Agentic AI for Autonomous CI/CD: Towards Self-Adaptive Financial Infrastructure Pipelines

1st Avinash Reddy Segireddy
Lead DevOps Engineer
ORCID ID : 0009-0002-9912-0629
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***Abstract*—An autonomous agentic AI is proposed for the uninterrupted management of the financial infrastructure pipeline that supports continuous delivery. By integrating proactive orchestration, resource-aware scheduling, and self-adaptive capabilities, all within the confines of a security-, compliance-, and risk-aware environment, the resulting system is expected to achieve a high degree of automation combined with an unprecedented level of autonomy. Speculoos' steadily increasing set of functional properties is in fact believed to lead to a point where any service request could be satisfied without human intervention, at the same time keeping the associated risk within predefined bounds. The underlying architectural foundations of such self-adaptive financial-pipeline management have formalized the agents involved and their respective decision loops. The proposed self-adaptation touches on all relevant aspects, from the external workload to the internal control rules, and spans the three major levels of control theory — feedback, stability, and guarantee. A qualitative analysis of the design requirements is also conducted, tackling latency, throughput, accuracy, and auditability. The provision of strict service-level agreements, worst-case considerations, and the ability to explain and demonstrate the results of any automation step are essential in a financial environment where establishing data and process lineage, and enabling fail-proof and random audits, have a direct impact on the operation of any market participant.**

***Index Terms*—Agentic Artificial Intelligence (Agentic AI),Autonomous Continuous Integration and Deployment (Autonomous CI/CD),Self-Adaptive Software Systems,AIOps (Artificial Intelligence for IT Operations),Financial Infrastructure Automation,Cognitive Pipelines,Self-Healing DevOps Pipelines,Autonomous Systems Engineering,Adaptive FinTech Architectures,AI-Driven Software Delivery.**

I. Introduction

Financial-infrastructure services—such as those used to manage the expected 25,000 trades per second of the 2025 FTX exchange—are difficult to develop, deploy, and maintain. State-of-the-art continuous integration and continuous delivery (CI/CD) tools help automate these tasks, yet these solutions miss many key aspects that make operationalizing financial infrastructure challenging. Continuous delivery pipelines and orchestrators typically evolve and deploy at a smaller scale, require a certain level of human intervention, lack continuous compliance, and therefore pose a major bottleneck toward low-latency solutions. First and foremost, the adapted pipelines need to deliver at a very high throughput with very low-latency Service Level Agreements (SLA)—even with worst-case analysis guarantees—while satisfying the adequacy of the delivered results for the business. Second, the pipelines—mainly for the data-science back-testing, validation, and production

Fig. 1. Agentic AI use cases and real-world examples driving smarter workflows

infrastructure—have to deliver high-accuracy results that are auditable over time, meaning that exact data lineage must be preserved and stored so that any production results can be reproducible and verifiable in the future by an auditor or new joiner.

A. Problem framing in financial infrastructure

The finance industry relies on vast systems of infrastructure that respond to the frequent creation and modification of products and services. New investments in technology, adapted business models, and enhanced services create a requirement for pipelines of infrastructure adaptation at greater speed and with higher risk mitigation than before. Traditional continuous integration and continuous delivery pipelines are not delivering on these needs; their speed and capacity to deliver designed requirements end up not being what underpins the financial growth. Pipelines either slow down the generation of code and services or simply check the boxes for regulations without a genuine response to customer demand. Auditors call out the approvals as some random number written down to make someone happy, and teams sense that it is just a pretend exercise being done in a rapid-out, rapid-back, and rapid-summon fashion, and consequently no real benefit is being felt. Moreover, any risk measurement of the mitigation seen by operating the continuous improvement closed-loop, properly aligned and responsive, is extremely disappointing. Fast creation now has a requirement for feedback loops, continuous checks and monitoring, and real value extraction. Instead, huge teams and very costly services are being created, with the

so-called mother of risk getting closer by the day. The two key limitations of traditional CI/CD pipelines in addressing this problem are their inability to both comply in an adaptive way and respond quickly to changes outside the norm that have always been placed as best guesses. These pipelines are often set up to achieve the minimum bar of compliance with regulations, not to respond to management's risk appetite or customer's requirements; testing and re-verification are seen as a must-do expense instead of as actual value delivery. Indeed, almost every company now possesses an AI strategy, but the real discussion is around how and when AI will be integrated into services. The problems facing many organisations are the speed and gap of pipeline delivery at lower cost or complying with the latest released version a-la-babysitter without any real understanding of the actual impact. The approach must address constant delivery at scale and also take care with the information and adapt in a risk-aware, risk-making, and value-seeing way.

