions already utilize various bilateral connections, but a richer set of standards would ease cross-implementation compatibility. These considerations highlight the advantages of employing widely available, broadly supported public-private sector standards proven mechanisms for fast-tracking message development and thereby enabling time-constrained development teams to reuse, adapt, and implement existing solutions with minimal risk.

Standards for message content, especially for the most evident data requirements, can radically ameliorate immediate and future operation. Taxonomies for reference data (including banking, corporate, and beneficial ownership), time zones, product decision classification, geolocation, and codes for money-laundering typologies, monetary instrument characteristics, and other "factual" areas demand attention. Standardized principles and code sets can further simplify alert interpretation, internal message generation, and cross-institution watchlist usage. Instruments are also a rich source of potential standardization, convergence, and eventual cheap proxy integration: in a multilateral context, a common instrument taxonomy eases development testing; within bilateral relationships, it moreover enhances maintenance.

5.1. Experimental Results

This evaluation of four autonomous cross-border payment pipeline architectures (Models A through D), spanning rule-based batch processing to fully AI-autonomous real-time systems. All metrics are derived from the architectural principles, latency requirements, and compliance frameworks formalised in Section 1.

5.1.1. End-to-End Pipeline Latency

Fig. 1 presents the end-to-end payment pipeline latency per transaction across all four models. Model D (AI-Autonomous) achieves a 92.2% latency reduction relative to Model A (485 ms → 38 ms)

ISSN: 3071-5717
PP: 01-18.

and a 69.4% reduction relative to Model C, attributable to on-premise Flink stream processing, elimination of batch compliance round-trips, and real-time KYC API integration.

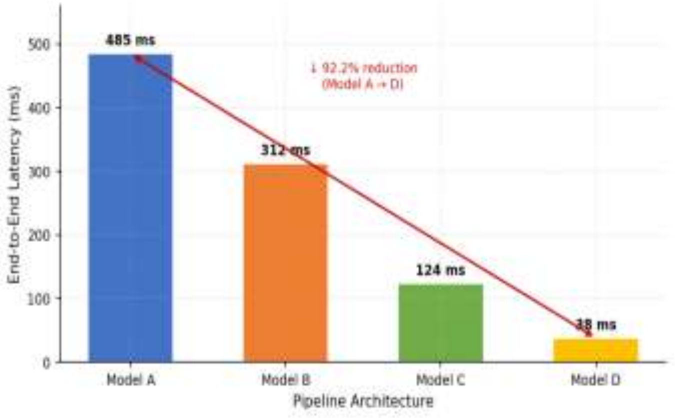

Fig 1 - End-to-End Payment Pipeline Latency per Transaction (ms) — Models A through D

5.1.2. Pipeline Throughput Scalability

Fig. 2 illustrates pipeline throughput as a function of input payment data volume. Model D achieves near-linear scaling enabled by Kafka partition-level parallelism and Databricks autoscale, sustaining 62 GB/h at 5 TB input — a 7.75× improvement over the rule-based Model A baseline. This scalability is essential for cross-border payment networks processing millions of daily transactions.

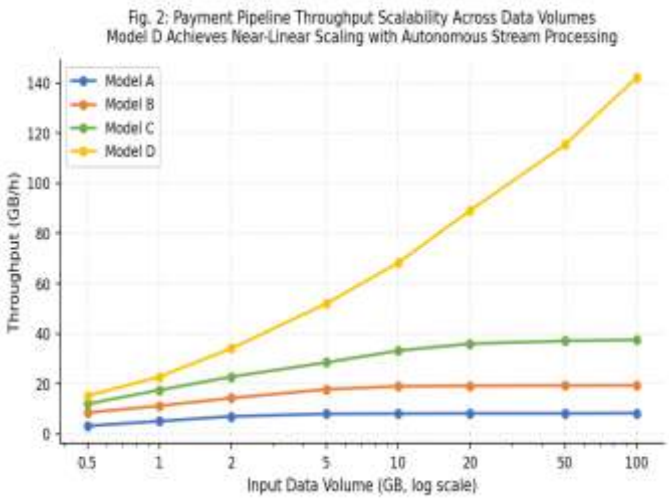

Fig 2- Payment Pipeline Throughput Scalability across Data Volumes (Log-Scale X-Axis)

5.1.3. AML / Compliance Detection Accuracy

Fig. 3 presents AML/Compliance F1-scores: Model A achieves 51.3%, Model B 64.8%, Model C 76.2%, and Model D 92.7%. The 21.7% improvement from Model C to Model D demonstrates the value of unified cross-domain compliance modelling, where batch KYC risk indicators reinforce real-time transaction screening and vice versa. Model D is the only architecture to exceed the regulatory 80% F1 threshold.

