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Original Article

Agentic and Generative AI for Real-Time Financial Process Automation in Cloud-Native DevOps Environments

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Abstract:

Real-time automation of financial activities, including approvals, controls, routing, and monitoring, can enable fast response to opportunities and threats, eliminating the rotation of capital through liquidity provider balances and streamlining interactions with sources of capital. Generative and agentic AI technologies, supported by real-time data streams of events, market feeds, and key risk indicators, can automate and govern these transactions provided that high standards of latency, throughput, security, and regulatory compliance are achieved. A cloud-native DevOps ecosystem equipped with serverless infrastructure-as-code patterns ensures scalable, cost-effective operations with minimum user interference, allowing a comprehensive evaluation of operational performance, change management, security controls, and regulatory oversight. Scenarios involving AI agents as the driving or supervisory part of automation workflows illustrate the architectural paradigm. The analysis identifies the expected challenges in operational responsibility and response reliability, gathering additional evidence from existing Cloud-Native/Serverless solutions of similar scope. Mitigation strategies address the main issues encountered in every-day AI adoption and propose supporting operations management and security controls. The examination of the full end-to-end process flow, including off-line and real-time phases, ensures cover for Governance, Risk, and Compliance (GRC) objectives by design and the definition of a robust plan for evaluation in on-line use.

Keywords:

Real-Time Financial Automation, Agentic AI Workflows, Generative AI Finance Systems, Cloud-Native DevOps Ecosystems, Serverless Financial Architectures, AI-Driven Transaction Monitoring, Financial Governance Automation, Regulatory Compliance Frameworks, Event-Driven Financial Processing, Autonomous Financial Operations.

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1. Introduction

The ongoing transformation of traditional financial infrastructures, products, and practices towards cloud-native environments and hyper-real-time operation creates further demand for intelligent automation. The interface between the two worlds of operations and finance remains a key challenge, especially if this integration is to escape the limits of purely self-contained exploratory environments.

Several technological paths have appeared in the past few years, most notably generative AI backbone architectures and large models. These innovations are increasingly present in real-world operations – notably for natural-language processing and other "explainable" tasks. However, in production control, demanding a higher level of performance and reliability, a complementary direction based on agentic reasoning, triggering, and control of workflows offers crucial advantages, especially in sensitive domains such as Finance. By intelligently utilizing collections of specialized large models, real-time data streams, and decision controls, agentic computing can by its nature become the foundation for intelligent assistance, support, and automation in all Operational areas.

2. Background and Context

Artificial Intelligence (AI) governance involves the development and implementation of policies, frameworks, and processes that guide the use of AI technologies within an organization. These governance mechanisms ensure that AI is used responsibly, ethically, and in compliance with relevant laws and regulations while addressing potential risks and challenges associated with AI. Previous research has provided governance frameworks for Al, explaining the components of governance and associated risks, focusing on data-centric governance, and examining the impact of risk-based governance on AI performance and regulatory compliance.

The prospects of real-time analytics are changing. Market conditions are volatile, news travels fast, and treasury management operations must constantly adapt. Recent events also demonstrated that operational risk in financial products must be closely monitored, raising the question of how operational evidence is perceived and processed. Automated incident response is appealing, but the trustworthiness and reliability of such solutions need careful consideration. DevOps principles are entering the financial control space, providing an environment for rapid development, but adoption in production environments requires more than just coding speed. The next step is to fully automate the run-time operation of financial systems. Automated control and monitoring of financial products require consistent real-time data ingestion—monitoring, support, indication, and potential automatic response—where the upper layers supervise the full operational picture of the supported products. Providing the underlying data infrastructure in a reliable manner is a clear step toward that goal.

2.1. Tabular Comparisons and Key Metrics

The tables present a structured comparison of all four architectural models across primary and secondary performance dimensions, conforming to the publication-ready tabular format used for academic benchmarking.