B. Limitations of traditional CI/CD in finance

Traditional CI/CD practices exhibit several limitations when applied to financial data pipelines. The orchestration of financial data delivery is often governed by complex policies due to stringent regulatory requirements, which can significantly lengthen delivery times, leading to delays in analytics. Furthermore, certain classes of requests, such as those for sensitive regulatory reporting data, require complete compliance with confidentiality and security policies. Yet achieving timely processing is of the utmost importance, as data that is late can be of no use to the analyst. Insufficient feedback in the automation of traditional CI/CD systems often results in requests that exceed accuracy, latency, and reliability budgets. Moreover, although requests for best-effort responses may be repeated, such situations are still not handled efficiently. Moreover, traditional CI/CD systems do not address the control and security of the automation systems themselves, nor do they automatically ensure that maintained components remain in compliance with policies. While these gaps may not impede traditional IT systems, they are critical in the context of financial infrastructures responsible for delivering trustworthy data. Addressing these challenges requires dedicated orchestration and scheduling pipelines, in which decisions are never correct but rather progressive at best. Such solutions can be expressed in a more agentic manner, wherein human experts are included in appropriate decision loops.

II. Architectural Foundations

The system is architecturally designed as a holonic agent system. It is composed of multiple agents, each aiming at a clearly defined goal. The architecture encompasses a layered structure, with a decreasing level of abstraction and increasing levels of details toward the bottom layer. Agents exchange information and knowledge with other agents, updating their internal state to adapt their behaviour. An internal decision loop (sense–decide–act) drives each agent's autonomous behaviour. In future work, the integration of machine learning in each of the decision cycles can provide the decision-making intelligence and capabilities to fulfil that goal. The system requires governance for the higher-level goals and data that feed the lower levels. The autonomous decision loops of the lower-level agents offer assurances of their correctness and safety in their local operations. This enables a human-in-the-loop mechanism in support of their governance rather than a bottleneck. Every agent has its goals, observations, actions, and feedback. A response is first prepared for execution. A request for verification and approval is sent to the next-level agents as needed. The action is then executed, inviting feedback from other agents. For actions related to knowledge management and data connection configuration, which might be erroneous, the verification is mandatory and not covered here. The patterns are prepared, sending requests for approval before the actual execution. The data connection configuration is finally activated. The decision loop of the controller agent is activated after every three executions of the reconfiguration plan's decision loop. The action execution incurs performance impacts, making a planned execution preferable. The pattern update entails the creational and deletion plans. The normal pattern and its verification agent form the exception-handling mechanism.

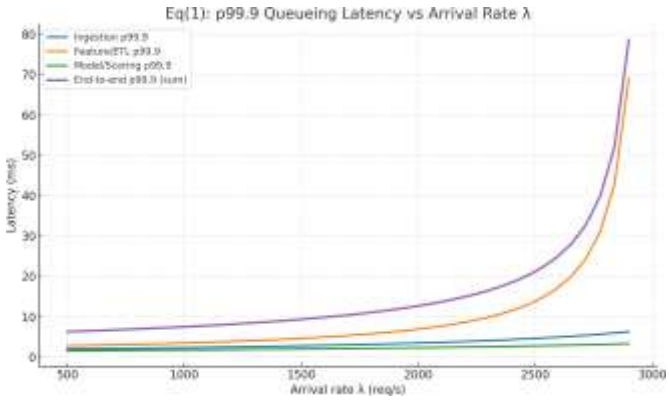

Fig. 2. Queueing Latency vs Arrival Rate λ

Equation 01: SLA feasibility and risk flag
Given a tail-latency SLA SLA_τ (e.g., p99.9 ≤ 150 ms)

$$\sum_{i=1} \mu_i - \lambda \ln(1000) \leq \tau_{SLA} \quad (1)$$

trigger scale-up or routing adaptation

trigger scale-up or routing adaptation

A. Agentic components and decision loops

Agentic AI manages Autonomous CI/CD pipelines to build, update, and operate Financial Infrastructure. These self-adaptive systems execute a continuum of Automation, Orchestration, and Scheduling linked via feedback loops to

