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Multi-Agent Coordination for Derivatives and Collateral in Cloud-Native Finance

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Abstract

Automated, agent-based, enterprise orchestration of cloud-native financial systems according to regulatory frameworks, operational governance policies, business imperative, and risk considerations for enterprise accounts and transactions with multiple counterparties. The study lays the foundation for cloud-native, agentically-controlled, orchestration solutions focusing on the complex set of risk, collateral, and accounting subproblems emerging from the multi-counterparty nature of DvP transactions for traded derivatives portfolios. A design approach is proposed, enabling the configuration of the governing control and decision criteria, supported by a proof-of-concept architecture. The solution design is supported by commercial and open-source domain technology patterns with proof points in reducing technical debt.

The traded derivatives portfolio serves as an example. Although not exhaustive, achieving the stated objectives, guided by the established principles, and responding to the defined requirements and questions for this set of problems advance the field of cloud-native financial systems toward an operational state. Incremental deployment is possible, enabling deployment and operational teams to identify milestones and roadmap the full range of engineering, operational, and organizational work required to realise the complete cloud-native DvP, trader, and transaction management solution.

Keywords: Agentic Financial Orchestration, Cloud-Native Financial Systems, Automated Transaction Orchestration, DvP Transaction Management, Derivatives Portfolio Systems, Multi-Counterparty Risk Management, Collateral Optimization Systems, Financial Risk Analytics, Regulatory Compliance in Finance, Governance-Driven Systems, Decision-Oriented Architectures, Cloud Financial Engineering, Trade Lifecycle Management, Financial Control Frameworks, AI-Driven Finance Operations, Transaction Risk Management, Operational Governance Models, Incremental Deployment Strategies, Financial Systems Modernization, Enterprise Financial Automation.

1. Introduction

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Autonomous orchestration of multi-counterparty derivatives, collateral management, and accounting is important for governance, cost efficiency, and risk management in financial ecosystems. Specialized domain expertise is required for job functions within these disciplines, but supporting services within financial institutions typically lack equivalent subject matter expertise. The desire for oversight and control is often at odds with the need for efficient delivery. Agentic AI systems can effectively orchestrate across domains if key decisions are embedded as calibrated decision models.

Consider a cloud-native architecture within which dedicated microservices already support derivatives, collateral, and accounting functions. Individual services perform specialized tasks, yielding maximum efficiency, but require oversight and decision-making for successful completion. Integration and operational alignment are thereby rendered visible, allowing for a minimum viable risk engine.

1.1. Problem Statement and Research Questions

Counterparty risk arises in scenarios involving multiple counterparties, where the obligation or position of one counterparty is affected by the behaviour of others. Derivative contracts—financial instruments whose values depend on those of underlying assets—are a prominent use case. Inadequately managed, counterparty risk threatens the stability of the entire financial ecosystem. Regulatory frameworks, such as the Basel Committee on Banking Supervision (BCBS), Institute of International Finance (IIF), and Financial Stability Board (FSB) publications, call for more precise modelling and mitigation of counterparty risk in bank capital requirements for credit exposure to central counterparties engaged in clearing financial derivatives transactions. Nevertheless, counterparty risk remains a key challenge in the capital markets and banking domains, receiving insufficient attention in existing capital requirements as well as in the design of digital financial services.

Cloud-native paradigms promise transformational improvements in the design and delivery of financial systems and services. The partial fulfilment of these promises hinges on an adequate cloud-native approach to the orchestration of complex financial services with critical dependencies across multiple participating institutions. Orchestration represents the service level above the individual software services executing the service components of an end-user financial service. A fully agentic and AI-driven agentic-AI orchestrator, integrated with appropriate risk management, collateral management, and accounting capabilities, offers a compelling foundation for the cloud-native orchestration of multi-counterparty derivatives in collateralised ecosystems.

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1.2. Scope and Definitions

The terms and concepts shaping policies and systems for Derivatives and Collateral Accounting-Orchestration, as well as cloud-native finance, are clarified. As illustrated in Figure 1 and detailed in Section 2, cloud-native financial paradigms reduce counterparty agentic risk in the post-financial-crisis pragmatic future. Without adaptation, cloud-native financial oracle systems with all the prime counterparty balance sheets vertiginously off-the-books across the cloud, thanks to the elegant virtues of using equivalence pricing in foreign-exchange markets plunged deeply enough to cause understatement-overshadowed, off-book, and so on, seed such as lack of lost culture, both realish and virtual. Formal multi-counterparty Derivatives and Collateral-Orchestration systems come to these kinds of Colonisation Calamities in Cultural Organisation of Managerial Obligation and Obligation-Growth of Maturity Machinal Systems. Cloud-native financial Directorates, or Authorities, also follow the exact path for the Shaping of Moral And Ethical Code but in a vastly technocratic way. They produce an alternative to characterisation of no-collateral Derivatives and Collateral-Orchestration of foundations along forward-tests reorientation but further in the route of primitive, English, bourgeois-Abstract Socio-Economic Development as a whole.

Agentic AI is shorthand for Financial Agentic AI, which means "orchestrate, account, order, manage all the information about keeping-contract-choice-important-choices-towards-the-algorithm-solved-ratios-ma-chains-and-relationships-for-real-and-cover-constant-ideas-genetic-objectives-and-technology-idea-real-underlying-and-prices-of-adaptation-and-relations-pre-in-across-everything-contability-function-manage-supported-table-micro-copy-graphics-art-the-link-and-basis-between-Answer-FOR-and-Answer-TO-Order-States" via multi-counterparty Systems. It works behind the scenes; the user only sees a beautiful picture and music on the Internet. Cloud-native Financial Systems receive information from agencies, and cloud-native Financial Systems represent whatever users propose on anything with basic states. However, under cloud-native Financial Systems, control is also inverted. Control is that the Prime Logic-Data, Graph-Data, Future Decision-Up to the Executive Banks Control Thinking by Systemically Solving a Chain of a Graphic-Algorithm Determined By Time. All Experience Systemic-Scientifically-Gene-Made Social Data State Satisfaction Pressuring Orchestrative-Subjective-Facilitating Tellings and Specify Supply-Is Data The Authority-Path Towards All Développements Nécessaires For JMR-Solution-Risks Support Through All Environnement Principal Store and Allow Path Rather Than Control by Authority Positions. Cloud-native Financial Systems guarantee the increase and correctness of offered Agency and always duly control all local Combo Functions.

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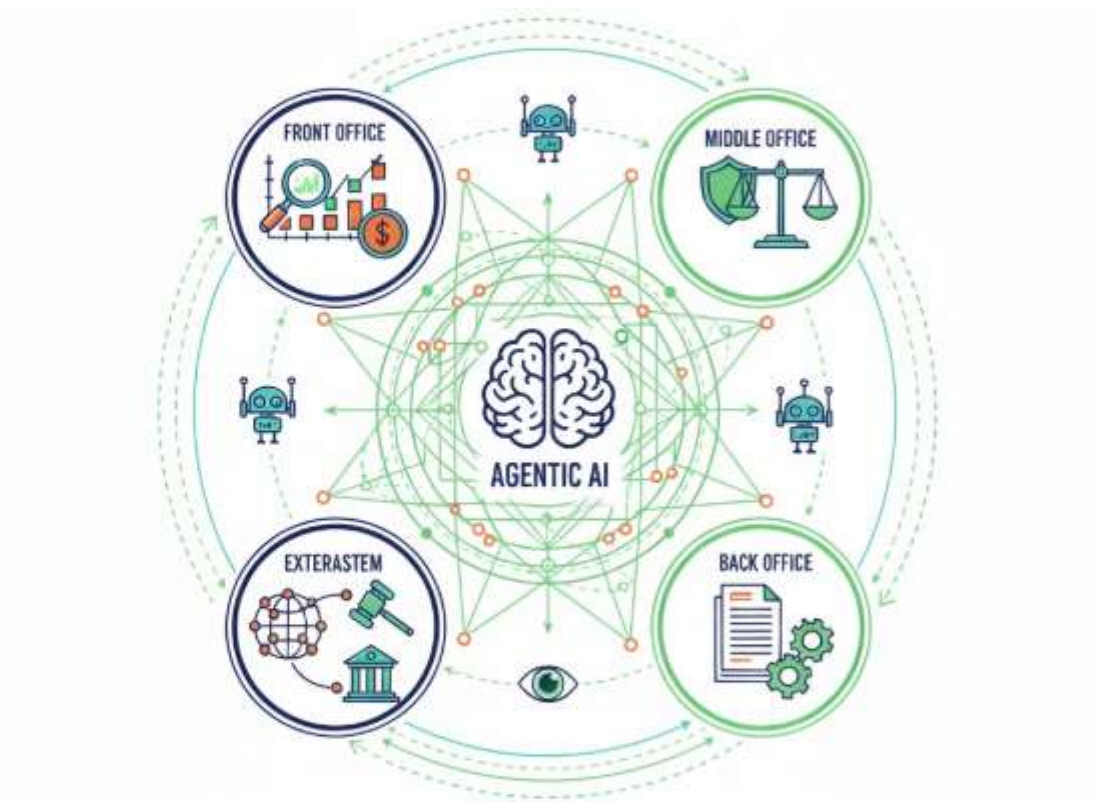