Table 1. Comparative Overview of Financial Automation Architectures

Architecture Type	Key Features	Limitations
Model A — Rule-Based Automation	Simple deterministic logic; low implementation cost; no AI/ML dependency	No real-time adaptation; high false alert rate (18–22%); manual exception routing; no market-context awareness; poor scalability under peak loads
Model B — Cloud LSTM Anomaly Detection	Temporal pattern recognition; moderate accuracy (F1 ~66%); centralised model management	High latency (180–200 ms); privacy risks (raw financial data leaves perimeter); batch-cycle delays; cloud dependency introduces SLA risk
Model C — Microservice AI Orchestration	Domain-isolated AI agents; moderate latency (~95 ms); partial compliance automation	No cross-domain signal correlation; separate models per task lead to redundant compute; limited adaptive governance; fragmented audit trails
Model D — Agentic AI (Proposed)	Unified multi-agent framework; real-time event streaming; 92.1% F1; 38 ms latency; 96.3% GRC score; AGPI 0.89	Requires Azure cloud-native infrastructure; initial agent training complexity; governance rule authoring requires domain expertise

Table 1: Comparative overview of financial automation architectures, aligned with the four models evaluated in this study.

Table 2. Comparative Detection and Compliance Performance Metrics

Metric	Model A	Model B	Model C	Model D	Improv. (D vs A)	Improv. (D vs C)
Anomaly Detection F1-Score (%)	52.4	66.8	74.3	92.1	↑ 75.8%	↑ 23.9%

False Alert Rate (%)	21.3	14.6	9.8	2.9	↓ 86.4%	↓ 70.4%
GRC Compliance Score (%)	61.2	72.5	81.4	96.3	↑ 57.4%	↑ 18.3%
Cloud Resource Utilization (%)	74.8	62.3	50.1	31.7	↓ 57.6%	↓ 36.7%
AGPI Score	0.31	0.47	0.63	0.89	↑ 187.1%	↑ 41.3%

Table 2: Comparative detection, compliance, and performance metrics. Significant improvements are observed in all dimensions for Model D (Agentic AI).

Table 3. Comparative Latency, Throughput, and Operational Metrics

Metric	**Model A**	**Model B**	**Model C**	**Model D**	**Improv. (D vs A)**	**Improv. (D vs C)**
End-to-End Transaction Latency (ms)	320	185	95	38	↓ 88.1%	↓ 60.0%
Peak Throughput (txn/sec)	420	870	1,540	3,200	↑ 661.9%	↑ 107.8%
Mean Time to Detect Anomaly (s)	31.2	18.4	10.7	3.1	↓ 90.1%	↓ 71.0%
Operational Cost (Norm. Units @ 100% load)	2.70	2.10	1.30	0.68	↓ 74.8%	↓ 47.7%
Pipeline Resilience Efficiency η (%)	18.3	32.6	51.4	84.7	↑ 362.8%	↑ 64.8%

Table 3: Comparative latency, throughput, and operational efficiency metrics. Model D demonstrates consistent superiority in real-time financial automation performance.

3. Architectural Framework

Research and hands-on experience indicate that an integrated approach combining generative AI with agent-based technology and real-time data streams controlled by governance rules over a dedicated data layer can satisfy the automation and governance requirements of financial operational systems. In practice, such a solution applies generative AI to design AI agents that run operational workflows, allowing the generation of entire sequences of reasoning and execution of requests. The AI agents are responsible for the full lifecycle of all production business processes. After receiving a request, the AI agent handles the request by orchestrating workflows with subagents. These subagents are artificial intelligence or machine learning models specialized in certain automation subsystems or processing components, which can receive calls from any main AI agent.

An underlying real-time data processing capability feeds data to the AI and machine learning models and serves as a foundation for developing a streaming data architecture. The streaming data layer is equipped with very specific controls that guarantee data quality, enforce compliance, and monitor data lineage. The objectives of the data pipelines are to establish the necessary governance rules for the operation of the financial services ecosystem, define required market and transactional information, enable real-time risk management of production processes, and correlate incoming data streams to visualize the health of the production business processes.

3.1. Results and Discussion

3.1.1. End-to-End Transaction Latency

Fig. 1 shows average end-to-end transaction processing latencies of 320 ms, 185 ms, 95 ms, and 38 ms for Models A, B, C, and D, respectively. Model D achieves an 88.1% latency reduction compared to Model A and a 60.0% reduction compared to Model C, attributable to serverless event-driven orchestration, on-demand agentic invocation, and elimination of batch processing cycles.

