JOURNAL OF INTERNATIONAL CRISIS AND RISK COMMUNICATION RESEARCH
ISSN: 2576-0017
2022, VOL 5, NO S12

Implementing Databricks Unity Catalog For Centralized Data Governance In Multi-Business-Unitenterprises

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Abstract

Multi-business-unit enterprises often struggle with fragmented, loosely governed data landscapes that hinder compliance, erode trust, and jeopardize risk management. Stability and resilience depend on swift, reliable access to accurate, consistent, secure data. Enterprise data strategies require inter-business-unit data-sharing capabilities, preferably served from a single platform. At the same time, the risk of data leaks, privacy violations, and misrepresentations drives the need for stringent policy supervision. The Databricks Unity Catalog aims to provide a centralized governance and security offering across the Databricks Lakehouse solution with a focus on data sharing and security. It enables a single source of policy truth applicable across all Databricks workspaces, simplifies metadata tagging and classification, and keeps data lineage within a single platform.

A reference architecture for Unity Catalog is defined along with the organizational processes required for its effective and efficient operation. Systematized management for identity and access, attribute-based access control, policy enforcement, data quality, security observability, and operationalizing Unity Catalog completes the analysis. Together, the components lay the foundation for deliberate data governance economics: the collection of policies appropriate for the business with robust processes to govern compliance to those policies. Unity Catalog is not a shortcut to good governance, but rather a structured enforcement framework that provides support and clarity for the often-chaotic realm of policy governance and risk management.

Keywords : Unity Catalog, centralized data governance, multi-BU enterprises, data stewardship, policy enforcement, metadata management, data lineage.

1. Introduction

Multi-business-unit (BU) enterprises often confront a painful dilemma: the need for disciplined data governance clashes with the desire for local autonomy. Responsibility for data governance is decentralized while the data itself is fragmented across a variety of distribution and analytics platforms. Business-unit leaders would prefer not to share sensitive data with other units. Conflicting policies and duplicative work result in data silos. And yet, the absence of formal data stewardship roles makes it impossible to know whether cataloged data products are of sufficient quality to support critical decision-making. The resulting data environment is increasingly hard to manage and no longer supports the original business plan.

A reasonable course of action for a multi-BU enterprise is to implement a centralized data governance program—one that provides a single point of accountability for establishing policies related to data residency, sensitive-data exposure, and enterprise-wide observability of data quality. A successful implementation of a centralized governance program relies on the careful design and operationalization of

a supporting data governance architecture. Currently, enterprise-wide data-management practice is both fragmented and informal in a multi-BU enterprise that deploys the Databricks data-and-analytics platform. Databricks Unity Catalog is a feature of the platform that enables formal data governance processes, centralizes policy management and enforcement, and provides a well-defined foundation for metadata management and lineage recording. Unity Catalog is, therefore, the logical choice for implementing a centralized governance program.

1.1. Background and significance

Multi-BU enterprises often face fragmented governance of business-critical data. Distributed data processing and storage in isolated environments create silos, with neither data owners nor the central function possessing a complete view of the data landscape. Governance policies established by individual BUs may not align, conflict, or be absent altogether. Meeting regulatory requirements becomes challenging due to data residency issues. Some data resides in the wrong country or region, while sensitive data may be kept longer than allowed. Policy enforcement gaps can lead to the unaudited, surreptitious, or unauthorized use of personal data. Such weaknesses undermine analytics quality and, ultimately, the organization's ability to compete. These challenges increase the risk of financial or reputational damage, regulatory scrutiny, and litigation.

To address these challenges, the data strategy blueprint advocates the adoption of Databricks Unity Catalog, which combines policy governance with a multi-cloud metastore for sensitive data processing. Unity Catalog serves as a centralized data management and governance solution that provides automated policy enforcement across diverse data workloads. A reference architecture indicates how Unity Catalog can be established. Processes for managing the data lifecycle, including governance touchpoints, are articulated. Implementation details are outlined for ensuring that access control policies reflect each organization's unique regulatory compliance requirements.