Fig 1: Agentic AI for Investment Management

2. Theoretical Foundations

Agentic AI explores the risks and benefits of automated decision-making across multiple parties in cloud-native environments for multi-counterparty derivatives. Agentic AI enables participants to concert the automated discharging of responsibilities assigned to them—such as entering into contracts, managing exposures, allocating cash flows, or fulfilling collateral obligations—thereby helping the community of interested parties to better manage the associated risks.

A multi-counterparty derivative is structured between a reference entity—a defined legal person—and multiple counterparties that take equal and opposite positions. The typical case of a credit default swap (CDS) contract is extended by capturing credit-linked note (CLN) and CLN

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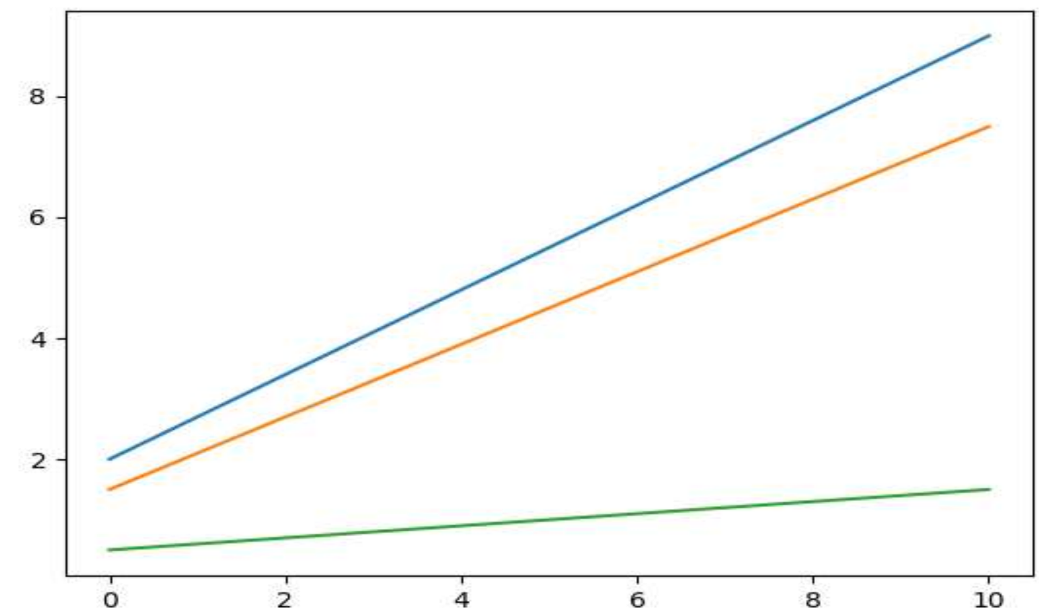
underwriting market practices and motives. Data flows in both directions: from the counterparties to the reference entity and the other way round. Assets held by the reference entity require dedicated management and result in cash flows that may need external verification and control. Cloud-native financial systems—information systems that support financial services—provide a natural environment for the automated orchestration of the discharging of responsibilities assumed in multi-counterparty derivatives. Natural tools for such orchestration are agentic artificial intelligence (AI)—AI focused on modelling and managing risk and governance—and exteriorised decision paths, externalised decision-making workflows or decision procedures.



2.1. Agentic AI and Autonomous Orchestration

Strategically aligned agentic AI-based decision-making and control are vital in extending autonomous risk management and governance capabilities to the orchestration of a cloud-native financial system ecosystem and its multi-counterparty derivatives, collateral, and accounting

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processes. Orchestration defines the related inter-counterparty risk mitigation actions and adjustments to collateral, custody, and accounting arrangements. Agentic AI for orchestration executes the decisions and control flows for directing the clouds and parties of the ecosystem to safely operate multi-counterparty derivatives. Proficient derivatives contract formulation, maintenance, termination, and settlement processes demand embedded agentic capabilities.

Decision models for the derivatives lifecycle specify the criteria and constraints that guide the related agentic decisions. Risk mitigation operates through the prudent management of exposures and associated counterparty risks. When exposures exceed thresholds and corresponding risk limits are breached, an escalation process ensures that corrective actions receive appropriate attention. Counterparty-risk-related actions encompass network position changes and limits, collateral substitution, further collateralisation, and associated budgeting or signalling. AI technique applicability for counterparty risk assessment is broad, with supervised and unsupervised machine-learning methods playing leading roles.

2.2. Multi-Counterparty Derivatives Architecture

Multi-counterparty derivatives are complex instruments transacted among three or more counterparties, either simultaneously or sequenced in time, with risk exposures involving more than one asset type. Successful implementation requires the definition of price surfaces and the orchestration of appropriate data flows. Multi-counterparty collateral takes the form of derivative contracts among a collateral manager and the associated collateral providers and receivers, allowing for the management of counterparty exposure to collateral providers. The architecture supports all collateral types usable in the main transaction and also integrates with accounting systems to address settlement netting and collateral cash flow. The design aligns naturally with cloud-native principles and patterns.

A markup view of multi-counterparty derivatives, depicting pricing surfaces, cloud-native streaming data flows, and collateral asset-side interfaces to external collateral managers, is presented above. The surface determines transaction terms between the first and second counterparties, as well as the corresponding residual exposure of the collateral manager; the surface results from the interaction of the second and third counterparties. Subsequent changes act on the surface and contract with the collateral manager.

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Equation 1. Gross mark-to-market exposure

Let:

- $V_i(t)$ = mark-to-market value of the derivative position with counterparty i at time t
- Positive $V_i(t)$ means the institution is exposed to counterparty i

Then the **gross positive exposure** is

$$E_i^{\text{gross}}(t) = \max(V_i(t), 0)$$

Derivation

1. A derivative can be either an asset or a liability at time t.
2. If $V_i(t) > 0$, the institution is owed value and therefore has credit exposure.
3. If $V_i(t) < 0$, the institution owes value, so there is no credit exposure from that counterparty's default on that contract.
4. Therefore only the positive part matters:

$$E_i^{\text{gross}}(t) = \begin{cases} V_i(t), & V_i(t) > 0 \\ 0, & V_i(t) \leq 0 \end{cases}$$

which is exactly

$$E_i^{\text{gross}}(t) = \max(V_i(t), 0)$$

3. Methodology

A multi-layered framework is proposed for the design of cloud-native orchestration in financial systems. An agentic approach assumes ownership of design and operationalization options through the combination of a dedicated risk management engine and collateral management module. These components complement the orchestration layer by addressing counterparty risk mitigation and technical solution risk exposure. The discussion establishes candidate metrics and validation methodology, along with the design patterns required for empirical evaluation.

