AI-Driven Secure Transaction Governance in Cloud Finance

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Abstract

Financial governance may benefit from generative AI as it promotes augmented governance by design. The resulting capability is operationalized as a blueprint for real-time secure transaction processing in cloud ecosystems. Through the design and integration of the various system layers, desired characteristics of transparency, explainability, auditability, and trust become built-in features that support and enhance the risk management, control, and decision-making processes of stakeholders across the value network by providing and assuring consistent information, even in the presence of uncertainty.

Generative AI is applied to define the decision-making process, specifying how the Generative AI Governance Decision Proposal defines financial policy and compliance. Consequently, the related sense—analyze—respond model of augmented governance identifies the roles, responsibilities, decision rights, escalation paths, and governance rituals that provide the operational framework for governance. Data ingestion pipelines enrich the provenance of information to support enhanced risk–control–accountability. Transparency is specified from a governance perspective, defining policy alignment for trust in the AI–enabled financial decision outcomes.

Keywords: Generative Artificial Intelligence in Financial Governance, Augmented Governance by Design, Real-Time Secure Transaction Processing, Cloud-Based Financial Ecosystems, AI-Driven Policy and Compliance Automation, Governance Decision Proposal Frameworks, Risk–Control–Accountability Integration, Explainable and Auditable AI Systems, Transparency in Financial Decision-Making, Trust-Centric AI Architectures, Provenance-Enriched Data Pipelines, Compliance-Aware AI Deployment, Secure Cloud Governance Models, RegTech-Enabled Financial Oversight, AI-Supported Enterprise Risk Management.

1. Introduction

Generative Artificial Intelligence (GAI) is a domain of technology that employs data and machine-learning models to enable sophisticated capabilities such as automated content generation, dialogue and interaction, simulation, and storytelling. These capabilities go beyond traditional Artificial Intelligence (AI) systems for perception and prediction. GAI is gaining popularity in creative industries. Finance has been a latecomer in utilising AI, but its recent adoption appears to be accelerating. Established companies like Microsoft, Infosys, and Canva now offer assorted GAI capabilities. A consequence of cloud computing is the transfer and concentration of data and GAI in cloud ecosystems, opening up new avenues for attack or exploitation. Financial institutions and actors must therefore address the security and privacy of the systems, services, and decision-making processes across such ecosystems.

These various aspects of decision-making and governance are increasingly examined in the context of creating and harnessing Trustworthy AI, governance of the underlying models, governance of policies, rules, and procedures for safe and ethical applications, and auditing outcomes in terms of fairness, bias, explainability, reliability, and accountability. Clusters of communication, social-cyber, and even philosophical models are beginning to appear to support a better understanding of the AI-enabled environment, but research is still in its infancy. GAI, being an interactional model, also creates new types of

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engagements among the various actors and stakeholders involved in managing resources and crisis incidents. Research is beginning to propose new models of research, training, and analysis that acknowledge the role of AI in facilitating, simplifying, or complementing complex processes and decisions. GAI's potential advantage lies in its ability to enable rapid on-demand or near-real-time simulation and testing of crisis scenarios and plausible behaviours in multi-clouds and hybrid contexts for prevention, learning, and adaptation.

1.1. Overview of Generative AI's Role in Financial Management

Generative AI empowers businesses and society to achieve greater levels of financial governance by enhancing the management of risks, controls, accountability, and decision-making processes inherent in financial oversight. Generative AI systems enable complex tasks such as elaboration, dream and design, decision-making, development, and discovery. Other complex tasks such as forecasting, hypothesis generation, and modeling are also possible with shared interaction and purpose. Although human involvement and judgment are still important, AI-operated systems assist individuals in decision-making. Furthermore, the decision-making capabilities of generative AI models support financial governance by integrating stamped time and inputs from multiple sources to create a single auditable output. Therefore, financial governance decisions are evolving, influenced by the new capacities created by generative AI.

Generative AI scenarios are synthetic data created based on the original data, making it usable for testing and training models in data-resourced environments. Generative capabilities are different from deepfakes, where generating a fake video of a person is easy, but creating a lifelike video of an imaginary person is complex. Generative AI has grown from text-based data to other media types such as videos and images. While traditional AI models perform recognition, detection, and classification tasks, new models provide novel outputs and lend themselves to more complex activities. Generative AI supports real-time audit and control of cloud-based systems and facilitates trust in precision and timely recording of financial transactions.