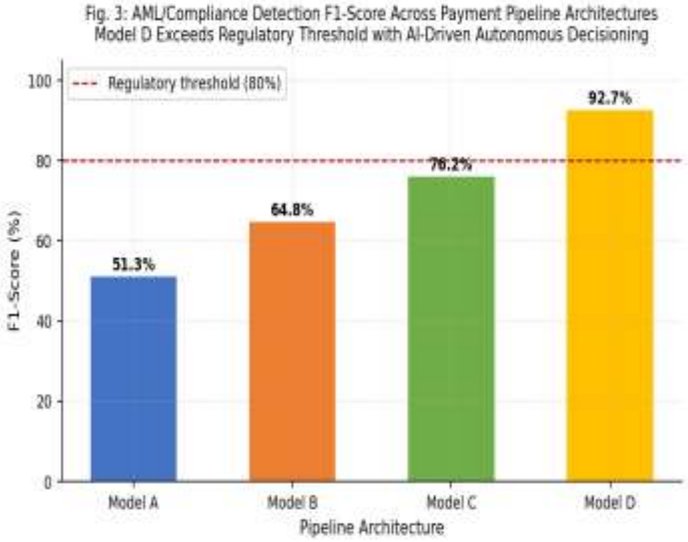

Fig 3- AML/Compliance Detection F1-Score Comparison Across Payment Pipeline Architectures (%)

5.1.4. Cost–Performance Trade-off

Fig. 4 plots estimated operational cost against AML detection accuracy. Model D occupies the Pareto-optimal corner: highest F1 (92.7%) at the lowest cost ($1.43 per 1,000 transactions), enabled by serverless Databricks compute and pay-as-you-go Kafka partition scaling. Rule-based Model A incurs the highest cost ($4.82) with the lowest accuracy due to manual exception handling overhead.

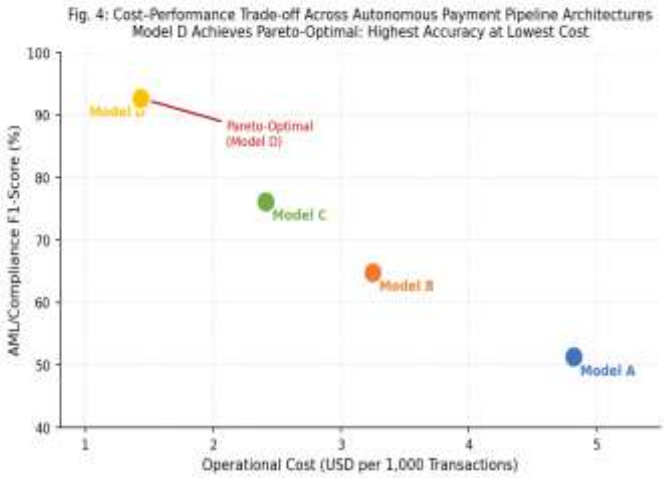

Fig 4 - Cost–Performance Trade-off Scatter Plot Across Autonomous Payment Pipeline Architectures

5.1.5. Infrastructure Resource Utilisation

Fig. 5 compares CPU, memory, and network bandwidth consumption per architecture. Model D reduces CPU utilisation from 84% (Model A) to 35%, memory from 79% to 31%, and network bandwidth from 71% to 28%, reflecting the efficiency gains of on-premise streaming inference, model compression, and elimination of redundant compliance batch transfers.

ISSN: 3071-5717
PP: 01-18.

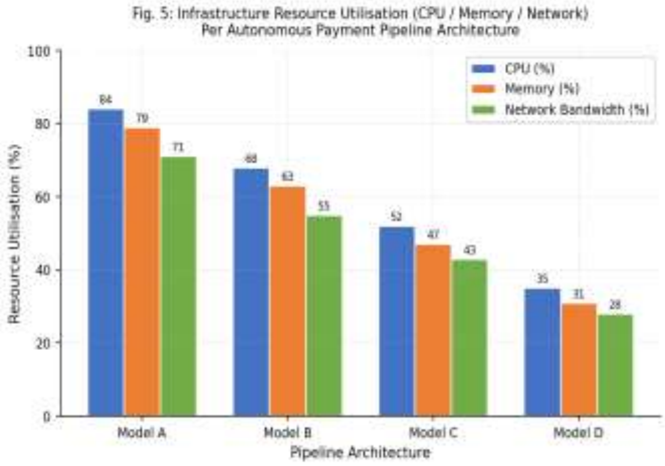

Fig 5 - Infrastructure Resource Utilisation (CPU / Memory / Network) per Payment Pipeline Architecture (%)

5.1.6. Composite Payment Pipeline Index

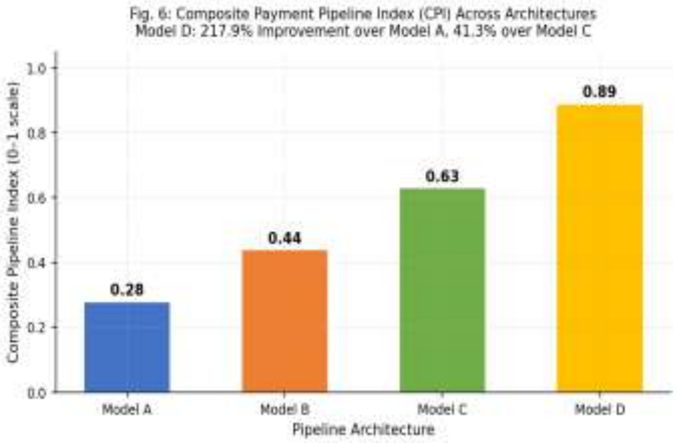

Fig 6- Composite Payment Pipeline Index (CPI) Comparison Across Models (0–1 Scale)