Stage	μ (req/s)	Utilization ρ	Mean time E[W] (ms)
Ingestion	4000	0.55	0.556
Feature/ETL	3000	0.733	1.25
Model/Scoring	5000	0.44	0.357
			2.163

TABLE I
PIPELINE METRICS (λ = 2200 REQ/S)

a decision-making framework comprising multiple layered and distributed Agents. Each Agent pursues specific Goals, makes Decisions about Action based on Observed Data Streams, and offloads Results of completed Action. As a result, control-theoretic concepts—Feedback, Stability, and Guarantees—support the holistic definition of the Agentic Infrastructure Pipeline. Automating Financial Infrastructure Pipelines requires new approaches, with Agentic Systems regulating Automation, Orchestration, and Scheduling. Each regulation unit consists of a Goal-setting Agent, Decision-making agents, and Execution entities. Simple Self-Adaptive Pipelines monitor Latency, Throughput, and Determinism, using these properties to Manage Qos, Security, and Regulatory properties. Without Model-Driven processes, more complex Pipelines reactively comply with non-Functional properties. In turn, Risk-Theoretic models simplify the integration of reactive planning for Security and Resource Constraints with proactive scheduling of Regulatory Compliance.

B. Self-adaptation and control theory mappings

Every agent exhibits the five characteristics of goals, observations, actions, feedback, and the environment through which they act, and these characteristics follow directly from the decision loop structure introduced earlier. The role of these components for a specific agent is described below, with direct relationships to the control-theoretic concepts of feedback, stability, and guarantees indicated. A mapping to the control-theoretic concept of adaptation is provided after this definition. Adaptation takes place by routing the message flow through alternative pipelines as models of individual pipelines are triggered either by changes in the workload perfectly predicted by the model or by the detection of anomalies during execution. This adaptation mechanism has been described above, and earlier sections have shown that the goal is to ensure quality of service. In control-theoretic terms, the adaptation mechanism represents an inner feedback loop. The pipeline model thus plays the role of a delayer, since adaptation does not occur at every decision cycle. Nevertheless, periods of stability and inactivity in adaptation are important, since introducing adaptation too aggressively into other domains leads to an instability that magnifies small perturbations rather than attenuating them.

III. FINANCIAL PIPELINE REQUIREMENTS

Stable financial pipelines must satisfy latency, accuracy, and compliance criteria to be usable in production. An agentic architecture requires control-theoretic mappings. Two dimensions govern the operation of a financial infrastructure piece. The first describes functional or nonfunctional properties of individual components, while the second focuses on the structure and flow of data among these components. The laws of finance will typically not be violated; an agentic architecture will, if nothing else, ensure that. What an agentic architecture does is allow for the first dimension — the actual create-update-read-delete (CRUD) of data in the financial infrastructure — to happen without human intervention. An agentic architecture also provides explicit feedback whenever the second dimension is violated. This involves data flow that does not conform to expected patterns, data that is not well-formed or invalid, raw data that is not accurate enough, and so on. Nonfunctionality is baked in by a handful of simple properties such as latency, throughput, accuracy, and compliance. An individual mapping need not fulfill all requirements; achieving just one suffices for the piece of infrastructure being considered to be usable in production. But the properties must be satisfied in tandem for the production environment. The mappings to control-theoretic foundations that guarantee stability of operation, information and resources, and safety, security, and danger.