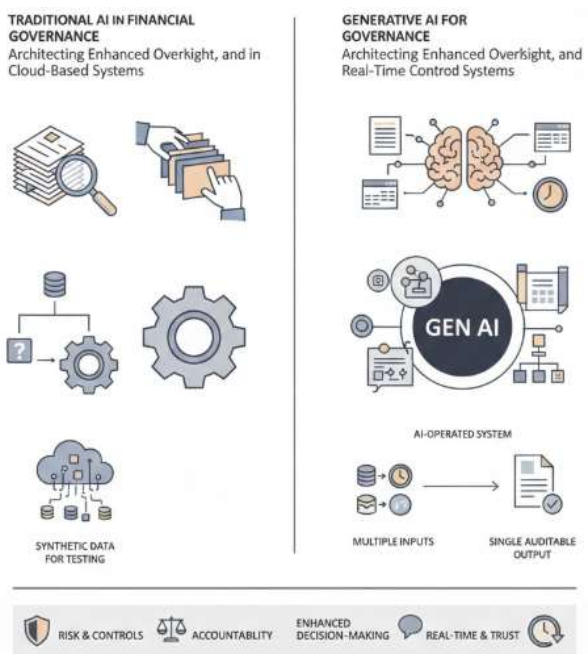

Fig 1: Generative AI in Financial Governance: Leveraging Synthetic Scenarios and Multi-Source Data Integration for Real-Time Auditable Decision-Making

2. Theoretical Foundations of Generative AI in Financial Governance

Generative AI bolsters financial governance via the core elements of risk management, control, accountability, and decision-making under uncertainty. Together, these forces shape a reliable and safe environment for responsible risk-taking—an indispensable condition for sustainable development in private enterprise—and form the essential theoretical foundations for a multi-cloud governance framework governing AI-based financial decision-making. Real-time architecture

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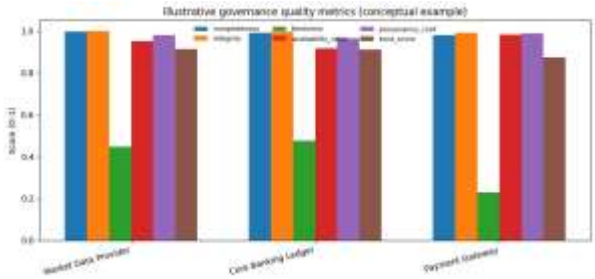
contributes by cultivating audit and explainability abilities that support transparency and trust. The emerging financial purpose enables resource allocation toward highly trustworthy generative AI initiatives while promoting fairness and adherence to existing policies. The specific aspects of assurance demand and generate capacity in turn reshape expectations of financial governance. These exchanges impact the stability and efficiency of co-production models, such as multi-cloud and hybrid setups.

Generative AI Connects Fundamental Concepts of Financial Governance: Risk Management, Control, Accountability, and Decision-Making Under Uncertainty—The Models of Governance, Transparency, Explainability, Auditability, and Trust in AI-Driven Financial Decisions Resonate through the Layers of Financial Architecture in Cloud Ecosystems. Financial transactions demand governance and security at multiple levels, requiring these elements to mesh for fostering trust and acceptance. Financial governance enables resource providers and society to accept the risks taken by decision-makers; it is affected by consequences of decisions taken and expectations for the conduct of all parties to the financial process.



Equation 1) Deriving the data-quality control equations (Comprehensiveness, Integrity, Freshness)

1.1 Comprehensiveness (are all required elements present and valid?)

Let:

- E = number of **expected** records (or expected required fields across records)
- M = number of **missing** required items (missing records or missing required fields)

Step-by-step

1. Missing fraction:

$$\text{MissingRate} = \frac{M}{E}$$

2. Comprehensiveness score (higher is better):

$$C = 1 - \frac{M}{E}$$

So $C \in [0,1]$ where 1 means nothing missing.