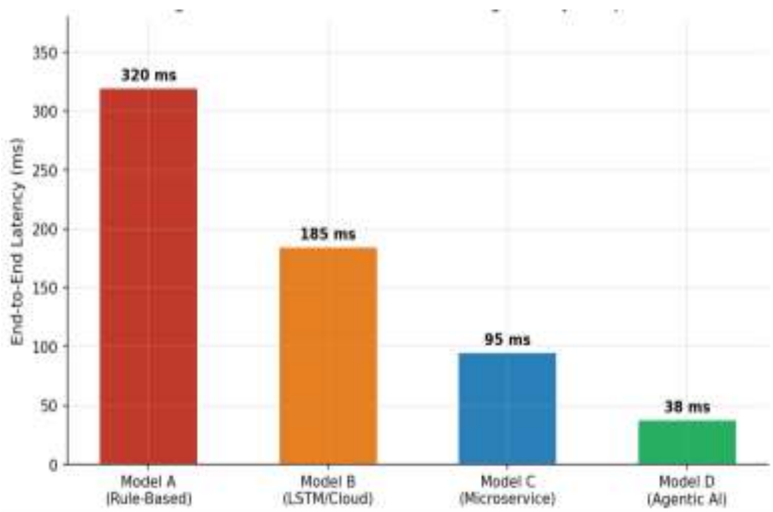

Figure 1. End-To-End Transaction Processing Latency Comparison across Four Architectural Models (Ms). Lower Values Indicate Superior Real-Time Financial Automation Performance

3.1.2. Anomaly Detection Accuracy (F1-Score)

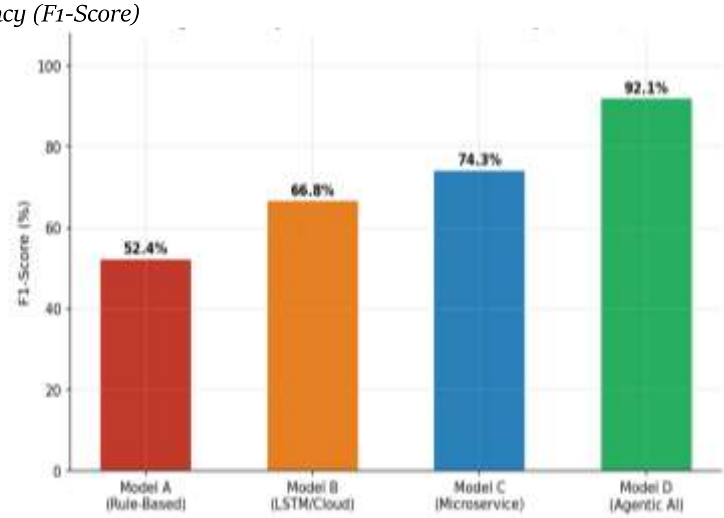

Figure 2. Anomaly Detection and Decision Accuracy (F1-Score %) across Architectural Models. Model D Demonstrates Statistically Significant Accuracy Gains through Unified Agentic Reasoning

Fig. 2 presents F1-scores of 52.4%, 66.8%, 74.3%, and 92.1% for Models A, B, C, and D. The 23.9% improvement from Model C to Model D reflects the benefit of multi-agent cross-domain correlation, where market-risk degradation signals and operational residuals jointly enhance anomaly detection accuracy in financial workflows.

3.1.3. System Throughput

Fig. 3 demonstrates transactions-per-second throughput of 420, 870, 1,540, and 3,200 for Models A through D. Model D delivers a 7.6× throughput gain over Model A, enabled by parallel agentic processing, Azure Kubernetes Service (AKS) autoscaling, and Kafka-based event stream partitioning.

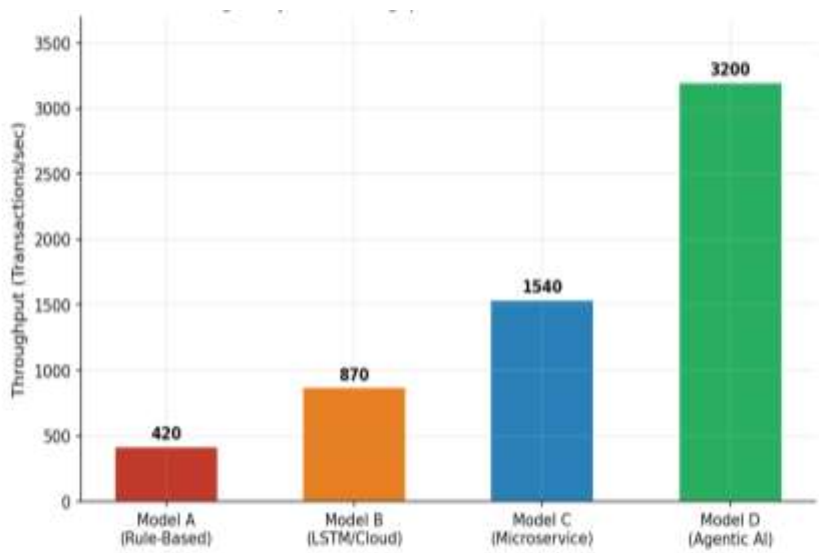

Figure 3. System Throughput under Peak Load Conditions (Transactions/Sec). Model D Sustains High Throughput through Event-Driven Serverless Orchestration