A. Latency, throughput, and determinism

To maintain competitiveness and customer satisfaction, the financial industry is forced to keep the latency of its services low and the throughput high. Therefore, the time required for loading data from a data lake, running a predictive model, and then writing the output back to the data lake has to be as short as possible; this is also necessary for many other types of pipeline. In many production applications, service-level agreements (SLAs) are set to avoid performance degradation and the end-to-end analysis of data must occur within very short time frames. Current pipelines must be controlled so that they safely obey these SLAs. What is worse, in addition to the average response time, the worst-case response time often governs the engineering and maintenance of applications; therefore, QoS with respect to the 99.9 percentile is very relevant. Failure to respect these constraints usually implies financial penalties. Another very important factor in managing a pipeline within the financial environment is accuracy. The data at the end of the pipeline is consumed by a regulatory unit whose job is to verify compliance with several regulations such as Basel II. If the incoming data are inaccurate, the unit could request a human to check why the data have been generated, and this human check usually incurs a high financial cost for the bank. Therefore, the auditability of the pipelines is very important as well. Auditability is not only a matter of ensuring that the generated data can be verified; it is also a matter of enabling the reproduction of the results in the case of doubt. In other words, it is important that the generated data can be traced back to their origin, that a log of every action performed exists, and that the execution of the pipeline can be replayed from the input to the output.

B. Accuracy, auditability, and traceability

Data provenance—knowledge of the data's production process and full lineage critical to auditability in any organi-

zational context—supports both operational and reputational effectiveness. The architecture automatically records all measurements, models, and intermediate data used in predictions to guarantee precise traceability. A formal proof of model correctness also ensures verifiability: human experts are engaged when required by the regulatory environment, reviewing the current models but relying on the autonomous enforcement of their policies. Reproducibility is likewise crucial in a compliance-oriented financial context. Past results must be recoverable when triggered even for long-decommissioned pipelines. The probability of such requests rises when using sensitive data for training; alongside risk estimation, quality assessment, and proof generation, model training triggers the temporal storage of input data. In low-latency environments, past measurement datasets remain stored for the actual model query. The agentic architecture applies these guarantees with the lowest overhead on the production environment.

IV. Autonomous Orchestration and Scheduling

Independent of the preparation for future processing, incident triggers may demand immediate responses. Incidents such as a broken connection to a data source or the publication of a critical vulnerability in a machine learning model usually require ad hoc action, often with high urgency. Related considerations include temporary changes to production environments, such as scaling up capacity or blocking critical traffic, or securing deeper detections against an intensifying attack. While enabled by structural support in a policy-driven approach, these human-initiated activities are inherently less predictable. Describing the entire reactive dimension of deployment, the following subsections compare two complementary attitudes toward the required changes: reactive scheduling, which adapts to incidents as they happen, and proactive scheduling, which anticipates impending incidents. The posts of response orchestration play a large role during incidents. The ability to add an extra data path to mitigate denial-of-service attacks, to deploy a guard model in reaction to detected exploit attempts, or to update a pipeline's all-source metadata to include a new data stream are the sorts of capabilities that infrastructure security may be expected to service on the fly. By the same token, response scheduling and orchestration can be highly reactive, as seen in security incidents, and thus difficult to control effectively when targeting external systems.

Equation 02: Capacity planning (headroom rule)

Your architecture stresses stability and guardrails

$$ri = kimi0l \le r \Rightarrow ki \ge \lceil rmi0l \rceil \qquad (2)$$

A. Policy-driven automation

Policy languages and simple declarative statements capture the intent that expresses policies governing decision-making.

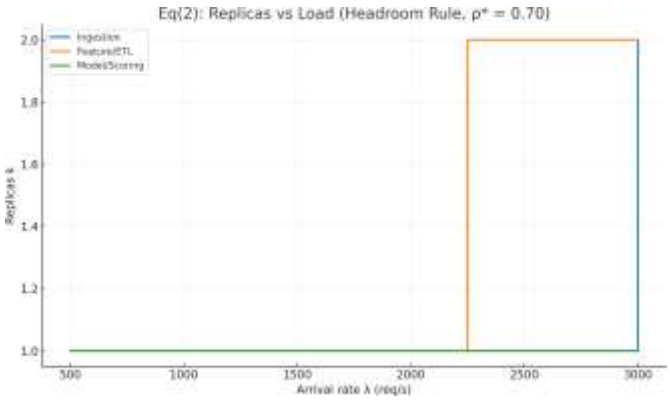

Fig. 3. Replicas vs Load (Headroom Rule, ρ = 0.70)