1.2 Integrity (no duplicates + structurally valid + format correct)

Let:

- O = observed records ingested
- D = duplicate records found
- S = schema/structure failures (format violations)

Step-by-step

2. Total "bad" records:

$$B = D + S$$

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3. Bad fraction:

$$\text{BadRate} = \frac{B}{O}$$

3. Integrity score:

$$I = 1 - \frac{D + S}{O}$$

Again $I \in [0,1]$.

1.3 Freshness (is the data recent enough?)

Let:

- t_{event} = timestamp when the source created the datum
- t_{ingest} = timestamp when it is ingested/usable
- $\Delta t = t_{\text{ingest}} - t_{\text{event}}$ = ingestion delay/age
- τ = maximum acceptable delay (freshness threshold)

Step-by-step

1. Compute age:

$$\Delta t = t_{\text{ingest}} - t_{\text{event}}$$

2. Define freshness as a bounded linear score:

$$F = \max\left(0,1 - \frac{\Delta t}{\tau}\right)$$

- If $\Delta t = 0 \Rightarrow F = 1$
- If $\Delta t = \tau \Rightarrow F = 0$
- If $\Delta t > \tau \Rightarrow F = 0$

2.1. Foundational Concepts of Generative AI in Financial Oversight

Financial governance relies on trust-based relationships focused on risk and control. The degree of transparency and the ability to explain, audit, and otherwise govern affect the nature and strength of a trustworthy relationship, regardless of whether the governing actor is human or machine. Generative AI, as a specific manifestation of AI, enables the generation of new content based on patterns in pre-existing data and is therefore expected to disrupt financial governance by augmenting the ability to perform closely related decision and prediction tasks while introducing new models and concepts. Central concepts that shape governance in a generative AI context concern transparency, auditability, and explainability and must therefore be appropriately integrated.

A governance model clarifies roles and responsibilities, ultimately shaping how a cloud service provider, service consumer, and other actors are connected to one another. Well-defined roles enable the delegations and risk-sharing necessary for successfully leveraging the technology without introducing excessive risk. The same applies on the consumer side: clear governance in terms of data used to train models and appropriate management of the resulting decisions are necessary for consumers to trust generative AI-supported services. Models of governance that describe this interplay between governing institutions and the citizens of these institutions feature prominently in the governance of human actors, and analogous considerations for generative models are crucial to understanding their impact.

source	expected	observed	missing
Core Banking Ledger	30000	29883	117
Market Data Provider	60000	59532	558
Payment Gateway	48000	47201	963

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3. Architecture for Real-Time Secure Transaction Processing

Reliability and scalability of financial governance supported with generative AI for the cloud depend on the architecture for real-time secure transaction processing. Such architecture consists of layers, components, data flow, and touchpoints of governance, including the ingestion of authoritative source data streams, the governance of third-party data sources, and provenance, lineage, and integrity across data streams and storage.

The foundations of data provenance, integrity, and availability are essential for financial governance, especially for transaction processing. Authoritative data sources can be known a priori (e.g., external market-data providers) or determined dynamically. For the former, pipelines must be established that implement the necessary controls prior to implementation. Such controls include comprehensiveness: are all the necessary data elements included, both in terms of set and range of allowable values; integrity: are the data complete (no missing or duplicate records) and in the required format and structure (e.g., Schematron); and freshness: do the data meet recency criteria. For the latter, the full scope of permitted and unfiltered data requirements must be established, along with the rules governing correctness, comprehensiveness, and freshness.

Any data-availability requirements must also be governed. In many cases, it will be impractical to duplicate third-party data sources. Hence, during operation, the availability of those sources must be confirmed against the relevant threshold before being integrated into the transaction processing. If third-party cloud services are being consumed, the required SLA can be formally linked to the financial governance SLA, and the acceptance tests for these providers must include these points. During operation, functionally redundant service paths can be identified for proactive risk management.

3.1. Data Ingestion and Provenance

Data ingestion pipelines appropriate for real-time secure transaction processing require explicit definition of data sources, data streams, storage repositories, and data products to be built keeping in mind data quality controls, validation of provenance and integrity at the points of convergence of data from different sources and streams, and metadata capturing necessary for provenance tracing, lineage tracking, and the validation of data quality. Conveying trustworthiness of data as it flows through the different functions of – collect, clean, analyse, and consume – is intrinsic to the operation of cloud-based architectures supporting its governance for financial transactions and decision-making.