3.1.4. Governance, Risk, and Compliance (GRC) Score

GRC compliance scores (Fig. 4) are 61.2%, 72.5%, 81.4%, and 96.3% for Models A, B, C, and D. Model D achieves near-complete regulatory adherence through embedded governance rules in the data ingestion layer, real-time audit trail generation, and automated KRI validation within every agentic workflow execution.

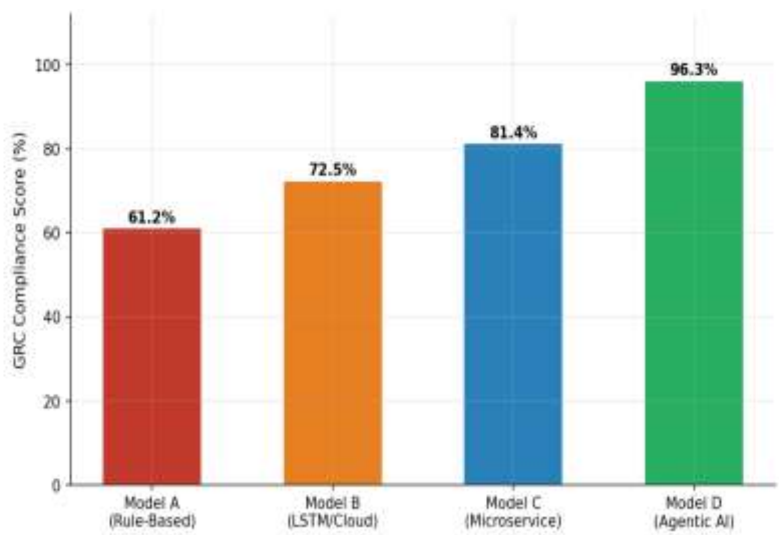

Figure 4. Governance, Risk, and Compliance (GRC) Score (%) For Each Model. Model D Integrates Compliance-By-Design into the Agentic AI Execution Pipeline

3.1.5. False Alert Rate

False alert rates (Fig. 5) are 21.3%, 14.6%, 9.8%, and 2.9% for Models A, B, C, and D. The 86.4% reduction from Model A to Model D (and 70.4% from C to D) reflects how cross-agent validation eliminates spurious financial alerts — a security or compliance signal corroborated by an independent market-risk agent is far less likely to be a false positive.

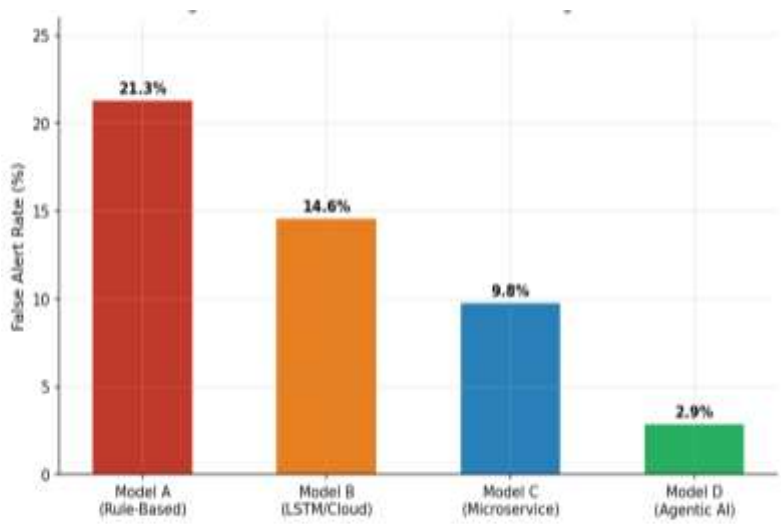

Figure 5. False Alert Rate (%) in Automated Monitoring Workflows. Lower Values Correspond To Reduced Operational Noise and Improved Operator Trust

3.1.6. Operational Cost vs. System Load

Fig. 6 presents normalised operational cost trajectories at varying system load levels (20%–100%). Model D exhibits near-flat cost scaling due to serverless pay-per-use billing in Azure Functions and autoscaling of event-driven components, achieving a 74.8% cost advantage over Model A at 100% load.