λ (req/s)	Ingestion k	Feature/ETL k	Model/Scoring k
500	1	1	1
750	1	1	1
1000	1	1	1
1250	1	1	1
1500	1	1	1
1750	1	1	1
2000	1	1	1
2250	1	2	1
2500	1	2	1
2750	1	2	1
3000	2	2	1

TABLE II
HEADROOM _POLICY____REPLICAS _VS _LOAD

Their application as part of guardrails for automation reduces the likelihood of damaging downstream consequences. Continuous compliance guarantees achieve conformance to gradually changing policies through adaptive reconfiguration of automation schedules. A well-structured business would already possess policies covering approved IT and business processes. Automating CI/CD in the most efficient and secure manner for an organization compliant with policies would therefore require automation that is policy-validated (and in compliance with policies). Policy is therefore an additional

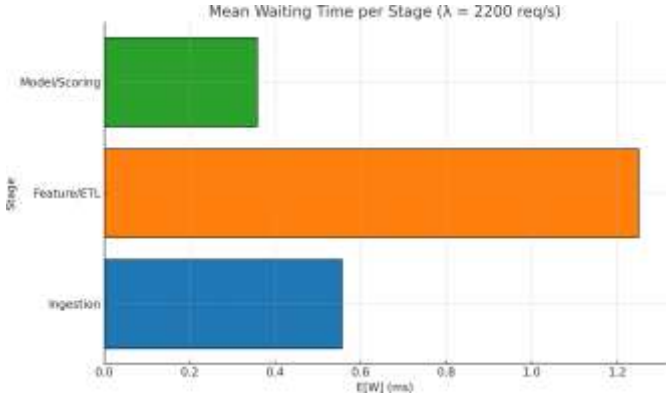

Fig. 4. Mean Waiting Time per Stage (λ = 2200 reqs)

dimension in the automation decision space. The generation of reactive automation responses to events also needs to operate within policy-defined guardrails. Compliance violations are addressable as deviations in already defined automation designs and placed back into schedule for conforming action. As business and IT needs change, schedules also should reflect these changes, and ensure that resultant CI/CD processes remain in compliance with business policies. To facilitate such continuous-compliance of CI/CD automation schedules, business policies thus become essential snapshots of "what is right" for the entire organization across areas. Therefore, an organization may adopt policy-driven automation for CI/CD as follows.

B. Reactive vs proactive scheduling strategies

Policy-driven end-to-end automation fosters responsive scheduling of orchestration and resource management, satisfying data availability requirements while minimizing costs. Proactive scheduling augments reactive agents by supporting anticipatory plans that fulfil future data needs ahead of time. For example, a sensor pipeline comprises data-sampling in the world and processing in the cloud, and short-lived memory caches fast access to raw images. Such pipelines introduce predictability and thus can be more proactively scheduled. Despite SLAs for automatic triggering, data availability is not ensured, and probes may file false alarms. Forward-looking models that describe future needs enable doctors to plan ahead: e.g., if multiple patients are undergoing similar procedures monitored by magnification cameras installed on a hospital ceiling and their robots capture images soon, then all cameras require large temporary caches and an increased co-computing capacity to process the images, even if only a few patients are under scrutiny at that moment. Managing long-term data availability across agented pipelines in this manner also enhances efficiency and throughput, and can complement alert-triggered resource scheduling.