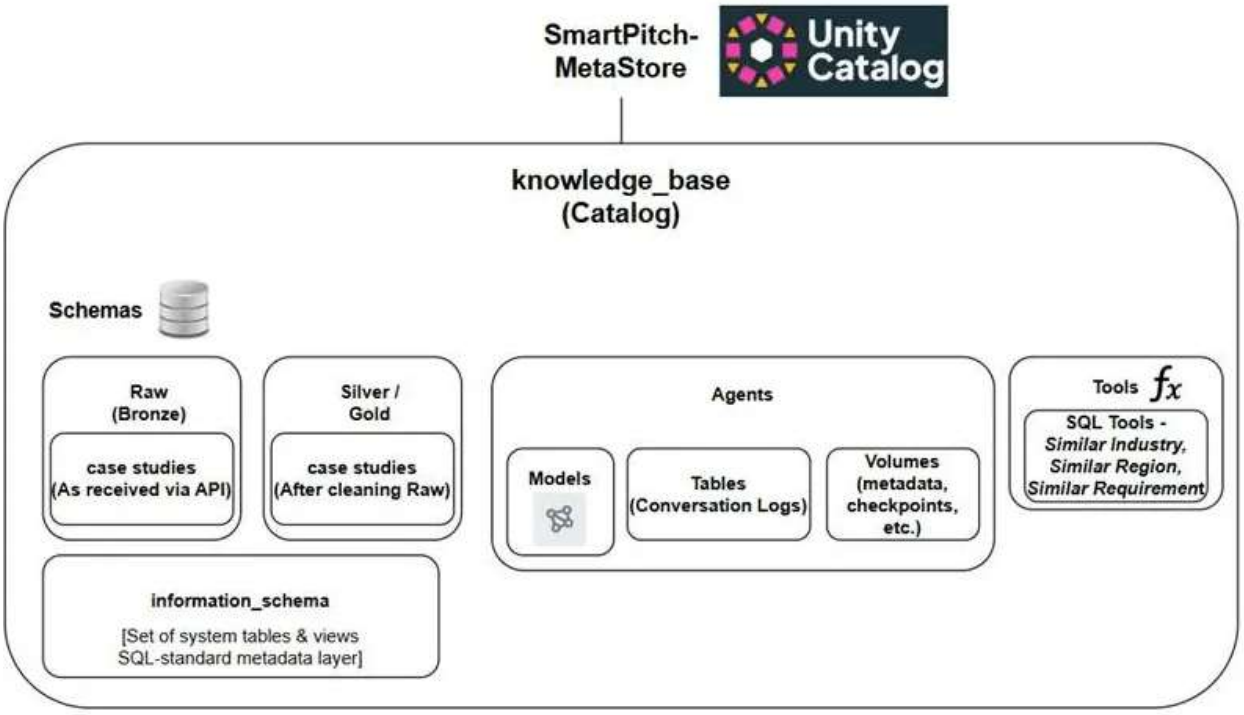


Fig 1: Unity Catalog in Databricks for Centralized Data Governance

1.2. Research design

Designing a strategy for implementing Databricks Unity Catalog in a multi-BU enterprise is modeled as a data governance and stewarding problem. A specific reference architecture describes the division of

business responsibilities and tasks across the data lifecycle and the metadata management cycle. Best practices for data classification, catalogs and schemas hierarchy, metadata standards, and cross-workspace collaboration are identified. These lessons are sourced from joint design-and-build work with various teams and BUs, complemented by guidance from Databricks and data governance literature.
An additional design facet concerns the operationalization of Unity Catalog: the required effort and potential risk associated with its rollout. The strategy approach considers sponsorship, stakeholder training, and change management. A phased deployment plan addresses risk mitigation and delivery timing. Automated CI/CD mechanisms for publishing data definition artifacts enable data-as-code practices.

Equation 1: Composite Data Quality Score
A natural overall quality score is a weighted average:

$$Q = w_c C + w_a A + w_s S + w_t T$$

where:

- C= completeness score
- A= accuracy score
- S= consistency score
- T= timeliness score
- $w_c, w_a, w_s, w_t$are weights with

$$w_c + w_a + w_s + w_t = 1$$

Step-by-step derivation
The paper says quality is evaluated across four dimensions. So the total quality should combine all four contributions.
Step 1: Represent each dimension numerically on a normalized scale:

$$0 \leq C, A, S, T \leq 1$$

Step 2: Assign importance weights to each dimension:

$$w_c, w_a, w_s, w_t \geq 0$$

Step 3: To make the final score remain normalized, require total weight = 1:

$$w_c + w_a + w_s + w_t = 1$$

Step 4: Form the weighted sum:

$$Q = w_c C + w_a A + w_s S + w_t T$$

Step 5: Because each term is between 0 and 1 and weights sum to 1:

$$0 \leq Q \leq 1$$

2. Background and Rationale
Data Governance Challenges in Multi-Business-Unit Enterprises
Multi-business-unit enterprises often struggle with fragmented data governance. Each business unit implements an independent approach, encouraging silos, conflicting policies, and lack of centralized oversight. Compliance and risk teams face substantial challenges ensuring data and analytics meet relevant regulations. These challenges hinder the enterprise's ability to trust analytics. The impact is not just a question of compliance; studies indicate better governance is directly correlated with better financial results. The wider use of analytics often creates new compliance and risk concerns, such as increased data privacy exposure and larger data footprints.
Databricks Unity Catalog provides a built-in framework for centralized data governance across Business Units (BUs) that use Databricks workspaces. Unity Catalog is a cloud-native solution designed to address

common governance requirements, including stewardship, policy enforcement, proactive metadata management, and observability. Data quality and residency controls are roofing considerations when assessing Unified Catalog capacity. The control framework also hosts a reference architecture for Unified Catalog.