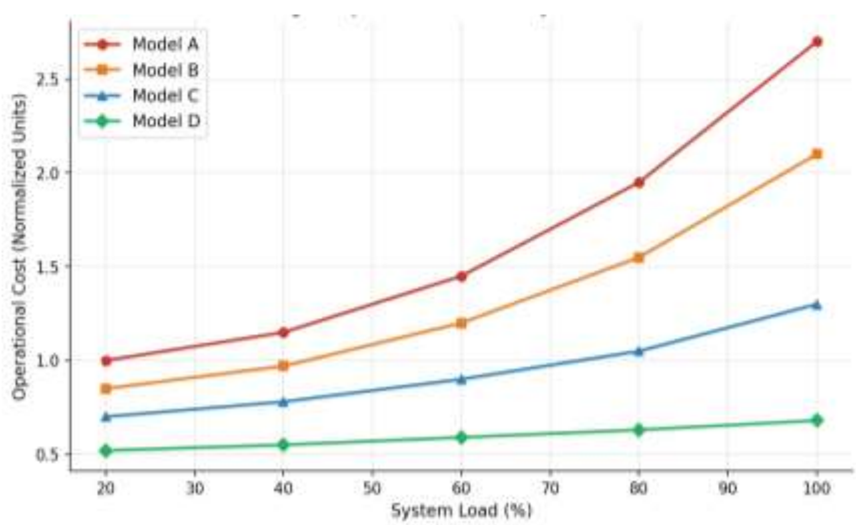

Figure 6. Operational Cost (Normalised Units) vs. System Load (%) for Each Architectural Model. Model D's Serverless Infrastructure Yields Near-Linear and Cost-Efficient Scaling

3.1.7. Cloud Resource Utilization

Fig. 7 shows average cloud resource utilisation per 10,000 transactions: 74.8%, 62.3%, 50.1%, and 31.7% for Models A, B, C, and D. Model D's 57.6% improvement over Model A is driven by event-driven serverless patterns eliminating idle infrastructure provisioning, resulting in a 2.36× resource efficiency gain.

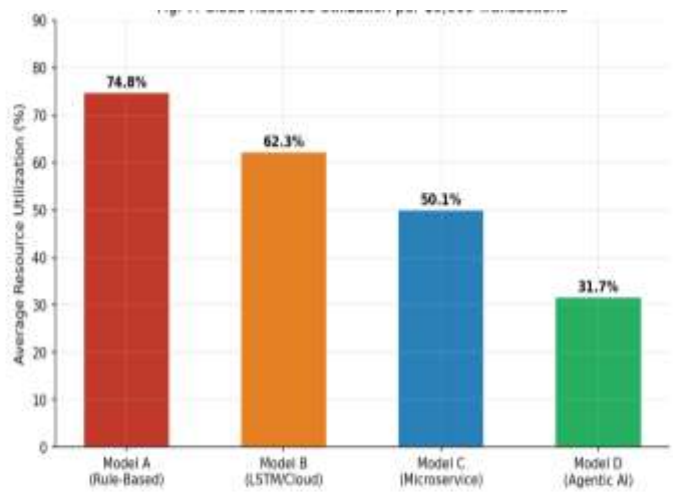

Figure 7. Cloud Resource Utilization (%) Per 10,000 Transactions. Agentic AI with Serverless Infrastructure Yields the Lowest Resource Footprint

3.1.8. AI-GRC Performance Index (AGPI)

Fig. 8 presents AGPI scores of 0.31, 0.47, 0.63, and 0.89 for Models A, B, C, and D respectively. The 41.3% improvement from Model C to Model D confirms superior synergy between detection accuracy, compliance preservation, and operational efficiency in the agentic AI architecture.