Having suitable data ingestion pipelines applied to data from cloud and non-cloud sources helps precisely meet the above requirements. Structured and unstructured data flowing into a multi-cloud data lake reside in first-cut form and are transformed, cleaned, and validated by dedicated functions before ingress into the data warehouse or data mart. These functions also build abstract features and data products for machine learning and simulation purposes. Community provenance captures the metadata corresponding to the processes executed within the data engineering life-cycle. In addition, technology adoption and process execution within these data engineering functions is made visibly transparent through the integration of a provenance traceability layer capable of recording, relaying, reconstructing, and visualising the lineage of data.

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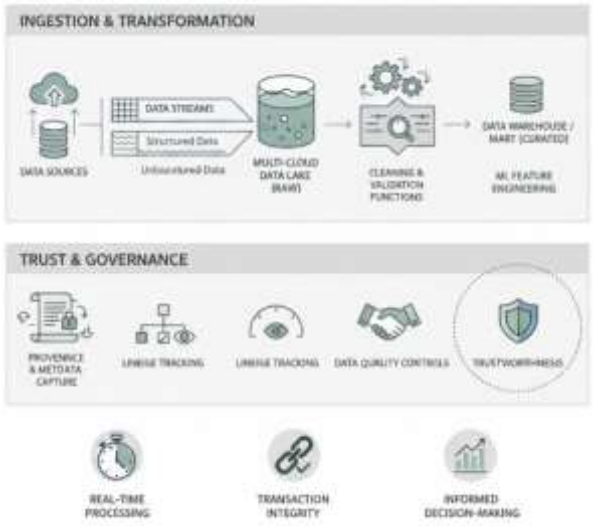
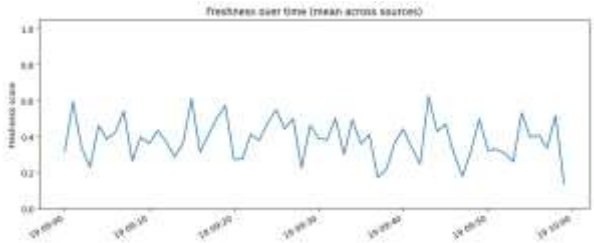


Fig 2: From Provenance to Trust: A Traceability Layer for Real-Time Secure Data Ingestion Pipelines

4. Security and Privacy by Design in Cloud Environments

Security and privacy by design in cloud environments address the interconnected and multi-tenant nature of these information systems, which arise from exposure to a wide attack surface and from deploying applications and services in multi-clouds and hybrid cloud ecosystems. The security and privacy envisaged in the design phase, considered a best practice for cloud application development, rests on the core security principles of having a threat model; applying the defence-in-depth approach; and establishing access control and data protection mechanisms. Security controls should also be assessed in relation to the threats they are meant to counteract. In addition to the standard information-security threats mainly associated with confidentiality, integrity, and availability, the business-impact resistance aspect should also be considered. The cloud-native design pattern that embraces local processing is recommended to mitigate privacy concerns and geographic jurisdiction limitations by performing data processing as close as possible to their data source, such as within an edge, fog, or local cloud.

The security architecture comprises the aforementioned design building blocks, which are depicted along with the principles. The cryptographic protocols and mechanisms defined govern the guarantees on transaction integrity, data non-repudiation, and verifiable audit trails also by clearly detailing the information and control-flows modelled in the security architecture. Formal models of cloud-data confidentiality, application- and service-level availability and strong cloud storage assure the correctness of the proposed security and privacy architecture of the cloud environment processing and running generative AI-supported financial-governance transactions. Exploratory analysis demonstrates that robust attack-defence modeling of the security functionalities identified through threat modelling strengthens the deployment of financial applications and services in multi-clouds and hybrid cloud ecosystems and enables application and service level agreements to provide guaranteed security against the identified attacks in the underlying cloud components and services.



Equation 2) Availability + SLA gating equation (should we ingest third-party data at all?)

Let:

- For each minute (or time bucket) k, $a_k \in \{0,1\}$ indicates source available/unavailable.
- N = number of buckets in the evaluation window.

