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Cloud-Native DevOps for Agentic AI in Automated Finance

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Abstract

Conventional automated trading and risk management employ deterministic models within a well-defined decision support paradigm. Emerging DevOps-driven cloud-native architectures, however, enable scalable, resilient, operable, observant, and automated systems where models are continuously updated in response to changing real-world conditions. Recent research suggests extending agent-based reinforcement learning beyond a decision support role toward direct decision-making responsibilities, underpinned by proper control and governance principles. The combination of such agentic models within automated financial systems presents novel challenges, while fulfilling requirements defined by supervisory authorities. A suitably architected cloud-native environment thus has the potential to not only expedite the delivery of financial AI models, but also to support their increasingly frequent deployment and operation with minimum effort and oversight. The specific considerations, from foundational concepts through to development and operational constraints, then govern the underlying implementation.

The ultimate goal is a DevOps-driven cloud-native implementation framework that guarantees the reliable delivery of agentic AI models into automated trading and risk management systems, quickly, frequently, and with minimal overhead. In this highly regulated domain, controls must therefore be embedded within the supporting infrastructure and processes rather than bolted on afterwards. The key metrics for measuring success then become the speed, frequency, and simplicity with which models are delivered, continuously improved, and retired, all while remaining compliant with a multitude of ever-present security, risk, governance, and operational requirements. By explicitly specifying these considerations, the intention is to present a coherent synthesis of the architectural rationale and a repeatable implementation approach.

Keywords: Agentic Artificial Intelligence in Finance, Reinforcement Learning for Trading Systems, Automated Trading and Risk Management, DevOps-Driven Financial AI, Cloud-Native Financial Architectures, Continuous Model Deployment (MLOps), Governance-Embedded Infrastructure, Regulatory-Compliant AI Systems, Real-Time Model Adaptation, Supervisory Technology (SupTech) Alignment, Scalable Financial AI Operations, Observability in Automated Trading Systems, Model Lifecycle Management, Secure and Resilient Financial Platforms, AI Governance and Control Frameworks.

1. Introduction

In automated trading and risk management, an increase in the frequency of decision-making may improve operational performance. One appropriate approach to greater operational efficiency is the development of agentic systems capable of meeting specified success criteria for decision-making without external influence or control. In an automated financial context, agentic systems are advanced analytical or algorithmic models executing trading or risk management actions for the endocrine-neural circuit of market operators, chief risk offices, and market regulators. Success criteria mirror the objectives and risk appetite of the appropriate stakeholders, whether revenue generation, risk mitigation, or another desired behaviour.

Trading activity is governed in part by regulatory authorities and compliance departments. Many emerging regulatory controls are ex post facto but require audit-proof decision-making capability. The

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combination of regulatory complexity, danger of knee-jerk market reactions, and overwhelming quantity of transaction information creates an opportunity for model-based systems able to meet success criteria. In finance, such systems are capable of meeting specified accuracy and governance criteria at scale, as determined by available data or computational constraints. They are not necessarily more accurate than human judgment; they merely have predictable error. The central use case for agentic systems is fulfilling repeated resourcing problems subjected to compliance-based constraints, with no desire other than to pass audit and achieve regulatory and compliance-condition objectives.

2. Foundational Concepts

The design of a cloud-native architecture strongly depends on the requirements and characteristics of finance workloads. Scalability, resilience, operability, observability, and automatable security controls must all be carefully considered, given the high transaction volumes and values of financial systems, their degree of automation and potential for loss, and their heavy regulation. Source systems tend to be very large and complex, requiring distributed systems to support data access and processing. Automated trading and risk management strategies often operate at high speeds, and Edging may be needed to reduce transport delays. Perceived costs must be optimised while correctness must be assured, requiring thorough testing, continuous monitoring of supervised models and data physics, and controls that cannot disrupt or even noticeably affect the application of agentic intelligent strategies. A high degree of automation is therefore essential.