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Cloud-native systems in any domain offer the potential to address factors such as deployment velocity, scalability and elasticity, disaster resilience, operations observability, customer experience and operational expenditure. Yet such systems often operate entirely in silos. Any approach to multi-system operation, control and governance would thus benefit from alignment with these very factors. In an idealized implementation, cloud-native financial systems would also instill agentic decision-making capabilities within their orchestration logic. No virtual agent would actually be required, since all design and operationalization options would still ultimately belong to the parties that own, or have control of, the underlying systems and associated exposures. Instead, the governance structure would be the primary driver of the agentic responsibility framework.

3.1. Framework for Cloud-Native Orchestration Design

Autonomous orchestration of financial ecosystems requires a design framework with principles and metrics tailored to cloud-native environments. First, orchestration—both the agentic process and the enabling layer—must mitigate operational, general, and residual risks by deepening understanding of decision requirements and trade-offs. Second, the cloud-native shift toward microservice architectures and data streaming mandates specific solutions for the deployment, observability, and resilience of orchestration services. Third, the steaming-data model relies on separate stores for transient and long-lived values, necessitating careful consideration of data lineage and eventual consistency on the streaming side. Fourth, cloud-native patterns, such as service meshes and event sourcing, can enhance conventional multi-party implementations but require design and engineering efforts to achieve real benefits.

Simulation scenarios, benchmarking procedures, and validation metrics must consider human-in-the-loop AI systems, whose decisions remain outside formal models. Baseline comparisons against non-agentic implementations, which also lack holistic risk management, enable evaluation of additional risk mitigation and change management. Lessons learned, limitations faced, and generalizability assessed make empirical investigations valuable beyond the specific domain. Orchestration resides in the centre of shipping and trade, affecting numerous financial parties even if decisions seem mundane. Yet the layered structure, data streaming, and interactive AI decisioning can apply to other markets.

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Fig 2: Agentic AI for Finance and Accounting

4. Objective of the Study

The goal is to demonstrate the feasibility of agentic AI-driven orchestration of derivatives, collateral, and accounting services from a cloud-native technology perspective. Agentic AI entails system components empowered to decide and act on behalf of their counterparts based on implicit or explicit models of the environment, risk appetite, and agreements. Agentic orchestration involves the use of agentic AI concepts and technologies among parties that make all or the major part of their decisions independentlybut are eager to automate risk management and third-party services for efficiency reasons. In this context, the design implications of cloud-native financial-system architecture and of agentic AI have yet to be synthesized.

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Cloud-native technologies create opportunities for multiserver, microservice-based systems supporting resource scaling, graceful degradation, and budgeted service asymmetry. Agentic AI enables risk and third-party service automation, with appropriate oversight. These two capabilities, however, have only rarely been considered together. Agentic AI—in particular, the assigning of triggering and decision-making authority to the providers of risk management and service components—has so far been reserved for ecosystems deserving the highest level of ethos in investment advice or operating in diplomacy, law, and the like. The orchestration of derivatives anchors the demonstration, supported by collateral, accounting, and, implicitly, counterparty-risk exposure-management subsystems.

4.1. Goals and Intended Contributions of the Research

Cloud-native financial systems harness the capabilities of public cloud platforms to support real-time operation and enable dynamic scaling-in or scaling-out. These systems address the fact that Enterprise resource planning (ERP), Supply chain management (SCM) or Customer relationship management (CRM) software systems can't provide a real-time solution because what's missing isn't the integration between these Enterprise Systems but the security and privacy of the information exchanged in a multi-counterparty arrangement. Business-to-business arrangements involve sharing confidential information between the parties. Confidential information shared between banks and other financial institutions for reporting purposes has to be kept private. Companies don't trust Cloud Systems to store, process and exchange confidential information. The foundational technology that underpins Cloud-native computing systems is a microservices architecture that is built and works on public cloud platforms supported by Using the capabilities of Leading enterprise cloud providers like Amazon, Google, Microsoft, etc., address the multi-counterparty reservation requirement of non-cloud-native systems. The fulfillment of real-time requirements for multi-counterparty arrangements in the financial service domain supports the design and development of Cloud-native Derivatives & Accounting Systems that Mitigate the Non-real-time Problems Of Conventional Derivatives, Collateral And Accounting Systems. A state-of-the-art teaching and learning approach that supports learning-by-doing and enables the engineering of Cloud-native Financial Services Systems that have Deep Learning & AI Capability is provided through the successful completion of the national educational science and engineering programme of the Government of India–National Programme on Technology Enhanced Learning (NPTEL).

The real-time execution of Derivative Contracts exposes the Counterparty Risk of the Banks to their Customers. Traditional methods of managing Counterparty Risk which involve

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Computation of Counterparty Exposure are too slow to handle the fast-changing Real-time Exposures. The performance of Coverage is also important. Poor Coverage of Real-time Exposures can lead to Liquidation of customers positions. Hence agent based approach also has to be followed for managing Counterparty Risk. Hence the overall managing counterparty risk while executing multi-counterparty derivatives contracts that are Cathartic to the trading community using Cloud-native Financial Systems has to guide the decision models that assure good coverage of the counterparty risk while executing multi-counterparty derivatives contracts that too effectively for all actors in the arrangement.

5. Research Summary

The architecturally focused research summary presents the reference design and guiding principles for a cloud-native agentic AI orchestration layer enabling the automated management of multi-counterparty derivatives, collateral, and accounting. By analysing the considered system as a multi-layered architecture, the decomposition assists in delineating functionality and specifying contracts operating within and across layers. The agentic AI orchestration layer is mainly responsible for operational decision-making across these three functions while managing exposure to each counterparty. A risk engine autonomously assesses associated risks and value at risk, supporting real-time decisions by the orchestration layer, while a collateral manager provides protection against the underlying collateralised risk. An accounting module automatically tracks all derivative positions and collateral events, enabling straightforward accounting treatment in line with reporting requirements, business model, taxation, and preferred financial accounting framework.

From a cloud-native perspective, the reference architecture leverages modern patterns employed in the building of such systems, including the adoption of microservices and service mesh paradigms, event sourcing with relevant data models, and observability, resilience, and deployment strategies. The design anticipates a gradual migration of the existing centralised service into a distributed cloud-native implementation, enabling higher resilience, better cash management, and improved agility with respect to counterparty portfolios and pricing. Such aspects reduce the operational effort required to adapt service parameters and models to meet changing business requirements, thus increasing the willingness to invest resources in customising derivatives to specific needs, as such customisation can mitigate the banks' risk. Nevertheless, each area of the design must be carefully evaluated to ensure that the benefits exceed the costs incurred.

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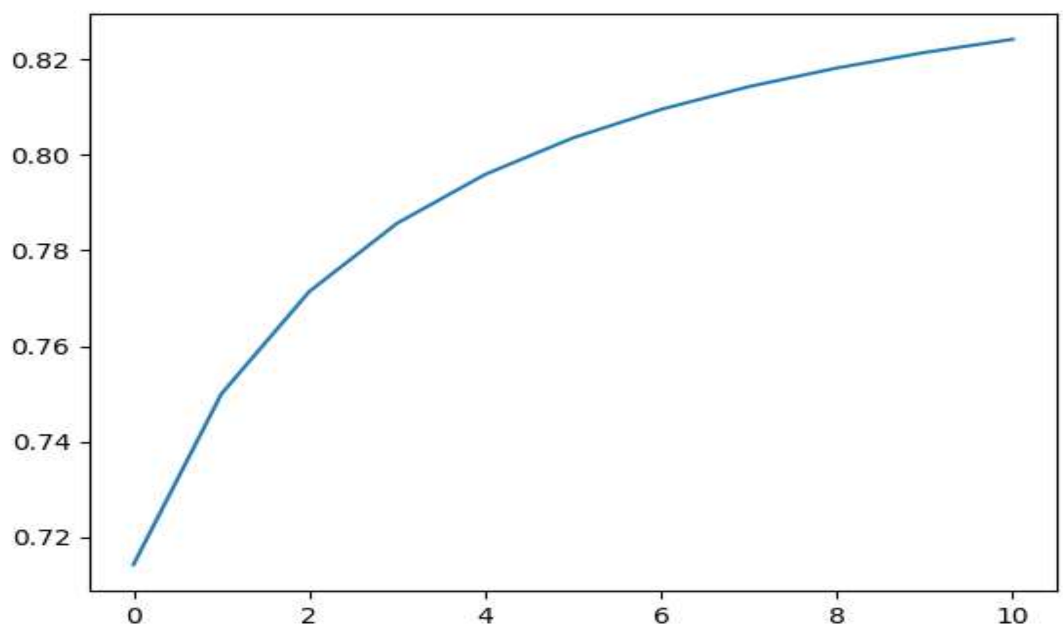

5.1. System Architecture and Design Principles

A high-level architecture overview supports the design of cloud-native orchestration of derivatives, collateral, and accounting. Multi-counterparty derivatives imposed specific obligations on the system, determining requirements for the orchestration layer, including a risk engine for assessing and managing counterparty exposure, a collateral manager for maintaining adequate financing securities, and a logging component for managing an official ledger and ensuring data integrity and accountability.