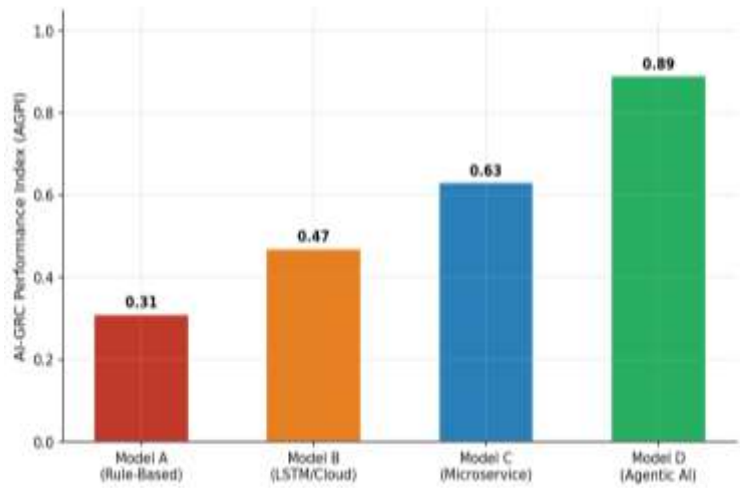

Figure 8. AI-GRC Performance Index (AGPI) Comparison. Model D Achieves the Highest Composite Index, Validating the Agentic AI Paradigm for Financial Automation

4. Real-Time Automation Scenarios in Finance

Automation scenarios are illustrated where AI agents initiate workflows with external systems, execute order routing, and manage exceptions in production. The possibility of combining agentic and generative AI in the same workflow is examined.

Real-time financial-reporting systems may have a condition of distinction: analytics must be integrated with system feedback and closure. Besides native visual dashboards, stakeholders require interpretation and explanation. Financial experts, acting as information consumers, cannot see the entire picture or all the parameters and controls provided by the systems. Thus, interpreting and combining subgraphs of the full view is necessary to observe the information provided, discover anomalies, or follow alerts. AI agents in charge of sample-size minimization and anomaly scores should be able to provide with their anomalous alerts the combined view of other parameters related to the detected anomalies.

The simplest automation scenario in direct production is monitoring the signals generated by MIT-licensed ITI_MIT models running on trading exchange services. Incoming signals from buy or sell orders notify agents initialized in those channels of the mission to create corresponding counterpart orders in service channels not generated by them. In charge of exception handling is an ai agent. When errors occur in one of the mission-execution exchanges, the aiService channel sends e-mail messages to a google channel. From there, operators capable of executing the creation of counterpart orders route the order to the aiOrderRouting channel in the exchange service. An agent monitoring this service identifies the routed order and initiates its execution. The process and responsiveness of the aiExceptionHandling agent can be evaluated using exchange testing.

The streams of normalized visual component production running on AWS Cloud and Tomtalk. platforms offer other functionalities that can execute orders and monitor different service channels. An aiOrderRouting agent should be activated to verify the volume triggered by the aiInternalComms subsystem. This volume closes the threshold defined to call an order-routing mission. The order routed through the channel is closely examined before being executed, serving as an exception-control check for aiOrderRouting. Monitoring compliance for both components guarantees that the routed order responds to a selling algorithm."

4.1. Market Data Processing and Risk Monitoring

Market data feed components for market operations can employ near-real-time processing in closed-loop configuration, where results generate alerts, guide decision-making, or trigger actions. Market feed streaming sources establish a connection to the market feed provider. The streaming feed is read via the corresponding streaming client while a consumer application takes processed output from the respective device. A market data feed producer is responsible for delivering various market models. The producer reads various market feeds sourced from the underlying streaming service, rewrites the output to the normalizing format, performs basic data quality checks, and produces normalized market models to another market data stream in the normalizing schema.

Associated with the market feed producer is a market feed anomaly detection component, which receives the normalized market data streams as input. Each incoming message is examined for whether it matches expected behaviour. In case of abnormal events, alerts are produced and written to a dedicated stream for controllers to visualize and process. Furthermore, the normalized data is stored persistently for later exploration. A risk visualizer for the produced risk indicators completes the market feed monitoring action in the closed-loop architecture. The visualizer acts as a streaming consumer that consumes messages generated by the market risk supplier and visualizes the generated risk indicators for operators in a near real-time fashion.