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Step-by-step

2. Availability ratio:

$$A = \frac{1}{N}\sum_{k=1}^{N} a_k$$

3. SLA threshold θ (example: 0.99)

4. Gating rule ("accept data?"):

$$\text{AcceptSource} = \begin{cases} 1 & \text{if } A \geq \theta \\ 0 & \text{if } A < \theta \end{cases}$$

4.1. Cryptographic Protocols for Transaction Integrity

Generative AI-Driven Financial Governance: Real-Time Secure Transaction Processing in Cloud Ecosystems

4.1. Cryptographic protocols and mechanisms are required to ensure transaction integrity, non-repudiation, and verifiable audit trails. Control-based mechanisms are important to provide indirect assurances that the required security properties are provisioned and in force, but they do not replace the need for protocols and mechanisms providing direct guarantees. The threat model considered here focuses on a cloud ecosystem that includes a number of unconstrained cloud users within the cloud native environment. The parties within the cloud native environment are assumed to collaborate, while unconstrained parties might attempt to mislead the others by sending false data or performing hostile actions. Consequently, a cloud native protocol and corresponding mechanisms are required to verify the identity and access rights of parties that interact with any system component in the cloud environment, including a cloud bank or cooperative system that might share the public data. Moreover, a mechanism and corresponding Stability Theorem are needed to guarantee that the output of a cloud data integrity scheme is consistent and correct.

Even though open standard technologies can mitigate some of the limitations of proprietary solutions, there are still security risks that organizations need to address. Some sophisticated and motivated cybercriminals can compromise the properties, causing a data integrity threat model violation. Seminal works investigate how cloud computing can influence the management of any organization. The investigation herein follows the cloud computing established by the National Institute of Standards and Technology (NIST), which recognizes three service models: software as a service (SaaS), platform as a service (PaaS), and infrastructure as a service (IaaS). In IaaS, the cloud provider delivers computer, network, and storage resources as services. The cloud customer is in charge of deploying its own operating system and applications; also, the behavior and security of the applications are the customer's responsibility. Saas is a software solution provided over the Internet on a subscription basis. PaaS provides a complete environment for developing, testing, deploying, and maintaining applications. The platform is hosted in the cloud infrastructure. The customer has control over the deployed applications and their configuration settings and is not responsible for the underlying cloud where the PaaS is hosted.

5. Governance Frameworks for Generative AI in Finance

To ensure secure, effective oversight of Business Generative AI and its influence across the organization, an AI Governance framework is required. This framework should extend to cover two types of Business Generative AI usage: the assets and services the organization creates in-house or via Managed Service Provider (MSP) partnerships, and Business Generative AI usage of external services such as ChatGPT. These two usage types introduce risks that must be proactively identified, managed, and monitored.

The first type of usage introduces operational risk related to delivery to customers, while the second introduces conduct and reputational risk associated with employees generating inappropriate content that may

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harm the organization and those it interacts with. An effective AI Governance framework for Generative AI Risk and Control should cover the key elements for good governance: Roles, Responsibility, Ownership, Decision Rights, Escalation Pathways, and Governance Rituals.

To be actionable, a Governance Framework for both Governing the use of Business Generative AI tools and using Generative AI to create assets and services must codify the elements above so that people understanding their daily decision rights involve AI can exist and be effectively monitored. Together with enterprise-wide policy and controls for the use of All Third-Party Services and the RCT, the AI Governance Framework must be actionable by the organization's operations business unit.

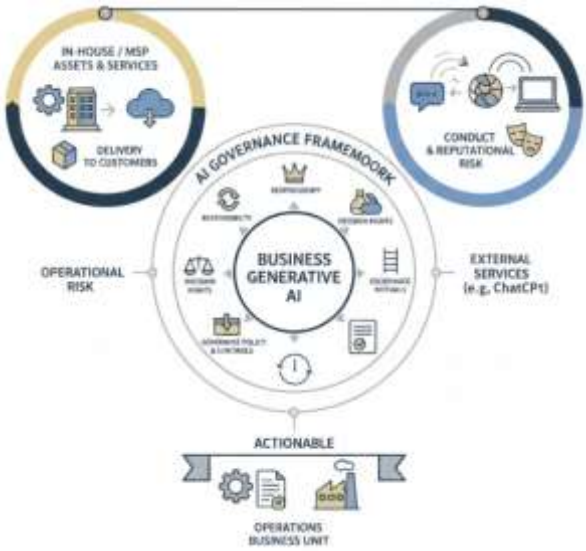

Fig 3: Operationalizing Trust: A Unified Governance Framework for Dual-Track Generative AI Integration, Conduct Risk Mitigation, and Decision Rights