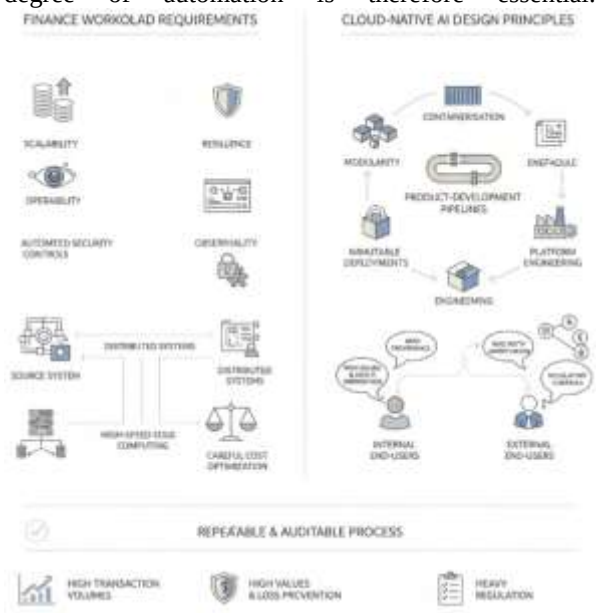

Fig 1: Cloud-Native Architectures for Agentic AI in Finance: Engineering Repeatable, Auditable, and Regulatory-Compliant Deployment Pipeline

The core principles of cloud-native design—modularity, containerisation, declarative infrastructure, immutable deployments, and platform engineering—are all important for safely maintaining and delivering AI systems in finance and provide a strong basis for the development of deployment and operational pipelines. The delivery of agentic AI is thus approached as a product, where the deployment and operational pipelines become the product-development pipelines for a repeatable and auditable process of delivery. Both external and internal end-users are recognised and are involved at key stages in the governance and operating lifecycles of the ready-for-production models, addressing issues such as data provenance and lineage, auditing, safety checks, bias detection, and fast and slow regulatory controls.

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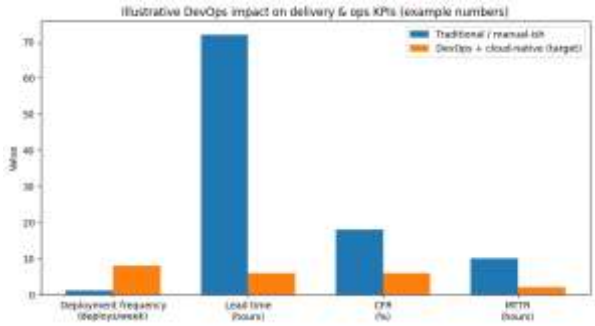

Equation 1) CI/CD "gating condition" using violation-rate threshold

Definitions (per time window):

- Let n = total predictions in the window.
- Let V = number of predictions flagged as violations by compliance/safety rules.
- Define **violation rate**

$$v = \frac{V}{n}$$

Gate trigger rule (direct from the narrative):

Trigger gate if $v > \tau$

where τ is the allowed maximum violation rate.

If you want the "statistical" form (recommended in regulated systems):
Model each prediction as Bernoulli: $X_i = 1$ if violation else 0. Then:

$$V = \sum_{i=1}^{n} X_i, \qquad \hat{p} = \frac{1}{n}\sum_{i=1}^{n} X_i = \frac{V}{n} = v$$

A conservative gate can use an **upper confidence bound** for p (true violation probability). Using a normal approximation:

$$\hat{p} \pm z_{1-\alpha}\sqrt{\frac{\hat{p}(1-\hat{p})}{n}}$$

Trigger if the **upper bound** exceeds τ:

$$\hat{p} + z_{1-\alpha}\sqrt{\frac{\hat{p}(1-\hat{p})}{n}} > \tau$$

2.1. Cloud-Native Principles

Cloud-native approaches embrace the ideas of modularity, containerization, declarative infrastructure, immutable deployment, and platform engineering, which allow rapid scaling in response to evolving demands while delving deeper into a larger operational and risk space. These principles neatly overlap with the discipline of automating AI in regulated domains, where security, process governance, risk management, and change are core concerns.