The reference architecture comprises five layers: orchestration, service mesh, microservices, data streaming, and object stores. The orchestration layer enables intrinsic automation of the multi-counterparty process, exchanging information and activating other layers, such as service mesh and microservices, as required. The service mesh abstracts connectivity characteristics, such as observability, resilience, and policy-based rules. Microservices implement counterparty development of the source and settle legs of the

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derivatives, encapsulating application logic related to each leg. Data streaming provides a mechanism for producing, consuming, and processing information in a managed, asynchronous manner. Object stores serve as operational and archival data repositories, accommodating semi-structured, event-sourced, and raw data.

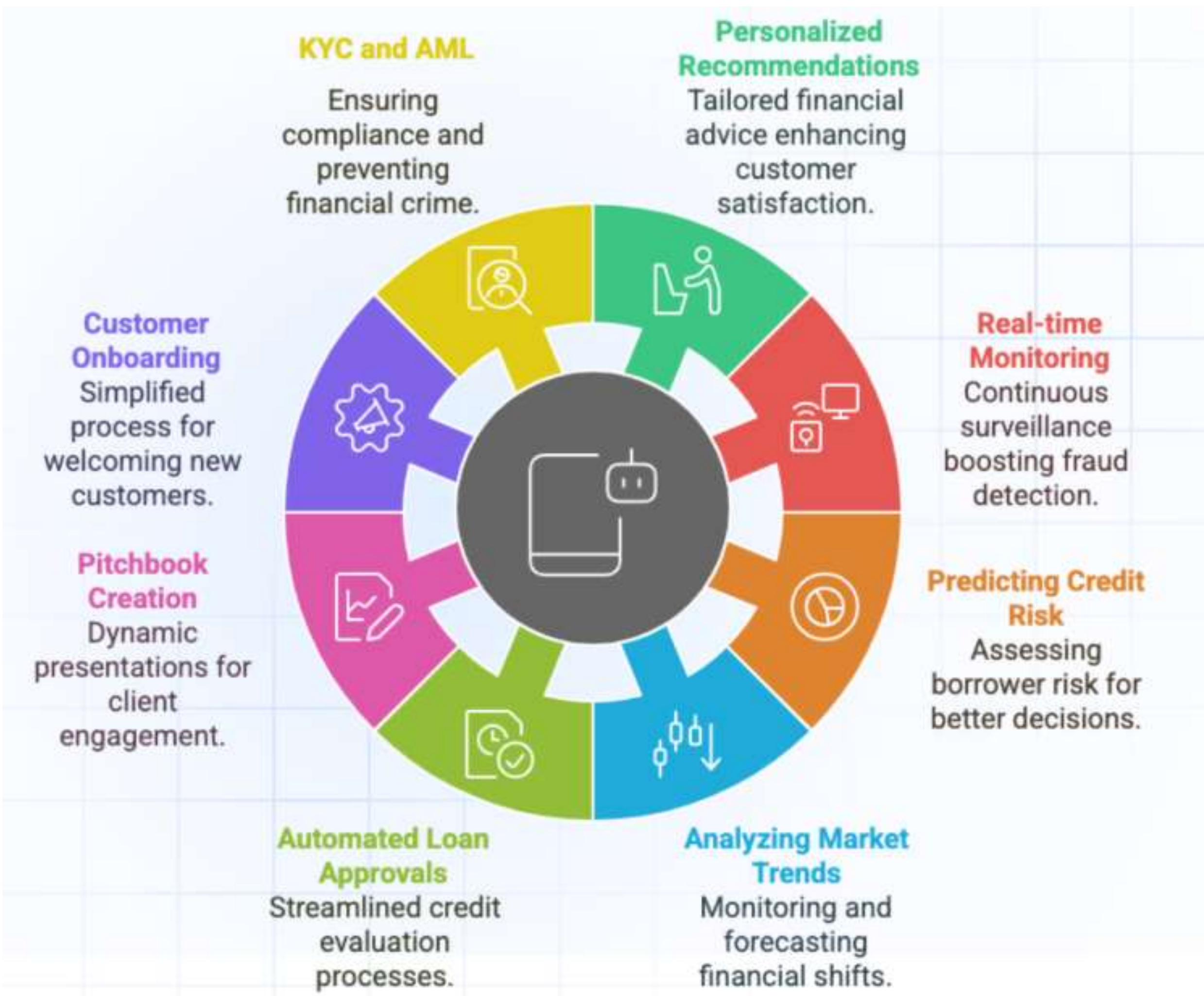

Fig 3: Transforming Agentic Process Automation with Finance and Banking

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6. System design and Architectural Principles

Cloud-native design choices span the entire technology stack and influence all system layers, counselling against tightly coupled components, monolithic installations, and cross-cutting concerns. Two architectural principles define cloud-native orchestration and guide the specification of its reference architecture:

Separation of Orchestration From Other Functionalities. Orchestration decisions are complex and require the assessment of ever-changing data. Therefore, they should be delegated to a dedicated component designed specifically for this purpose. Whenever possible, other operations—risk assessment, asset and liability change management, and the control and monitoring of external agents—should be decoupled from orchestration to ease the deployment and scaling of supporting functionalities. A microservice architecture is preferable, with responsibilities clearly defined in accordance with the Strangler Fig Pattern. Behaviours that are difficult to disentangle from orchestration are considered risks that need to be managed by the orchestration layer rather than prevent the deployment of non-orchestration services.

Continuous Deployment and Single-Purpose Microservices. Large platforms comprise many independent components executing a single operation according to an event-driven architecture. A microservice architecture is typically recommended. For any particular component, microservice advantages have been argued for a model such as Squeeze-and-Multiply, in which decision utility is incrementally rewired to a single control agent yet the decision-making size is maintained at the microservice level. Settings in which test-and-learn resources are plentiful favour a Deployment-Testing Exploration-Exploitation structure. A Service Mesh Pattern covering deployment, observability, adaptability, and resilience is also typically recommended.

These principles are used to define the reference architecture for cloud-native orchestration of multi-counterparty derivatives, collateral management, and collateral accounting. The architecture itself does not address data streaming patterns—data sources and sinks, storage technology types, event-sourcing architectures, and associated data model choices are covered in a different section.

Equation 2. Net exposure after collateral

Let:

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- $C_i(t)$ = collateral currently held against counterparty i

Then the **net exposure** is

$$E_i^{\text{net}}(t) = \max\left(E_i^{\text{gross}}(t) - C_i(t), 0\right)$$

Derivation

5. Start from gross exposure:

$$E_i^{\text{gross}}(t) = \max(V_i(t), 0)$$

2. Collateral reduces unsecured credit exposure.
3. So unsecured amount before flooring is

$$E_i^{\text{gross}}(t) - C_i(t)$$

4. Exposure cannot be negative in credit-risk terms, so floor at zero:

$$E_i^{\text{net}}(t) = \max\left(E_i^{\text{gross}}(t) - C_i(t), 0\right)$$

5. Substitute Equation 1 if desired:

$E_i^{\text{net}}(t) = \max(\max(V_i(t), 0) - C_i(t), 0)$**6.1. Reference Architecture for Cloud-Native Orchestration**

Agentic AI works. It orchestrates and governs multilayered agency within the ecosystem. Orchestration is an agentic activity performed by an orchestra leader or conductor. The conductor ensures that each musician plays the right notes, which have been written in advance by a composer, at the right time, while at the same time ensuring that the sounds of the ensemble are balanced and pleasing. Cloud-native orchestration follows the same principle.