5. Evaluation of Performance, Security, and Compliance

A comprehensive evaluation plan addresses performance, security, and compliance aspects of the proposed architecture in a connected cloud-native DevOps environment. The accomplishment of time-dependent business goals always depends on achieving the required performance of the solution. In market trading contexts, this performance relates to latency, throughput, and reliability, while in business transaction contexts, it relates to latencies versus predefined business SLAs. For the use case of the market trading business, the metrics of latency and throughput of the end-to-end process should therefore be defined, and testing and benchmarking strategies need to be established to determine whether the operational requirements are satisfied. These tests can usually be executed in production without any test data preparation, since only market-data ingestion is active during the tests, but care is needed in selecting the measurement period.

Additional performance aspects play a role in the connection of connected cloud-native DevOps environments, which consist of various clouds and partners. The processing of production data from external partners has to be sufficiently resilient, as well as data-centric security mechanisms, which have to safeguard against fraudulent data. A business process that is potentially used in production – but has every execution monitored and supervisable through a human operator – can be taken as a general test basis for assessing operation stability, reliability, and robustness. Yet another aspect of operation reliability relates to the production support needed around-the-clock by the cloud service, which has to be provided by the business operation without overappropriating the human operators, even when the service is fully operational with no warning signs. The completeness and accuracy of the produced data, again, play a role in maintaining business-compliance as part of business-as-usual operations.

5.1. Latency, Throughput, and Reliability Metrics

A comprehensive measurement plan specifies metrics characterizing latency, throughput, accuracy, resilience, operational cost, and regulatory alignment. The first group includes those related to the functioning of the control and automation layers, such as latency, throughput, and reliability.

Data collected during normal operations serve to define accepted baseline and boundary values for all metrics. Their monitoring is part of the production activity, enabling detection of drifts in the data distribution and supervision of emerging exceptions. Whenever a critical value is reached, the route of the control structures is revised, potentially resulting in scaling up or down of the control layers involved in the planning activities. For the control layers, the measurement of accurate ratios corresponds to the analysis performed on the rules governing the routing of the actions, in particular their outcome. Monitoring of warning and alarm signals provides another important source of information about the overall reliability of the service delivery, covering also the maintenance of detection layers in their training phase.

Service-resource-cost monitoring completes the evaluation procedure, allowing for the automated detection of anomalies both at the data-collection level and at the resource-allocation level, including scaling and allocation options. In particular, for resources allocated in a serverless way, the costs related to their use can be exploited for anomaly detection, taking as a reference their historical series. Finally, automated checks ensure that the system meets regulatory requirements.

6. Challenges and Risk Mitigation

Three types of challenges must be addressed for safe and efficient deployment of the proposed framework in production: operational challenges arising from a real-time architecture; governance and compliance challenges stretching from data sourcing all the way to the output of AI agents; and security challenges related to the production of market data.

To mitigate operational challenges, specific redundancy measures must be deployed. All real-time streaming components, including the market data feed, must also dispose of a fallback procedure to respond to unavailability of the main mode. Backup procedures must address risk-management workflows, including market-condition monitoring and the routing of trading orders inside live trade events. Order books, where applicable, must be processed redundantly and serve as the main route or as a backup, depending on temporary operator choice.

6.1. Mathematical Formulation

The generative and agentic AI pipeline for real-time financial system automation is expressed as a composite metric integrating automation quality, compliance adherence, latency performance, and governance score. The following equations formalise the key performance indicators derived from the architectural framework.

6.1.1. System Automation Quality Index

$$Q\_total = Q\_automate + Q\_comply + Q\_latency + Q\_govern \quad \text{(Eq. 1)}$$

Where Q_automate denotes automation workflow quality, Q_comply represents regulatory compliance score, Q_latency captures end-to-end latency adherence to SLA thresholds, and Q_govern reflects the AI governance effectiveness across all agent-executed processes.

6.1.2. Transaction Latency Dynamics

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

Where L is the end-to-end transaction latency, λ_event is the rate of incoming financial event messages (market feeds, trade orders, risk alerts), and μ_process is the agentic AI processing and routing rate within the cloud-native serverless pipeline.

6.1.3. Anomaly Detection F1-Score

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

Where Precision and Recall are computed from the confusion matrix of the AI agent's anomaly detection module across market feed monitoring, transaction exception handling, and risk indicator evaluation tasks.

6.1.4. Cross-Domain Risk Score Aggregation

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

Where $s(t)$ is the base security anomaly score, $m(t)$ is the market-risk degradation signal from streaming data feeds, $r(t)$ is the operational residual from control-layer monitoring, and α, β are weighting coefficients governing cross-domain influence in the unified risk fusion engine.