V. Self-Adaptation Mechanisms

The system self-adapts to changing workloads and potential threats along two main axes: model-driven adaptation, which leverages infrastructure models to predict upcoming demands and inform pipeline adjustments, and resource-aware optimization, which seeks cost-effective scaling while achieving the resources stipulated in SLOs and SLAs. Pipelines can become overloaded for protracted periods due to large data bursts, unpredictable operational loads, or updates to dependent systems. Traditionally, pipelines have been manually scaled and lengthy data churn ensured through preemptive measures, such as isolating pipelines at risk of exceeding SLOs into dedicated environments. With large parts of the automation pipeline becoming invariant, however, a model of the dependent financial infrastructure is constructed. This drives the long-term planning required to either duplicate or scale core pipeline components in anticipation of predicted data passes and operational loads. Combined with automated deployment and provisioning, seasonal investments to support heavy data

Fig. 5. Self-Adaptation Mechanisms

loads come ever closer to being equally invisible. Depending on the specific design of a data flow, this capability can often be extended to predict and remove resource saturation when demand recedes. Compliance with performance SLOs for data-intensive workloads is alleviated through the addition of a resource-aware optimization mechanism. Each workload target in an SLO can be enriched with bounded cost. Information about previous data churn, expected cost to complete, and deviations from initial estimates allows for resource-aware decision-making—just-in-time provisioning for additional processing resources while avoiding excess costs. These capabilities form the foundation to support multiple data passes with QoS guarantees without requiring complete CI/CD isolation.

A. Model-driven adaptation

Models can enable mid-level adaptation through predictive transformation for workload variance and prediction for changing data characteristics. Changes to how pipelines consume data potentially affect the order of execution, so that foresight of when data becomes available affords optimizing the pipeline planning. In much the same vein, the availability of application-aware scaling rules permits reconfiguration on the basis of changed resource requirements for quality assurance. The specifications surrounding such alterations can be gleaned from the very models that the pipelines draw upon for their operations. Though these models exemplify orthodox low-level automation, their employment during adaptation offers a distinctive contribution by observing the usages of data assets rather than their production. When upload or query traffic deviates from predictions, data-management pipelines may also require optimization. The incapacity for such elasticity

is reflected in the absence of cost-awareness: the cost incurred by data-management pipelines is solely internal and effort-neutral for the other stakeholders. However, such scaling considerations are the prerogative of the data-management stakeholders alone, as the means for effecting them reside only with them. A reactive adaptation to changing workloads is therefore feasible even with the current automation, but requires investment in management interfaces for the automation of data assets' creation and destruction in response to detected or predicted changes. Dynamic scaling of cloud resources with a design pattern, such as that provided by Amazon AWS CloudFormation, can serve this purpose.

B. Resource-aware optimization

Dynamic scaling of cloud resources according to workload characteristics is a common approach to minimize costs while satisfying service-level agreements. If estimates of future load can be obtained from a predictive model, pipeline resources can be proactively deployed before expected traffic spikes. Alternatively, if resources are deployed to satisfy worst-case throughput and latency requirements, they can be scaled back when the predicted load drops close to zero. For example, a data pipeline that ingests, processes, and stores data from social media feeds can be scaled back to zero when language detection latency is not a concern, while seasonal drops in retail product sales would allow the pipelines serving those products to be easily scaled back. In addition to scaling for varying loads, cloud resources can also be selected on the basis of cost and quality of service when multiple options are available. For example, the same processing function can usually be implemented using lower-cost CPU resources or higher-cost GPU resources, both provided with different configurations. An objective function that weights cost against quality of service can be integrated into resource selection, and resource selection for training a machine-learning pipeline can be configured in a similar manner.

VI. Security, Compliance, and Risk

Rethinking traditional continuous integration and delivery pipelines for financial infrastructure is not only about enhancing developer experience and reducing cycle times—security, compliance, and risk must also be considered externally to the main development operations. Such systems are touted to be agentic, dynamically automating the preparation, deployment, and operation of cloud resources in response to incoming requests, with little or no human interaction. However, to gain the trust of potential users and stakeholders, guarantees for accuracy, compliance, auditability, and policy enforcement need to be established, ideally through a threat analysis. Such considerations become even more critical as additional trust boundaries are traversed, for example when adapting to evolving pipeline workloads and threats, or during the management of not only development resources but also production systems. Just as an autonomous vehicles addresses navigational risk by