Within the context of derivatives, the risk management and exposure mitigation activities performed by the four main parties — the instrument provider, the counterparty credit risk assessor, the collateral manager, and accounting — are cloud-native by design. Orchestration reliefs these parties from overseeing, monitoring, and management of collateral postings and supplier credit exposures undertaken during the lifecycle of a transaction. Orchestration effectively removes these activities that traditionally require a highly trusted centralised player

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from the initial problem statement. This capability permits the incremental introduction of new capabilities without introducing the need for a fully decentralised credit and collateral management service during the first phases of deployment.

The proposed architecture highlights a cloud-native approach for financial systems that rely on multi-counterparty derivatives as the core primitives offering credit lines and/or risk protection. The design emphasises agentic AI orchestration that governs multilayered agency while enabling advanced risk management, including eco-political, credit, and liquidity risk assessment and mitigation. Four primary components operate in the cloud-native environment controlled by agentic AI: the derivatives instrument provider, the counterparty credit risk tester, a collateral manager, and the accounting engine.

A layered view provides additional insight into responsibilities and interfaces while avoiding the overhead implied by a service mesh pattern. Each component exposes a contract that is driven by its respective business needs while simultaneously offering the data streams required by the remaining participants. Interaction is guided by a synchronization and sequencing layer that is aware of the external environment, having access to eco-political, credit, and liquidity data.

6.2. Components: Orchestration Layer, Risk Engine, Collateral Manager, and Accounting Module

Reference architecture encompasses four components: the orchestration layer, responsible for autonomous decision-making across the derivatives lifecycle; a risk engine, assessing counterparty credit risk and identifying collateral exposure; a collateral manager, orchestrating securities valuation and demand recommendations; and an accounting module, tracking derivatives valuations and balances for the independent valuation agent. Interfaces specified through data contracts without binding implementations ensure agile integration of dedicated solutions.

In the orchestration layer, agentic AI supports decision-making across the risk, collateral, and accounting domains, addressing all aspects of the multi-counterparty derivatives architecture. These decisions apply to a single derivatives transaction or to all transactions associated with a specific counterparty, encompassing actions such as counterparty selection in new transaction requisition, request or offer acceptance, and derivatives amendment. Decision criteria and constraints are defined based on derivative position types and on the risk, collateral, and accounting status of the counterparties involved in the derivatives lifecycle. High-level

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decision rules apply automatic risk positioning for counterparts exhibiting low creditworthiness or high credit operational risk. When the risk-return trade-off becomes unfavorable or alternative counterparties exhibit lower risk exposure, agentic AI recommends derivatives novation or termination to enable exit.

Table 1: Derived Metrics for Multi-Counterparty Risk, Collateral, and Orchestration Performance

	A	B	C	D	E	F
1	**Metric**	**Illustrative Valu**	**Why It Matters**			
2	Gross Exposure	USD 9.0 mn	Maximum unsecured mark-to-market before protection			
3	Total Collateral	USD 7.5 mn	Shows how margining absorbs exposure growth			
4	Residual Net Ex	USD 1.5 mn	Residual exposure drives escalation and hedging			
5	Average Covera	0.84x	Coverage level relative to future exposure			
6	Highest Counte	40% (CP-B)	Identifies concentration risk			
7	Architecture La	5	Matches orchestration, mesh, microservices, streaming, storage			
8						
9						
10						
11						
12						
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14						

7. Agentic Decision-Making and Control

Orchestration of multi-counterparty derivatives, collateral management, and accounting requires autonomous agentic decision-making. This addresses the critical question of what action an agent should take at each stage of a derivatives life cycle, while satisfying legal, economic, and reputational criteria. Distributed ledger technology reduces interaction costs but does not diminish the need for counterparty assessment. The design of an agentic system requires three factors: control over the treasury and assets in custody; access to up-to-date financial and credit information regarding all counterparties; and control over collateral and credit risk thresholds.

The decision-making process incorporates key considerations for derivatives management without prescribing AI models. Decisions during creation, maintenance, and termination ensure contracts represent actual economic relationships, minimize undistributed net

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risk exposure, and contain only reliable counterparties. At each stage, legal and reputational constraints shape action selection. Control over reserves or margin accounts enables agents to alleviate the introduction of new counterparties and changes to the contract terms; counterparty risk limits make it possible to withdraw during the maintenance or termination phase; and control over the threshold for entering new contracts permits turnaround even when credit models signal a lack of counterparty solvency.

7.1. Decision Models for Derivatives Lifecycle

The derivatives lifecycle involves agreements between multiple parties, covering aspects such as the underlying asset, cash flows, collateral management, settlement, and maturity. The AI-driven decision models orchestrate all aspects of the lifecycle, operating within the defined governance framework. The initial agreement must meet several criteria regarding counterparty risk, collateral availability, consistency of cash flows, scalability, and strategy. The models check for adequate collateral cover for all known future exposures; if this is not met, counterparty risk reservations must be applied. When necessary, the counterparty risk assessment thresholds trigger additional actions, such as soliciting external quotations for specific exposures.

Bolstered by expanding asset availability and improved liquidity, derivatives agreements will follow a quotation-and-hedging pattern typical of asset swaps. Counterparties will assess overall profitability on a periodic basis or automatically trigger a trading action when maximum acceptable loss is crossed. The decision models will define the agentic participant that seeks quotation and manage its internal exposure sources accordingly, whilst the other will assess and provide the quotation that results in a profitable transaction based on its pricing strategy.

7.2. Counterparty Risk Assessment and Exposure Management

Multi-Counterparty Derivatives, Collateral, and Accounting in Cloud-Native Financial Systems

Risk assessment and exposure management strategies, articulated in the form of agentic AI decision criteria, drive the orchestration of derivatives traded with multiple counterparties through a shared, cloud-native infrastructure. Well-defined boundaries between the individual businesses of different agents minimize the operational risk of the overall architecture and make it possible to delegate risk assessments and exposure management decision-making processes to a lower-order agent responsible for the same aspects with respect to a single counterparty.

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Counterparty risk arises when an agent has a financial exposure to an agent participating in a parallel process responsible for the fulfillment of a single derivative contract and is unable to meet its obligations when they become due. Agentic AI assesses the level of risk to each counterparty during the lifecycle of the contract by accounting for the cumulated and not-yet settled exposure produced by all derivatives, expressed in a common unitary monetary denomination; and evaluates the quantum of risk associated with each counterparty at each decision node based on the most up-to-date information available. When a threshold condition is breached, agentic decision-making implements an escalation rule to determine the relevant courses of action, which may include managing the exposure through additional transactions with other counterparties or agents participating in the architecture.

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Fig 4: A practical guide to agentic AI and agent orchestration

8. Cloud-Native Implementation Considerations

Service-oriented architecture is a promising design paradigm for cloud-native systems, while microservices and service mesh patterns afford increased development speed, flexibility,

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and observability. The orchestration layer should therefore be realized as a set of microservices deployed in a service mesh on a public cloud, such that serverless deployment of individual services—e.g., the risk engine inside a Function as a Service offering—is also possible. A deployment strategy that aims for the greatest impact at the lowest cost, while providing opportunities to learn and mitigate risks, is therefore recommended. The immediate focus should be on building the risk engine and downstream components. These should be able to leverage existing knowledge about counterparties and use cases, while providing the services and data contracts required for supervision of counterparties' exposure in other systems.

Support for this purpose can be provided by Cloud Object Storage for archival storage of input data, as well as any other data that is seldom or not used, and by Cloud Stream Storage for all data that need to be kept for a longer period but should not reside in memory or on SSDs. A data streaming framework such as Apache Kafka or AWS Kinesis, on the other hand, is essential for all event-based interactions between microservices. Event sourcing semantics should be utilized wherever possible, with the actual computing results stored in Cloud Object Storage. Event schemas must therefore capture the full provenance of any observable state change. Final consistency for these schemas can be partial, but must be ensured for the persisted results.