Rapid scaling and catering to different operational requirements often require operating in a wider multi-tenant context. The key to achieving this while limiting risk lies in putting cloud-native principles into practice. Modularizing systems into coarsely grained decoupled functions enables convenient management of operational policies and ensures important security boundaries are respected. Deploying these functions through containers and exposing service interfaces suitable for a multi-tenancy context facilitates flexible scaling. A declarative infrastructure-as-code approach driven by platform engineering enables developers to focus on their contribution while minimizing high-risk and tedious operational work. Enforcing immutability of Deployment Units further reduces the risk consumed from layers outside the core development team.

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Metric/Concept	Equation	Why it appears in the paper's architecture
Inverse canary KPI delta	$\Delta = \mathrm{KPI}_{\mathrm{new}}-\mathrm{KPI}_{\mathrm{old}}$	Compare new vs existing model under matched traffic.
Data-quality (β-sensor) z-score	$z=\dfrac{x-\mu}{\sigma}$	Standardize feature/statistic vs baseline distribution.
Population Stability Index (drift)	$\mathrm{PSI}=\sum_b (p_b-q_b)\ln\!\left(\dfrac{p_b}{q_b}\right)$	Distribution shift between baseline (p) and live (q).
RL return	$G_t=\sum_{k=0}^{\infty}\gamma^k r_{t+k+1}$	Discounted cumulative reward for an agentic policy.

3. Architectural Paradigms for Automated Financial Systems

Technical literature identifies several architectural paradigms suitable for automated financial systems, each driven by a distinctive set of success criteria and capable of delivering value trade-offs among scalability, latency, fault tolerance, and compliance. The benefits provided by high scalability and low latency may be hard to realise for architectures prioritising fault tolerance or regulatory compliance. Consequently, all three non-functional constraints are rarely satisfied at an acceptable level with a single design choice. Microservices, service meshes, event-driven architectures, and stream processing are recognised paradigms for automated finance workloads. Although complementary and capable of coexisting, their distinctive operational characteristics warrant separate discussion.

Microservices and service meshes support deployment patterns where applications scale in accordance with demand and low latency is paramount. A microservices-oriented system comprises small, distributed services that communicate with one another through well-defined APIs. Each service implements a specific piece of business functionality and can evolve independently. Services within the architecture may use different technology choices and software release cycles, potentially reducing coupling between development teams. A service mesh manages the secure exchange of messages between microservices, often enabling mechanisms that guarantee observability, authentication, authorisation, and traffic management. Statelessness enables easy replication, while a mesh improves operator understanding of production behaviour. Failures can also be tolerated by routing requests to another region or cloud.

The open, often public, nature of financial interactions and the exposure of curated APIs to the outside world increase risk of exploitation and attack. Microservices-based systems must implement strong security boundaries. A security boundary is established around a collection of services that can trust one another's identity and adhere to the principle of least privilege. The mesh then supports fine-grained service, role, and attribute-based access control and audit logging of all service-to-service communication. API proxy services expose curated interfaces to external consumers and

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throttle access. APImate or API gateway solutions implement a choke point that enforces authentication, authorisation, logging, and other cross-cutting concerns relevant to all traffic and delegates requests to the appropriate back-end services.

3.1. Microservices and Service Meshes in Finance

Despite their clear value proposition, the use of microservices and service meshes in financial contexts remains underexplored. Developments in these areas should be pursued cautiously, given the additional complexity and operational overhead associated with their adoption. Nevertheless, when applied to high-frequency trading systems, for example, these solutions provide a degree of scalability and fault-tolerance that traditional service architectures cannot.

Service meshes are often seen as a way to mitigate the operational burden associated with microservices. However, their purpose is more fundamental: to compartmentalize a system into failure domains that can be monitored and managed independently. Just as a financial entity contains restricted-purpose entities—such as special purpose vehicles and subsidiaries—so too can a system be divided into zones with limited compliance and operational footprints. Rather than being tagged onto a microservices design as a means of supporting observability and deploying infrastructure "invisibly," service meshes formalize these ideas for scalable systems and should be part of the architectural approach from the outset. The decision to adopt a service mesh can be incentivized further if it is possible to host the mesh in a separate compliance zone with its own IAM policies and a TLS certificate obtained from a private root CA not used by the rest of the system.