5.1. Policy, Compliance, and Regulatory Alignment

Comprehensive governance frameworks for cloud ecosystems integrating generative artificial intelligence should encompass the entire breadth of interactions that intelligence-engined services have with the financial transactions they support, as well as with the multi-cloud environment leveraging the AI services. The purpose here is to provide guidance on structuring the mapping and alignment of such interactions against established policies, standards, regulations, and laws, under the functional workstream of an organisation's external relations and risk management functions. The mapping structure should delineate designated roles for accountability, compliance, ethics, privacy and data protection, risk management, and security. The breadth of consideration is encapsulated by ISO 37301 in its proposed set of roles and responsibilities for an effective compliance management system.

Addressing financial transaction risk management priorities and the requisite policies, supporting standards and practices established in that regard kicks off the mapping in a logical sequence, since these inherent risks are the reason for investing resources in the governance of the multi-cloud operation. Scapens and Bromwich's six identified sources of risk-management frameworks, and the derivative components of operational risk management presented by Decker provide a useful guide. The comprehensive set of priorities extend beyond the establishment of policies that derive from the financial transactions themselves (i.e., Budgeting Policy, Treasury Management Policy, Revenue Recognition Policy, etc.), thus only influencing the governance of the AI services indirectly, and highlight the foundational policies that impact the AI services directly: Data Classification Policy, Data Management Policy, Privacy Protection Policy, AI Ethics Policy, Information Security Policy, Cloud Computing Policy.

6. Operationalization in Multi-Cloud and Hybrid Environments

Proposed operationalization strategies accommodate deployment in multi-cloud and hybrid environments.

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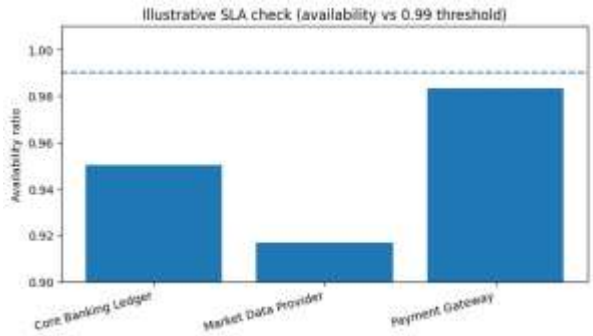
Various patterns are examined — clouds as data sources, clouds as transaction processor, clouds as business service provider, cloud as data warehouse — to highlight possible resilience gains as well as cost governance opportunities. Generative AI quality-related elements are identified, emphasizing the importance of determining whether multi-cloud or single-cloud deployment better fits a specific use case. Further elaboration on key aspects of deployment across multiple clouds includes integration, abstraction and standardization, and interface contracts.

The appeal of Cloud Computing lies in its capacity-ondemand nature that shifts business cost structures from CapEx to OpEx via pay-per-use billing systems. However, from a financial perspective, it is highly tempting for organizations to use data centers only when demand warrants such service, while for the rest of the time, business operations may continue with on-premises infrastructure. Public Cloud Services Providers (CSPs) remain mindful of addressing these needs: computation and storage in the cloud can be provisioned for both short- and long-term periods (Amazon Web Services, 2021b). Hence, business environments leveraging both a Private Cloud and one or more Public Clouds are becoming increasingly common (Mell & Grance, 2022), with Business Services (e.g. Sales, Customer Services, Finance, Research) being the typical workloads that are addressed in Public Clouds.

Requirement for particular components and layers comprises holistically defining how clouds assist Data Sourcing, Business Process, Storage of Results, and Management of Information. Multi-Cloud setups can use several Public Clouds to enhance business resiliency and increase service responsiveness for end-users. Additional dimensions considered are those concerning Data Reporting and Audit as defined by the Proposed Architecture.