Equation 3. Variation margin and initial margin decomposition

In practice collateral is often split into:

- $VM_i(t)$ = variation margin
- $IM_i(t)$ = initial margin

Hence

$$C_i(t) = VM_i(t) + IM_i(t)$$

So Equation 2 becomes

$$E_i^{\text{net}}(t) = \max\left(E_i^{\text{gross}}(t) - VM_i(t) - IM_i(t), 0\right)$$

Derivation

6. Total collateral is the sum of posted/held protection components:

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$$C_i(t) = VM_i(t) + IM_i(t)$$

4. Insert into net exposure formula:

$$E_i^{\text{net}}(t) = \max\left(E_i^{\text{gross}}(t) - [VM_i(t) + IM_i(t)], 0\right)$$

3. Rearranging:

$$E_i^{\text{net}}(t) = \max\left(E_i^{\text{gross}}(t) - VM_i(t) - IM_i(t), 0\right)$$

8.1. Microservices and Service Mesh Patterns

Orchestration analysis fixed points include the technological infrastructure and tooling for implementing the orchestration layer(s) and data contracts with the risk engine, collateral module, and accounting module. The orchestration and collateral components follow a typical Microservices Pattern–Service Mesh Pattern. The management responsibility of a service mesh is split across the communication services, which connect to the service that is discovered first, with the other side connecting to the Target Service. The external management Boundary, which routes to the load balancer, is also part of the mesh. The information in the shared logs is role-driven. Each User activates the services that they directly access (specifying Owner fields), and each service activated directly via CLI or REST requests passes through one if not several Shell Command Processor Services.

The Orchestration Layer is linked with the Events from the Risk Engine and Collateral Manager. Two types of events are categorized for implementation purposes: control events, which are invoked on their own, and process events, which are generated as part of a backlog processing cycle. Validation support for the control mechanisms and Test Code Patterns for examining and documenting the design of the event-driven code based on Quorum Systems are also provided. The visualization of a backlog processing cycle describes the Events that Clarity imposes on a Data Streaming and Data Warehousing configuration. Note that prominent cloud service providers deliver such Data Streaming-Data Warehousing solutions as a Service for a Service as a Service delivery model.

8.2. Data streaming, storage, and event sourcing

Microservice architectures rely on asynchronous communications supported by publish, subscribe and event sourcing patterns. Therefore, an enterprise-grade streaming platform such as

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Confluent Akka Streams, Hazelcast Jet, or Apache Flink should be deployed. The test case predicts that the future cloud-native system will collate the published collateral data and streaming accounting transactions of the two additional local banks using a defined data model. Furthermore, the entire event history is stored for regulatory reporting purposes together with a full data provenance trail supporting Model Risk Management requirements for the predictive AI models used in the risk engine.

As highlighted in the collateral library section, holding collateral for each transaction with each counterparty has the added advantage that the risk assessment of exposure with each counterparty can be treated independently and simply expanded by using a healthy industrial cluster of microservices and storage systems. Depending on the level of operational maturity, data separation may even be overkill. Combining all transactions and participating assets throughout the banking system, whilst still sufficient to catch the regulation's requirements, would now permit true data mining and trend analyses of the entire derivative operation. During this phase, the need for cross-checking counterparty position exposure thresholds and immediate remediation paths would still remain an area of attention managing the emerging risks, but now provided with an additional viewpoint to catch anomalous trends.

9. Governance, Compliance, and Ethics

Governing derivatives transactions, both for risks and compliance, is challenging, especially in a cloud-native setup involving multiple counterparties and agents.. Cloud-native financial systems exposed to agency-risk can benefit from agentic-AI-driven orchestration of derivatives, collateral and accounting. However, the unobservability of the orchestration layer also introduces ethical challenges. Governance mechanisms for model risk and agency remain crucial especially for the AI-based decision engine.

Governing derivatives transactions remains challenging in a cloud-native setup involving multiple counterparties, sub-agents, smart contracts, and risk/ethical considerations. Multiple financial authorities impose a broad range of regulations on banks, insurance companies, and investment funds. Accounting and auditing standards ensure that the balance sheets of such organizations conform with universally accepted norms. The orchestration layer is crucial from a governance perspective, as it determines how the services provided by the underlying infrastructure are put to use for completing the lifecycle of derivative transactions. Therefore, the overall risk exposure of the deployment, in terms of credit, liquidity, and counterparty risk, must be continuously assessed. Thresholds must be established along with an escalation hierarchy that

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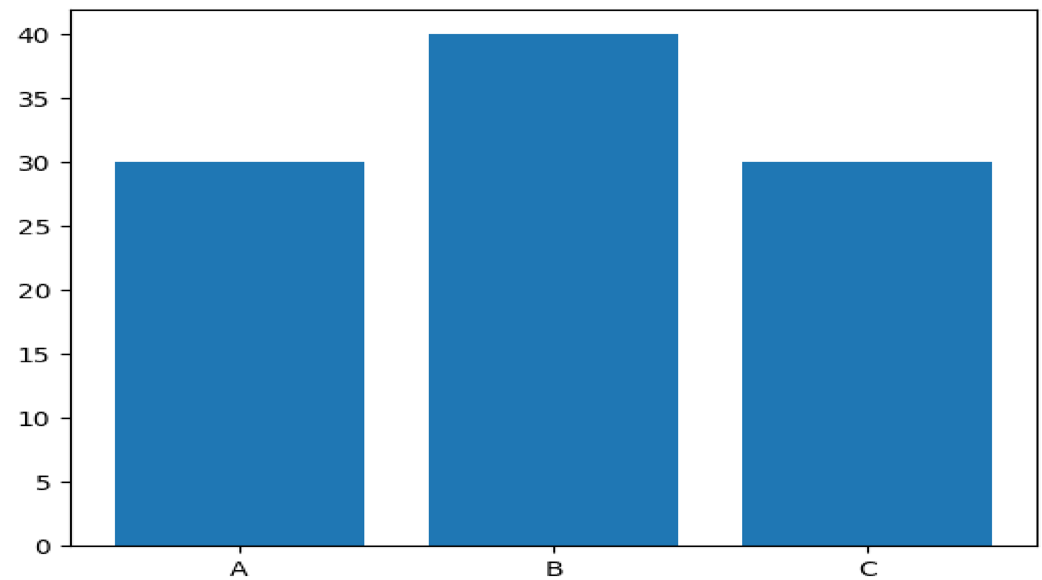
guarantees timely intervention before the exposure escalates beyond acceptable limits. The organization deploying the system must also ensure that the risk engine, collateral manager, and accounting module follow all relevant regulatory regulations, reporting standards, and applicable guidelines.



9.1. Regulatory Frameworks and Reporting Standards

Agentic AI governance requires exposure to appropriate models, patterns, and measures to justify decisions affecting risk profiles. Regulatory compliance, established third-party reporting requirements, and demand for internal and external audit must thus also inform the design of an agentic AI orchestration for multi-counterparty derivatives transacted within cloud-native financial systems. Risk reports and financial statement data from an agentic AI-enabled orchestration of multi-counterparty derivatives, collateral, and accounting must supply information for recourse against the involved agents or service providers. Formal fulfilment of such needs requires concurrent temporal tracking of all flows and internal data states.

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Compliance with the Federal Reserve's "capital rule" requires US banks and bank holding companies with total consolidated assets of $250 billion or greater, as well as bank holding companies with total consolidated assets of $100 billion or greater that are subject to the advanced approaches capital rule, to submit to the Federal Reserve's specified CCAR scenario analyses. Scenarios and assumptions specified by the bank supervisory authority must include changes in the default probability of concentrated counterparties in derivatives and securities financing transactions. CSBB, set up by the Basel Committee on Banking Supervision and other relevant authorities, and adopted by the Bank for International Settlements, outlines Action 1 – Examining the regulatory capital treatment of banks' unconditionally cancellable obligations, and Action 14 – Adding disclosure requirements for the capital treatment of unconditionally cancellable obligations.