Service meshes remain relatively immature. At the supply side, automating networking and security policy decisions remains a challenging problem. On the demand side, solutions lack cloud-native ingress and egress management, and the controls they expose are often perceived as excessive. Nevertheless, it is possible to deliver a satisfying service-mesh experience for microservices and—possibly—a broker–spoke architecture.

Fig 2: Compartmentalizing Compliance: Architectural Formalization of Service Meshes for Resilient Financial Microservices

4. DevOps-Driven Cloud-Native Patterns

DevOps principles increase the reliability of the entire financial AI delivery, emphasizing the construction of architecture patterns that enable financial AI to be developed, tested, and deployed with repeatable and auditable processes. Specifically, continuous integration and continuous delivery (CI/CD) pipelines are defined for financial AI. In addition to the traditional software-related aspects, CI/CD for financial AI requires tailored validation and governance gates to ensure the reliability of model quality, compliance to legislation, and risk exposure.

Continuous Integration and Delivery Pipelines. Financial AI obeys CI/CD principles that ensure reliable, repeatable, and simple delivery, reproducible by the development teams. Delivery processes follow

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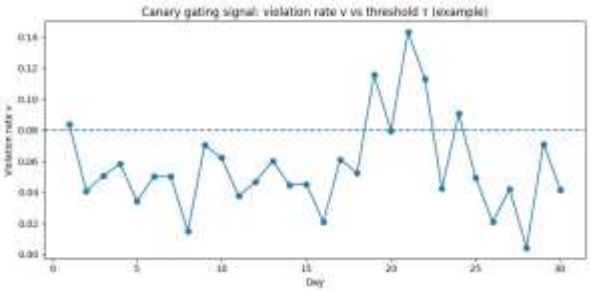
the DevOps sequence of plan—build—test—release—deploy—validate—monitor—learn. CI/CD pipelines for financial AI models include cyclic model and data validation frameworks that verify and test inputs expected by AI delivery. Canary-release strategies, allowing small groups of trusted end users to test AI on non-sensitive datasets before full deployment, and model rollback during delivery failures provide additional reliability, despite non-standard deployment patterns.



Equation 2) Canary release math (traffic split + KPI comparison)

Let:

- Total request rate R (req/s)
- Canary fraction $c \in (0,1)$

Then:

$$R_{\text{new}} = cR, \qquad R_{\text{old}} = (1-c)R$$

Let KPI be any monitored metric (PnL proxy, risk score, error rate, latency, etc.). Over a window:

$$\Delta = \text{KPI}_{\text{new}} - \text{KPI}_{\text{old}}$$

A simple operational rule:

- promote if $\Delta \geq 0$ and constraints hold

rollback if $\Delta < 0$ or constraint violations occur

4.1. Continuous Integration and Delivery for Financial AI

Reliable delivery of financial AI workloads hinges on repeatable and auditable DevOps processes. Continuous integration (CI) and continuous delivery (CD) pipelines tailored to the lifecycle of financial AI models make risky model releases safer by validating models against historical data, deploying them through canary strategies, rolling back when risks materialize, and gating releases through appropriate risk and compliance approvals. At a minimum, CI pipelines for financial AI models include acceptance tests that verify that models do not breach compliance requirements. These checks can take the form of bias-detection tests or data-lineage validation for trading strategies contextualized with the historical data available during training. Such tests are implemented as staged queries to a version-controlled data warehouse. When deployed to production, models are automatically tested against rules that classify model predictions. If more than a threshold percentage of model outputs are flagged as violations in a specific time interval, the gating condition is triggered. When these tests are integrated into a CI pipeline, risky model releases become less likely.