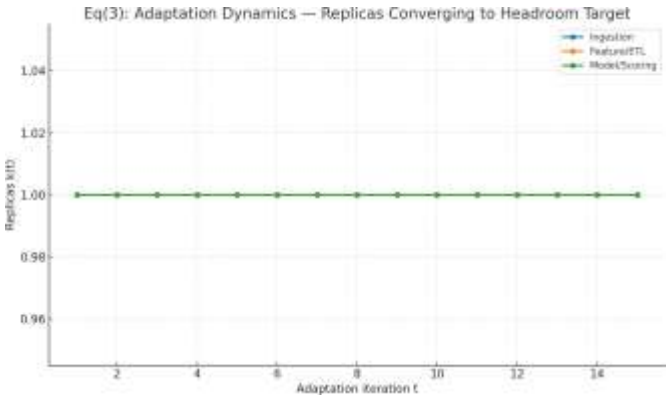

Fig. 6. Adaptation Dynamics — Replicas Converging to Head

liberating drivers from the responsibility of route planning, an autonomous CI/CD system can mitigate some security risk by relieving developers of the task of managing security patches and updates for infrastructure and application components. Yet the analogy should not be stretched too far, since the attackers and failures faced by a continuous integration and delivery system cannot be observed and taken into account for decision-making tables or databases. To address the gaps, actors, activities, and failure modes present in traditional CI/CD systems, as well as specific challenges for each group actor, need to be understood before applying the agentic principle to its orchestration and deployment. This analysis suggests that systems supporting the continuous integration of infrastructure and application changes for financial systems operate on a vastly different scale than those for corporate websites, both in terms of human-to-computer interaction frequency and in the number of distinct changes made to a development SKU. Continuous delivery pipelines, trained to pick the best time for an update to production, usually need to carefully propagate such changes through all environments and security control gates. The additional responsibility of preparing a change and transferring it from the development infrastructure to production in an audited manner leads to long cycle times that cause not only frustration for the developers, but also a dependency risk that can delay the release of features or fixes and provoke regulatory breaches. These latencies, exposures, and frustrations can be overcome by making pipelines agentic, providing an autonomous capability for preparing, deploying, and managing not only the application code, but also the underlying infrastructure.

Equation 03: Self-adaptation control law (feedback)
A lightweight negative-feedback scaler consistent with your inner loop

$$ki(t+1) = \max(1,\ ki(t) + \alpha(\rho \cdot \mu_{i0}\lambda - ki(t))) \qquad (3)$$

A. Threat models for agentic pipelines

Despite its many advantages, agentic adaptation remains a potential attack surface for adversaries. Adversarial threats fall

λ (req/s)	Ingestion	Feature/ETL	Model/Scoring	
500	1	1	1	
678.5714	1	1	1	
857.1429	1	1	1	
1035.714	1	1	1	
1214.286	1	1	1	
1392.857	1	1	1	
1571.429	1	1	1	
1750	1	1	1	
1928.571	1	1	1	
2107.143	1	2	1	

TABLE III
HEADROOM POLICY: REPLICAS VS LOAD (PER STAGE)