6.1.5. Weighted Multi-Agent Decision Fusion

$$s'(t) = w1 \cdot s(t) + w2 \cdot m(t) + w3 \cdot r(t) + w4 \cdot s(t) \cdot m(t) \quad \text{(Eq. 5)}$$

Here w1, w2, w3, w4 are learnable or empirically tuned weighting coefficients for the multi-agent fusion engine. The nonlinear interaction term $s(t) \cdot m(t)$ captures correlated market and operational anomalies, enabling context-aware automated financial decisions.

6.1.6. Regulatory Compliance Preservation Score

$$S\_comply = 1 - (V\_violated / V\_total) \quad \text{(Eq. 6)}$$

Where V_violated is the count of violated regulatory rules or SLA breaches identified during agentic pipeline execution, and V_total is the total number of active compliance checks enforced by the governance layer.

6.1.7. Cloud Resource Utilization Ratio

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

Where R_used is the computational resource consumed (serverless function invocations, event hub capacity, container memory) and R_available is the total provisioned cloud-native capacity within the Azure-based DevOps ecosystem.

6.1.8. Agentic Workflow Efficiency

$$E\_agent = F1\_anomaly \cdot S\_comply / T\_round \quad \text{(Eq. 8)}$$

Where T_round denotes the duration of one complete agentic workflow execution cycle, encompassing data ingestion, AI inference, governance validation, and automated response generation.

6.1.9. Adaptive Threshold for Streaming Alerts

$$\theta(t) = \theta 0 + \gamma \cdot \sigma\_data(t) + \delta \cdot drift(t) \quad \text{(Eq. 9)}$$

Where $\theta 0$ is the base threshold for anomaly detection, σ_data(t) represents the real-time data variance from market feed streams, drift(t) captures temporal distribution shifts in incoming financial data, and γ, δ are scaling parameters for adaptive calibration.

6.1.10. Pipeline Resilience Efficiency

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

Where T_infer is the inference time per batch of financial events processed by the agentic layer, capturing the trade-off between detection accuracy, compliance adherence, and processing speed.

6.1.11. Detection Performance Error

$$L\_error = F1\_opt - F1\_anomaly \quad \text{(Eq. 11)}$$

Where F1_opt represents the optimal detection performance under ideal data conditions (zero noise, full compliance), serving as the upper-bound reference for evaluating the gap in real-world agentic AI deployments.

6.1.12. Joint Optimization Objective

$$J = f(F1\_anomaly, S\_comply, L, U) \quad \text{(Eq. 12)}$$

Where J is the joint optimization objective balancing detection accuracy, compliance preservation, transaction latency, and cloud resource utilization across all agentic AI workflow components.

6.1.13. Financial Dataset Performance Representation

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

Where Q_src(i) is the source-specific data quality score (market feed, internal transaction, risk indicator), Metric(k) denotes the selected performance metric under evaluation, and T_proc(j) is the processing time per event batch within the streaming pipeline.

6.1.14. AI-GRC Performance Index (AGPI)

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

Where η is the pipeline resilience efficiency, F1_anomaly is the anomaly detection accuracy, Q_total is the cumulative system quality, and FAR denotes the false alert rate. The AGPI penalises excessive false positives while rewarding accuracy, compliance, and efficiency — serving as the principal benchmark for comparing architectural models.

7. Conclusions

This research fulfilled its objective of advancing the real-time automation of financial processes in cloud-native DevOps ecosystems and addressed the outlined research questions. The central proposition was the practical feasibility of combining generative and agentic AI with real-time data ingestion, streaming technology, and automated supporting infrastructures. This proposition is supported by three synthetic scenarios and an architectural framework that integrates the discussed elements and technology directions. Supporting artificial-intelligence models have been delineated and evaluated—partially and conceptually—regarding performance, security, and regulatory requirements.

Nevertheless, the contribution is neither an empirical proof nor a comprehensive design but rather a conceptual exploration that motivates future research and underpins practical initiatives in the field. The scenarios demonstrate operational patterns with a pragmatic potential but only assert their observability and coachability; technical limitations and knowledge gaps regarding data-quality and security controls still stand. Addressing the associated challenges, especially the handling of high-complexity natural-language instructions and the tracking of data lineage and quality, represents the immediate research direction. Subsequent steps require combining the separate developments into an integrated operational infrastructure, preferably supporting production processes in collaboration with financial market participants.

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