Canary-release strategies mitigate risks associated with model updates by deploying candidate models to a subset of traffic before a full rollout, while automated rollback mechanisms reduce the impact of candidate-model failures. Using such strategies, more models can be updated simultaneously while still conforming with the separation of duties required by regulatory frameworks. A practical inverse canary approach compares the performance of the new model with that of the existing model while using an equal fraction of the requests for both models. By maintaining light-touch governance gates as a percentage of model updates, the canary approach becomes a method of controlling risk for both model developers and operation teams. The combination of canary releases for all models and inverse canaries for risky models moves the responsibility of governance from model developers to the financial institution.

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5. Security, Risk, and Governance

Security, risk, and governance underwrite agentic financial AI and must be considered primary architectural constraints. Trusted ownership of agentic AI decision-making requires identity and access management, and the principle of least privilege is paramount. Role-based access control (RBAC) governs internal agents and human stakeholders, while sensitive data and elevated-risk actions employ attribute-based access control (ABAC). Secrets management controls sensitive information, and supply-chain security mitigates the risk of code execution.

Identity, Access, and Secrets Management

DevOps pipelines require appropriate access to sensitive resources. Identity and access management (IAM) ascribes and governs these access privileges. IAM partitions users into groups and roles. Group membership determines role assignment as a secondary mapping, with (a) roles for dev team members who require principle-of-least-privilege access for daily development; (b) roles for CI/CD execution, including source code repository access, external secret management systems, and privileged resources, such as deploying to production; and (c) a cloud account that assumes the specific production role at runtime. Non-human actors—agents and production AI—accept semantic and procedural constraints. ABAC governs their permission sets, aligning allowed actions with specific contexts, such as sensitivity of input data, external counterparty identities, or internal trust level.

Supply-chain secret management satisfies the need to share secrets, such as API keys and certificates, among multiple stages of the CI/CD pipeline. Security teams select appropriate solutions, such as HashiCorp Vault or AWS Secrets Manager with KMS. Runtime retrieval of secrets is managed through code configuration. Code that accesses secret management systems during build time is forbidden, preventing leakage of secrets into the CI/CD pipeline code repository.

Fig 3: Architectural Constraints for Trustworthy Autonomy: A Framework for Identity-Centric Governance and Risk Mitigation in Agentic Financial AI

Control and Compliance

Security, risk, and governance must be baked into DevOps processes, ensuring end-to-end compliance. Financial institutions enforce elevating control governance over risk products that may not always operate within risk boundaries. Similarly, financial AI must have governance gates throughout the model lifecycle. Three sets of measures should be integrated into operations, allowing activated gating in cases of potential breaches:

1. Validation tests ascertain that incoming data, features, meta-models, or meta-data conform to controlled definitions. β sensors verify data quality and consistency—a necessary condition for AI safety.

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2. Model monitoring examines performance vis-à-vis history or service-level objectives. Trained regression classifiers protect against model deterioration.

3. Risk factors specify states of the marketplace or the organisation that elevate toxicity for AI model utilisation and demand governance closure before usage, such as stressful market conditions that suggest reducing risk capacity and elevating risk tolerance.

Equation 3) Inverse canary (equal split A/B)

Set $c = 1/2$:

$$R_{\text{new}} = \frac{R}{2}, \quad R_{\text{old}} = \frac{R}{2}$$

Now the KPI delta becomes a standard A/B test. If KPI is a mean of samples:

- Let $\bar{x}_{\text{new}}, \bar{x}_{\text{old}}$ be sample means
- Let $s^2_{\text{new}}, s^2_{\text{old}}$ be sample variances
- Let $n_{\text{new}}, n_{\text{old}}$ be sample sizes

Then:

$$\Delta = \bar{x}_{\text{new}} - \bar{x}_{\text{old}}$$

and a standard error:

$$SE(\Delta) = \sqrt{\frac{s^2_{\text{new}}}{n_{\text{new}}} + \frac{s^2_{\text{old}}}{n_{\text{old}}}}$$

A conservative promotion rule:

$$\Delta - z_{1-\alpha} SE(\Delta) \geq 0$$

5.1. Identity, Access Management, and Least Privilege

Managing identity and access has become increasingly complex, due to multi-account multicloud environments, authenticated third-party services, cross-organizational collaboration, and a myriad of devices and users requiring frequent access. Least privilege requires careful vetting as well as frequent monitoring and adjustment. To lower exposure, solutions based on role-based access control plus attribute-based access control can be provided, together with dedicated secret management services. Tools to define zero-trust security for the different services and tenants help to provide a clearer security perimeter, especially when data are flowing between different managed services, either within or across cloud vendors.