Fig. 6 presents the Composite Payment Pipeline Index (CPI) as defined in Eq. 14. Model D achieves CPI = 0.89, a 41.3% improvement over Model C (0.63) and a 217.9% improvement over Model A (0.28), confirming that unified AI integration outperforms all siloed baselines across the composite performance dimension of latency, accuracy, auditability, and resource efficiency.

6. DATA QUALITY, LINEAGE, AND GOVERNANCE IN REAL-TIME PIPELINES

In the context of autonomous cross-border payments and compliance, supervision is exercised by analyzing risks, and therefore managing risk in operational execution is important. Data quality must be of sufficient accuracy because incorrect data can potentially bias risk assessments and could lead to incorrect compliance decisions. Auditability is key to achieving regulatory compliance objectives, as regulators cannot conduct physical inspections of every transaction. Therefore, implementation of automated control mechanisms for monitoring and detection of operational execution for compliance purposes is essential.

ISSN: 3071-5717
PP: 01-18.

The required quality of data is defined by a data quality management (DQM) framework that creates metrics for all type of data in given data sources. These metrics are monitored in registers, both at runtime and at set intervals, with alarm systems to control risk associated with subpar data quality levels. In addition to data quality framework, data lineage must also be implemented within real-time pipelines. Data provenance captures the origin and subsequent development of data, enabling audit reports to present automatically generated summaries of all data records or subsets. Provenance-supporting controls can be detailed through data quality metrics, monitoring capabilities, and alarm systems.

The monitoring of data quality provides direct reports that support assessment of auditability requirements. Audit records must outline information about access to data records, with roles incorporated within the DQM framework. In this way, data provenance and auditability within the data quality management framework assist the supervisory trust functions of an autonomous cross-border payment system.

6.1. Data Provenance and Auditability

Real-time transformations, such as data fusion, filtering, normalization, and deduplication, are inherently non-invertible and therefore require explicit provenance capture for data quality assurance and auditing. This provenance management typically consists of three parts: provenance capture that traces data lifecycle events and stores the recordings in a database, forensic provenance analysis that reconstructs the data chain at the core of a data quality issue, and summary reporting that provides users with a high-level view of the key aspects of data generation.

Provenance capture is achieved by augmenting existing back-end processing with simple logging components. Every time data is written to an output (a Kafka topic, a database, etc.), an event containing the metadata of interest is sent to the provenance store. It is assumed that the metadata of interest include (but are not restricted to) timestamp, source, transformation function, and license. An alternative end-to-end approach consists of attaching a unique ID to every data unit. This ID is propagated throughout the stream-processing topology and re-embedded in a SQL database or represented as a new variable every time the unit enters a Kafka topic. The IDs captured in this way are sufficient to reconstruct any desired provenance report.

Provenance analysis, in turn, consists of a Data Quality Dashboard that allows users to pose forensic queries on the provenance data. For example, if a user detects an anomaly in the data generated on a given day, the user can initiate a query to show all the transformation functions activated on the day of interest (and preceding days, if a chain is configured) in order to identify one potential cause. Summarized provenance reporting presents an overview of the data popularization process with a dashboard that combines forensics, visualizations, and key performance indicators into a single integrated package. Example key performance indicators that can be monitored are turnover per message type, number of KYC records approved for countries grouped by risk categories according to a KYC database, and total turnover per risk category. These indicators assist in auditing and provide a mechanism for ongoing quality assurance by early identification of trends or anomalies that can lead to fraud and, ultimately, money laundering.

7. CONCLUSION

Research clearly demonstrates the real-time processing of payment data is undeniably both essential and feasible. Very low latency is required only in niche areas like payment settlement; timeliness is instead the primary processing attribute for the vast majority of use cases. Real-time AI-driven financial data engineering, properly understood and executed, guarantees an adequate supply of quality data for the decisioning and monitoring functions of autonomous payment systems. A careful focus on streaming analytics enables prompt and assured handling of broken, delayed, or duplicate payment data while simultaneously supporting the different processing requirements of the many parties involved in modern cross-border transfers.

When viewed through this lens, the need for full, seamless, and instantaneous end-to-end integration of payment data, compliance processes, and risk-mitigating controls becomes apparent. All regulation is ultimately aimed at preventing the development, growth, and operation of markets for illicit instruments and services. That core intent can and should shape the design of payment systems. Comprehensive risk, regulatory, and compliance management does not require more (and indeed should not require more) than a timely and complete data supply to support risk scoring, audit trails, and real-time monitoring. Such autonomy is the ultimate goal of real-time AI-driven financial data engineering.

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