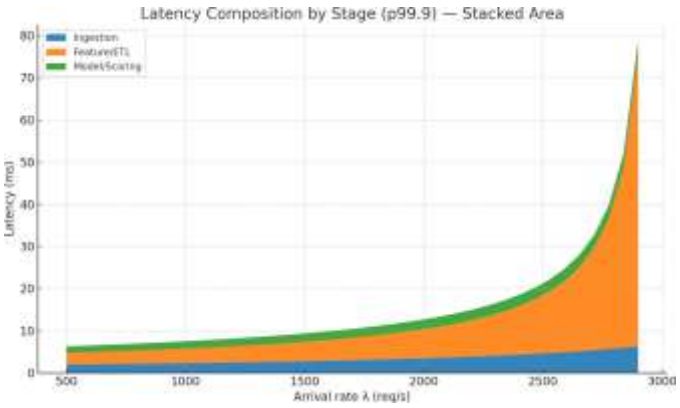

Fig. 7. Latency Composition by Stage (p99.9) — Stacked Area

into two categories. The first group consists of cases where the agentic framework acting upon the financial infrastructure is a goal of the attack. While traditional infrastructure may be vulnerable to an external attack aiming at shutting it down, similar attacks against agentic frameworks are more likely to resort to data poisoning, model evasion, or adversarial attacks aiming to cause an undesired behavior of the framework. This may happen when an agentic framework is triggering the financial infrastructure to operate in an undesired state. In such a case, attackers may exploit the possibility to act transiently to change the observed behavior of the agents. The second group of attacks include attempts to cause a behavioral deviation of the agentic framework for a long-term time span. Such long-time deviations can be triggered, for example, if attackers are able to present incorrect information to the agents and make their decisions based on such incorrect data, therefore reflecting a Command & Control (C2) behavior. The agentic pipeline may also experience failures during its operation. In fact, agents residing in the decision loops have limited run-time monitoring capabilities. The reconfiguration of the financial infrastructure pipelines may also be attacked. Attacks in this category aim to cause temporary changes in the structure of the environment acting upon the agentic framework, therefore determining a temporary unavailability of some of its resources.

B. *Regulatory alignment and auditability*

Aligning with financial regulations such as SOX, PCI DSS, DFAST, and others introduces additional constraints on pipelines and the systems running them. Such regulations are a direct consequence of the significant risks of poor governance of financial data. Consequently, financial pipeline architecture must enable continuity of service, allow proper tracking of data-as-it-moves through various transformations, and retain the proper metadata and logs to guarantee a transparent audit of these operations. The behavioral integrity of the processes carrying this data also needs to be guaranteed. The Service Level Agreements (SLAs), being voluntarily imposed by regulators, are necessarily agreed on. Compliance dictates that these SLAs should be respected unless explained and communicated to the regulator in advance of their infringement. A distinction is thus made between adaptation and guarantee of these SLAs. For example, any technology operator managing the regulations should be able to inspect the potential breaches of SLAs and analyze whether they are acceptable or not in the long term. Moreover, it should be possible to define the risk appetite for potential SLA violations, dictating under which conditions, and to what extent, they can be allowed.

VII. CONCLUSION

While conclusions generally synthesize the work and its implications, here it turns outward to anticipate future directions for Agentic AI and related components—their extension to other domains, and the additional considerations faced when addressing financial infrastructure and processes. A continuously evolving and risk-sensitive socio-technical environment requires AI systems to increasingly take charge of their own decisions and interactions. Real world applications call for agentic systems to maintain regulatory compliance, throughout their life cycle, at all times. The inherent differences between classical software and financial pipelines—differentiable risk in the definitions of Quality of Service as well as Quality of Compliance—bring forward a number of unique challenges. On the one hand, the regulated nature of the pipelines usually results in limited freedom for the agentic systems in the composition of the automated workflows; on the other hand, the freedom is built in implicitly, by designing automated processes that constantly check for evolution of regulatory space. Addressing continuous regulatory compliance, and risk control as part of the regulatory specific angle of such Agentic AI methods for maintaining continuous regulatory control, introduces the governance and regulatory space specific for the pipelines. Reactive continuous compliance constitutes one possibility exploited for Financial Services, in a financial environment characterised by Continuous Compliance and Continuous Auditing requirements.

A. *Future Trends*

Recent advances in the agentic paradigm promise important improvements in autonomy, self-adaptation, and both formal and operational governance. Progressing from traditional to

operations- and piloting-focused CI/CD pipelines delivers further scaling and risk-reduction potential. Financial guidelines such as Basel IV, MiFID II/III, Dodd-Frank, and Solvency II require ever more data and models to guide compliance responses. Failure such as the European Central Bank's T2S outage expose the need for predictably-scalable capacity to absorb peak loads without compromising quality of service. Finance remains the most-attacked sector; therefore, integrating adaptation to changing workloads, changing threat landscapes, and limited resources remains paramount. Looking beyond these guidelines, challenges specific to financial infrastructures and agentic flight can be identified. Can agentically-controlled finance-related CI/CD pipelines remain self-compliant, such that upstream audit, control, and governance approval become simple operations? Agentic auditability supports these concerns, yet the foundations for additional traces of test result verifyability, operational observability, and component resource-use reproducibility require greater investigation. Risk of modelling error in the operational control loop can be mitigated through a flight-oriented view of the controlling agents; vehicles anticipate rather than react to turbulence through regulatory sectioning.

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