Identity, access, and secret management properly integrated into the overall security model reduce vulnerabilities and make it easier to interact with and cross-check data among agents. Defining access rights through a single source of truth and a natively support access control on a per-service basis reduces the attack surface.

Identity management (who can do or access what) and access management (how to authenticate and authorize) require a central source of truth on permissions, such as cloud-native identity management, synchronizing with external solutions such as Azure Active Directory or AWS Cognito and providing a dedicated self-service portal for all accounts. All cloud resources supporting security rely on IAM and permissions should be granted to the minimum number of specific service accounts required for a given business process. General-purpose accounts should never be used within automation processes. Attribute-based access control enables access management based on user attributes, thus simplifying the process of defining rules and supporting user delegation without requiring manual changes to service rights.

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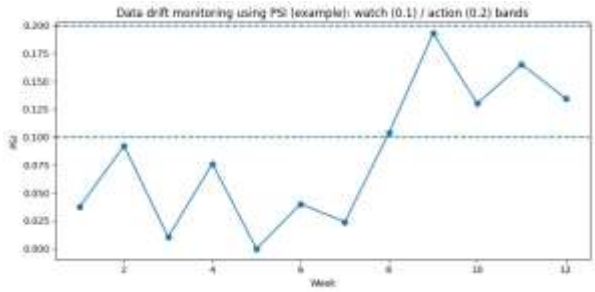

6. Agentic AI Lifecycle in Financial Systems

Grounding the previous discussion in the life cycle of models, it is clear that developer and auditor communities require immutable records of how models and inputs behaved as decisions were made by the service. Data provenance and lineage should record complete details of inputs and feature engineering; model versioning should create immutable recall points; auditing should track all operational decisions; safety checks must ensure that model outputs remain performant in calibration and acceptable across risk thresholds; and both explicit bias detection and implicit model drifting must trigger a complete retraining, build, and deploy cycle to maintain model risk thresholds. Active connections with any other agentic AI service must guarantee that model outputs are considered for final service operation.

The integration of these ideas into a continuous integration/continuous delivery (CI/CD) pipeline adds a governance gate to the deployment lifecycle, ensuring that stakeholders can couple formal bias testing and operational response analysis alongside their normal work. Such a community-focused, repeatable, and audited process can accelerate decision-making while still ensuring appropriate risk governance.

Equation 4) "β-sensors" for data validation (data-quality consistency checks)

A standard derivation starts from **baseline distribution** for a monitored feature statistic x (mean, variance, missing-rate, etc.):

- baseline mean μ
- baseline std σ

Compute a standardized deviation (z-score):

$$z = \frac{x - \mu}{\sigma}$$

Define a pass/fail check:

$$|z| \le z_{\max} \quad \Rightarrow \text{pass}, \qquad |z| > z_{\max} \Rightarrow \text{fail}$$

A "β-sensor score" can be a weighted sum across checks i:

$$Q = \sum_{i=1}^{m} w_i \, \mathbf{1}\{|z_i| \le z_{\max,i}\}$$

and gate if $Q < Q_{\min}$.

6.1. Data Provenance and Model Governance

Systems making financial decisions, especially without human intervention, are subject to considerable scrutiny. Regulatory requirements mandate that systems are built and operate securely, with operational risks minimised and controls in place for effective risk oversight and management. Financial institutions must know why their systems make their decisions, how those decisions arise, how long they remain valid, whether they are safe, and whether they may introduce or perpetuate unwanted bias. Governance processes must also be defined and enforced, and authorities placed during the model lifecycle to observe and sanction breaches—especially for those models that create the processes of other models.