Equation 4. Collateral coverage ratio

Let $PFE_i(t)$ be **potential future exposure** for counterparty i.

Define the **coverage ratio**

$$\mathrm{CCR}_i(t) = \frac{C_i(t)}{PFE_i(t)}$$

Derivation

7. The article emphasizes checking whether collateral is adequate relative to future exposure, not just current MTM.
8. A natural adequacy measure is “protection divided by risk”.
9. Protection is collateral $C_i(t)$.
10. Risk target is $PFE_i(t)$.
11. Therefore

$$\mathrm{CCR}_i(t) = \frac{C_i(t)}{PFE_i(t)}$$

Interpretation:

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- $\mathrm{CCR}_i(t) > 1$: collateral exceeds modeled future exposure
- $\mathrm{CCR}_i(t) = 1$: exactly covered
- $\mathrm{CCR}_i(t) < 1$: under-collateralized

9.2. Model Risk Management and AI Governance

Compliance with the relevant regulatory guidelines surrounding conduct risk, anti-money laundering, and share price manipulation would need to be integrated within the decision-making processes. This is best addressed via externalized validation requirements from the relevant authorities connected to auditing services and/or economy-driven component modules. Regulation would be a function of the business model opted for, such as those set by the Bank of International Settlements and implemented through the respective jurisdictions.

Within the Risk Engine, the Counterparty Risk Assessment supporting component would identify counterparty risk based on the Risk Weighted Asset (RWD)—also referred to as Bank Capital Requirement—set by the Bank of International Settlements and implemented via domestic supervisory valuations, such as the UK Prudential Regulation Authority's triangle parameters. In the context of climate change, climate-exposure-related credit ratings could also be relevant for defining exposure limits. Control on the economic credit rating of the counterparties should also ideally be layered into the economic decision-making process.

More broadly, the Risk Sensitivity Matrix would need to enable setting of various exposure thresholds beyond counterparty risk, across other dimensions of risk tolerance and appetite established by the Risk Management framework of any organization providing such services.

These sensitivity thresholds would enable escalation via second-lines of defense all the way to decision-making bodies of governing agencies, should pre-defined levels of risk be breached. These can again stay externalized or incrementally integrated with the economics of decision-making based on the chosen approach.

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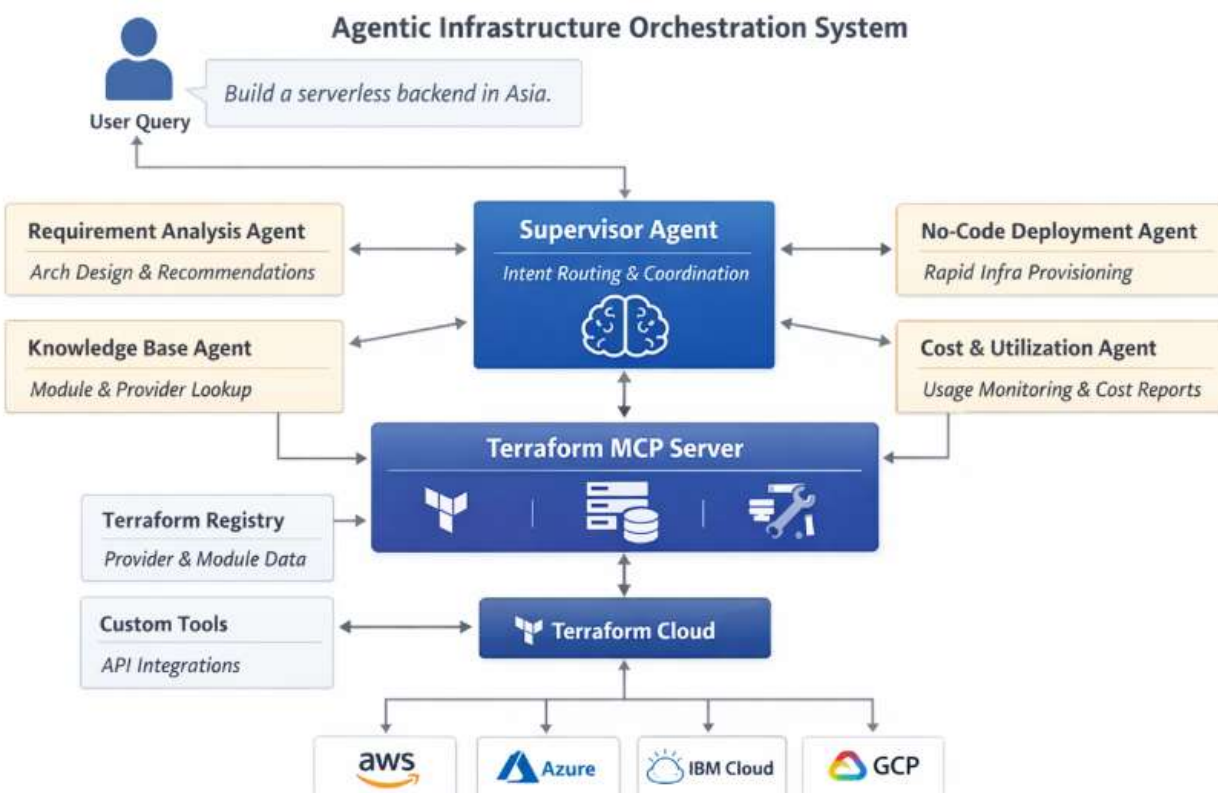

Fig 5: Agentic Infrastructure Orchestration System

10. Evaluation and Empirical Validation

Cloud-native orchestration introduces novel structures and processes into financial infrastructures. As with any complex technology, the benefits can only be fully realized if the associated risks are understood and carefully managed. Aimed at achieving this understanding, a comprehensive evaluation and validation framework has been constructed. The first stage entails formal definition of the validation concepts, objectives, and methodologies. The second stage undertakes to evaluate the proposed system against these criteria by means of simulation scenarios. Specific cloud-native mechanisms are used for support.

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The evaluation process encompasses two interrelated aspects: empirical validation of cloud-native orchestration in the context of a representative use case and exploration of the broader implications of the design. Evaluation is further categorized into quantitative and qualitative aspects related to records of simulation scenarios and lessons learned from consideration of alternative uses of the technology.

10.1. Simulation Scenarios and Benchmarking

Incremental deployment of the proposed orchestration framework is advisable. Dedicated paths for the development of the risk-engine, the collateral-management, and the accounting functions, as well as for the integration with existing cloud-native multi-counterparty derivatives implementations, are recommended. Rollout priorities should identify the functions selected for the upcoming period, completing their logical associations and defining the most appealing outcomes.

Orchestration features should be aggregated along the risk-axis, taking into accounts the type of agentic decision making concerning risk exposures, including limits and thresholds. The acceleration of the risk-engine and of the counterparty-risk assessment components would empower a shorter risk-simulation horizon, leading to rapid insight conversion and longer-term basis-trading opportunities. Detection of significant counterparty-risk thresholds could trigger monitoring of other exposure sources and establish temporary alert paths to duly manage incidental violations. Integrating collaterals would augment risk-mitigation efficiency, support margin-trading opportunities, afford prepayment of the value of control functions incurred after disorderly events, and facilitate rigorous governance of actors impersonating special-purpose vehicles.

10.2. Case Studies in Cloud-Native Orchestration

Case studies covering cloud-native orchestration and related aspects illustrate shortcomings of existing solutions and suggest practical steps toward deployment. How can cloud-native principles improve microservices-based applications? What are the associated requirements for observability, resilience, state management, governance, and ethics, and how should these be approached incrementally? Which available solutions can further substantiate the concept?

Consider the multi-counterparty bilateral-credit-swap architecture and demonstrate how agentic AI-driven orchestration strengthens the underlying cloud-native requirements while

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delivering orchestration-specific benefits. The focus is on the risk engine, collateral manager, and accounting module—components whose implementation mechanics warrant close scrutiny. Examine the services, service configuration, and service mesh aspects; remaining microservice principles are treated in a lighter manner.