Equation 3) Provenance/lineage confidence (from "traceability layer" to a numeric trust signal)

A practical way to model this is to treat provenance confidence P as a function of:

- Integrity I (if data is corrupted, provenance is less meaningful)
- Availability A (persistent outages reduce confidence in end-to-end traceability)
- Coverage of lineage metadata $L \in [0,1]$ (how much of the pipeline is actually traceable)

Step-by-step

3. Assume lineage coverage:

$$L = \frac{\#\text{ steps with captured provenance}}{\#\text{ total required steps}}$$

5. Combine with weights α, β, γ where $\alpha + \beta + \gamma = 1$:

$$P = \alpha I + \beta A + \gamma L$$

6.1. Interoperability and Standardization

Future integration into multi-cloud or hybrid architectures addresses standardization challenges across providers. Financial governance technology solutions must interoperate with diverse cloud services

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seamlessly, as seamless service functional interfaces are an essential multi-cloud architecture property. These external services belong to at least one other cloud infrastructure and can be any Computation-as-a-Service (CaaS), Platform-as-a-Service (PaaS), Storage-as-a-Service (SaaS), Database-as-a-Service (DBaaS), or Security-as-a-Service (SecaaS) technology with a clear contract defining input message structure. Warning signals must trigger execution of a prevalidated response template or security playbook dedicated to that provider. These contracts define the functions made accessible remotely with the parameters for each, with cloud providers offering interface specifications.

Standardizing the functional services' external connection is not sufficient. Financial governance technology functions, including automation, processing, or computing, must internalize other external direct connections of CaaS or PaaS, ensuring the same message structure in the incoming response and subsequent internal process requirements. An adequate data governance strategy, supported by data management technology, must cover both the provider and financial technology. For example, when a financial governance technology function retrieves sensitive information for a sensitive playbook or warning signal, data protection controls must start on each platform and ensure these controls follow the data into any internal application or platform function.

7. Conclusion

Informed by the preceding synthesis and analysis, generative AI significantly enhances financial governance, especially in real-time processing and cloud computations. Real-time governance facilitates the establishment of controls that permit levels of risk tolerance consciously accepted by an organization's stakeholders. A multi-stakeholder, multi-cloud, or hybrid architecture allows financial arguments for the extensive cloud ecosystem developing for digital business. Financial governance addresses operational risks related to management actions, digital footprint vulnerabilities, third-party risk exposure, and regulatory compliance.

Fig 4: Operational Risk & Vulnerability Focus

The proposed real-time, security-by-design architecture bridges financial governance from all cloud transaction sources and across multiple cloud environments. Generative AI enables reliable audit trails at all processing and storage stages, assists in meeting policy mandates, and operates within defined RACI frameworks. Challenges include scaling financial-groups and regulatory-coverage AI-expertise across a broad-spectrum transaction volume, ensuring adequate assignment of risk tolerance and sense-making across all transaction functions, and shaping controls that do not hinder business agility and responsiveness.

7.1. Summary and Future Implications of Generative AI in Financial Management

Empowered by continual advances and widespread uptake of Generative AI and the pursuit of real-time processing, financial governance is beginning a step change: automated generative systems are supporting property and treasury functions in generating financial decisions that are responsive, trustworthy and encompassing of financial risk and accountabilities. Generative AI makes possible continued processing of unstructured, semi-structured, and structured data coming from known and unknown sources, streamed through raw, cleaning and prepared stages and

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connected to storage solutions across clouds and data centers. Emerging solutions deploy External Processors for compute-intensive elements that are better located closer to storage but are designed with cross-cloud flexibility.

The required pillars are yet to be fully realised, offering opportunity for financial practitioners, academics and consultants exploring the applicability, practicality and implications of Generative AI to and for financial governance across its varied domains in scale-up, scale-down, operational execution and monitoring, regulation, sanctions and compliance, external transactions and more. The core property, external funding and treasury functions have identifiable policy, process and control requirements that can be met with GenAI support. Property and treasury GenAI systems offer responsive and trustworthy decisions: Generative AI Technology, Computing and Cloud, Models of Governance, Transparency, Explainability, Auditability and Trust work together for GenAI systems follow principles known to applied risk, control and decision-making theories and frameworks dealing with risk, effect and importance of accountabilities within and for outsourced activity.

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