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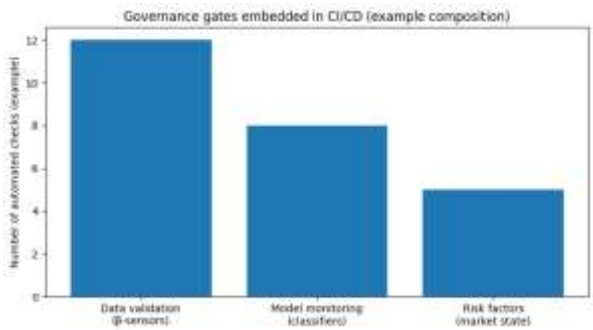
Provenance systems capture information about all aspects of the data used during training and evaluation. End-to-end data-lineage systems track the complete flow of data, including the paths through which data enters, traverses, and leaves the institution. Tracking data provenance and lineage allows reporters to present the required evidence in a timely manner, and provides evidence for confirming that data used for model evaluation and testing remains separate from that of production use. Provenance systems are not confined to data—model information must also be tracked, via a checked-in register of all artefacts created during the process that creates or alters the model. When a particular model is recalled, these records should provide the basis for confirming the required provenance of the model's origin, training, testing, and approval. A thoughtful design increases the probability that the advantage gained can be sustained, and a model register helps to confirm these requirements.

Governors can also define safe conditions for a model, including ranges of input variables for which the model becomes unsafe. Fast-acting safety-check models may be used to surge inputs into simpler and faster operations suitable for production deployment, and detect whether the inputs are bad, and hold, delay, or surge these inputs into a degraded set of other models operating in such conditions. Caution is needed to ensure that correctness, safety, and avoid introducing or amplifying bias are considered in the governance throughout the lifecycle.



7. Conclusion

Development of DevOps-driven cloud-native agentic AI systems for automated trading and risk management satisfies the requirements of actors and stakeholders confronted with ever-increasing trading volumes and market volatility. Evidence of success includes decreasing latency between market events and trading decisions, increasing accuracy of trading and risk predictions, and reduction of reporting breaches—internal and external—that prompt costs or worse.

Fig 4: Trading & Risk Performance Outcomes

Integration of security, risk, and governance considerations as integral constraints across the model development lifecycle further mitigates exposure to the threats associated with automated trading and near-zero-latency risk management and reporting. Such controls encompass identity and access management, role-based or attribute-based access control and least privilege principle, secret-, sign-, and copy-protection of sensitive credentials, protected supply-channel composition, and a practical alternative to practical governance—the foundation of "limited foresight"—that is ever-present in agentic systems.

7.1. Final Thoughts and Future Directions

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The proposed DevOps-driven cloud-native architecture creates a foundation for safely and securely delivering agentic AI to automated trading and risk applications in financial systems. It integrates observability, risk-and-governance gates, and repeating, auditable processes into the development life cycle, ensuring security, risk, and governance concerns are addressed in every aspect of model delivery. Built with agentic AI in mind, it formalizes continuous integration and delivery patterns for financial AI that include model validation, continuous monitoring and backtesting, canary deployments, rollbacks, and explicit approval steps to minimize risk exposure during delivery. When it comes to agentic AI, it matters less whether the delivered application has a trading edge than whether it detects and avoids a disastrous decision.

Positioning agentic AI applications inside the DevOps-driven cloud-native ecosystem brings the advantage of infrastructure–resource elasticity, which allows executing safety nets in a cost-effective way. The ability to orchestrate a large number of requests in parallel can detect rare event catastrophes in a backtesting phase. Examining larger or smaller subsets of the training data can reveal unexpected biases as well. A second aspect gaining importance in this AI era is the multimodel setup enabled by microservices or service meshes, where all major sensorium areas are handled by different AI models or full pipelines. A third aspect is operational transparency; risk monitoring and auditing cannot stay on the periphery anymore, but must move closer to the model action. Distributed sensorium governance is key in a world where controllers outside of the financial system can cause large impact. And in the AI era, auditability no longer can be addressed only ahead of time, but must accompany every major decision.

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