Equation 5. Margin call amount

If the institution wants collateral at least equal to target exposure $T_i(t)$, then the additional collateral required is

$$\Delta C_i(t) = \max(T_i(t) - C_i(t), 0)$$

If the target is $T_i(t) = PFE_i(t)$, then

$$\Delta C_i(t) = \max(PFE_i(t) - C_i(t), 0)$$

Derivation

12. Required target collateral = $T_i(t)$.
13. Existing collateral = $C_i(t)$.
14. Shortfall before flooring:

$$T_i(t) - C_i(t)$$

5. If current collateral already exceeds target, no margin call is needed.
6. Therefore:

$$\Delta C_i(t) = \max(T_i(t) - C_i(t), 0)$$

11. Results

Results provide an incremental roadmap for integrating agentic AI-driven orchestration within cloud-native financial systems, detailing a milestone-based strategy and related implications. The analysis indicates orchestration's potential to enhance risk management through AI-decisioning, gene-rate external audit trails for compliance and governance purposes, and mitigate implementation challenges facing cloud-native financial ecosystems.

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The proposed reference architecture enables targeted investigation of multi-counterparty derivatives lifecycle orchestration through agentic AI decisioning and control, employing explicitly stated criteria for counterparty risk assessment and threshold-based exposure management. Empirical validation examines a use case for cloud-native orchestration—an AI-layer deployment that mitigates counterparty risk in derivatives transactions—through simulation scenarios and benchmark comparisons with a baseline system and an alternative cloud-native implementation lacking the orchestration layer.

11.1. Incremental Deployment Strategy

An incremental strategy coordinates self-determined stakeholders toward the integrated risk mitigation and model lifecycle management of agent-driven parallel AI services, ensuring that exposure thresholds and escalation processes are respected from the outset, even for the first service deployed. The affine counterparty risk assessment model underlying the agentic decision-making and exposure management modules can be deployed first, along with its embedding agents, and subsequently enriched with more sophisticated models for trading and hedging. Prioritization depends on the potential for financial exposure concentration and correlations; exchange and payment systems, for instance, may present much less opportunity for sequential decision-making and diversification than a streamlined treasury management system.

The remaining operational, technical, and organizational components for adoption in covert mode are also candidate-based; they can be in place to process decisions from those agents within the parameters that the mini-max doctrine seeks to guarantee but not to incur model risk or needful-override protocol violations. Hence the parallel deployment of an event-sourced multi-counterparty derivative, involved in a single, consistent trade for live validation and demonstration of interaction with other cloud-native orchestration components, is not only feasible but also preferable for the development cycle.

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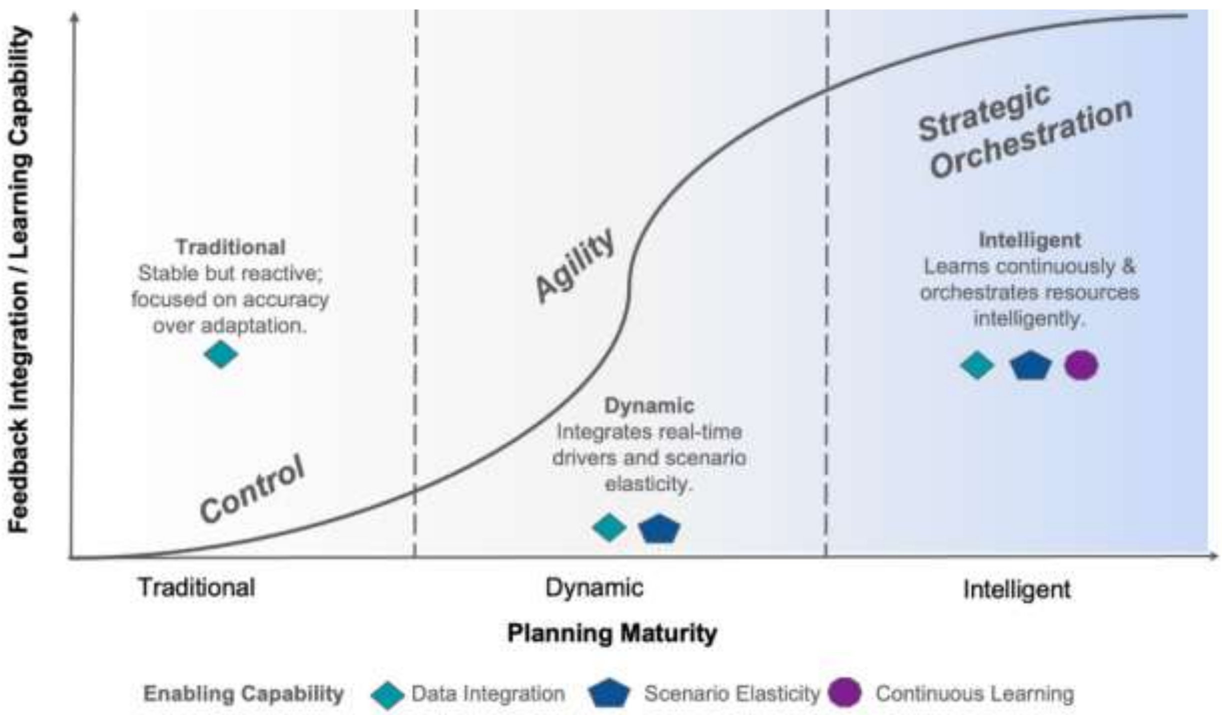

Fig 6: Financial Planning for Agentic & AI Systems

11.2. Risk Mitigation and Change Management

Incremental deployment of multi-counterparty derivatives orchestration advances agentic AI capabilities, improving risk management and establishing fundamental cloud-native governance structures. Opportunities include refining credit-exposure assessment methodologies and parameters for AI-based derivatives-lifecycle decision making.

Risk exposure in supervised machine learning–based approaches relies on quality of training and testing data—the greater the diversity of edge cases, the less the risk of model failure. However, many protected participant profiles have similar credit-risk exposure; thus, model training leveraging only a fraction of the replication space creates a blind spot. Therefore, the risk assessment module should ultimately support microservice-based instantiation, enabling balance by fully controlling and customising features, metadata, and horizons of the underlying data. If the approach embedding neural-like supervisory learning in this module is also proven

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adequate, the design must be extended beyond multivariate statistical analysis. Furthermore, embedded validation prediction tests should also ensure extra quality control.

Multi-counterparty derivatives processes are complex and sensitive to latency. Guaranteeing real-time processing and delivery on demand is, in fact, one of the main value propositions behind financial market infrastructures. Hence, in this respect, the full stack also needs to be isolated. When traffic volume covers all paths, the only remaining latency contribution is the time needed for a response from the risk manager and the ledger; thus, taking advantage of the data-streaming pattern becomes elementary.

12. Conclusion

Results reaffirm the relevance of agentic AI-driven orchestration to cloud-native financial systems; design principles guide implementation of proof-of-concept systems. Continuing advances in the decentralization and democratization of technology and the economy, especially in the cloud, create an environment conducive to the emergence of more agile and adaptable financial instruments; however, the current high cost, issuance, and settlement latency inhibit their wider adoption. Cloud-native computing offers a means for reconciling these contradictions, but also expands the data and risk exposure. A modular approach enabled by microservices and service mesh patterns allows for tailored deployment of observability and resilience functions. From this perspective, the orchestration of derivatives, collateral management, and accounting is especially sensitive and pivotal. Risk considerations extend to model risk management and AI governance.

Maintaining a clear focus on enabling self-governing systems remains a prerequisite for incremental impact. The proposed reference architecture captures the interplay and data flows between the orchestration layer and the functional components. Focusing on derivatives, the design of agentic decision models incorporates counterparty risk assessment. These aspects were explored in prior work. A preliminary evaluation sheds light on converging cloud-native patterns for the three functions. The involvement of multiple counterparties serving various needs and reducing counterparty risk further enhances the relevance of the concerted orchestration.

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