2.1. Data Governance Challenges in Multi-BU Enterprises

Data governance poses an enduring challenge in today's complex, globalized, and highly regulated economy. With multiple lines of business (LOBs) trying to capture maximum market share and maintain competitiveness, neither profit maximization nor cost-minimization is sufficient to deliver a winning combination. Companies must also comply with a multitude of laws and regulations. Data governance should therefore be an abiding goal of every data-centric organization. Yet these same companies also face the unrelenting threat of cybercrime and data theft. How can such cross-organizational centralized governance be achieved? The answer clearly lies in the use of a powerful central data governance tool capable of addressing the challenges and enabling the organization of other data governance controls.

Multi-business-unit (multi-BU) companies, which possess separate revenues dollars from different lines of businesses but function as a single legal entity, encounter specific data governance challenges as a result of their organizational structure. The distribution of the data governance function across BUs creates data governance silos, where the data governance strategy for each BU is developed independently. Policies often contradict or conflict, particularly regarding data residency, access controls, and security classification. This fragmentation not only results in the wasteful duplication of effort but also leads to gaps in data governance coverage, increasing the organization's risk exposure. It is hardly surprising that audits often identify data governance shortcomings in such multi-BU enterprises.

Fig 2: Data Governance Challenges and Dynamics

2.2. Databricks Unity Catalog: Overview and Objectives

Databricks Unity Catalog is a data governance solution that provides policy enforcement and metadata management capabilities across a Databricks ecosystem. It replaces existing metastore services with a centralized metadata repository controlled through an enterprise-wide governance framework. Using a simple catalog/schema/table model, metadata across one or more Databricks workspaces can be brought together to support complex data discovery use cases. Catalogs, schemas, and tables can be linked across workspaces to support cross-workspace development and consumption patterns.

Databricks Unity Catalog enables a vastly simplified approach to centralized data governance for a multi-BU enterprise. Catalogs and data assets can be organized, governed, and designed once, enabling a streamlined operational experience for teams ingesting and consuming data. Classification schemes,

retention requirements, access controls, and policy rules can all be governed in a single place and enforced ideally at ingestion time. Key enterprise demands for data residency, data quality, data stewardship, and policy compliance can all be addressed in greater detail than with a legacy scattergun approach or even a piecemeal attempt.

Equation 2: Completeness Score

One basic completeness equation is:

$$\mathrm{C} = \frac{\mathrm{N}_{\text{present}}}{\mathrm{N}_{\text{expected}}}$$

Step-by-step derivation

Step 1: Let N_{expected}be the number of values or records that should exist.

Step 2: Let N_{present}be the number actually available and non-missing.

Step 3: Completeness is the fraction present out of expected:

$$C = \frac{N_{\text{present}}}{N_{\text{expected}}}$$

Step 4: Since

$$N_{\text{present}} = N_{\text{expected}} - N_{\text{missing}}$$

substitute into the formula:

$$C = \frac{N_{\text{expected}} - N_{\text{missing}}}{N_{\text{expected}}}$$

Step 5: Split the fraction:

$$C = 1 - \frac{N_{\text{missing}}}{N_{\text{expected}}}$$

So the equivalent forms are:

$$C = \frac{N_{\text{present}}}{N_{\text{expected}}} \text{or} C = 1 - \frac{N_{\text{missing}}}{N_{\text{expected}}}$$

3. Research Summary

An end-to-end overview of Databricks Unity Catalog is presented, covering the reference architecture, data lifecycle and metadata management, and access control and policy enforcement mechanisms.

The reference architecture comprises catalogs, schemas, tables, the metastore, and cross-workspace integration. Catalogs are the primary containers for organizing access to data and provide logical boundaries for administration within a Databricks workspace environment. Managed schemas serve as wrappers for tables and provide inheritance of storage format and other table properties. Exposure of tables allows consumers to identify available datasets, determine an appropriate storage location, and establish data freshness expectations. The metastore allows multiple workspaces designed for collaboration on a single project to share and synchronize data. Cross-workspace data sharing and aliasing simplifies discoverability and access for users in other workspaces.

The data lifecycle is defined from ingestion through retention and disposal of tenant-owned datasets, along with associated metadata management processes. Governance touchpoints within that lifecycle are highlighted. Key decisions arise in three areas: the curation of major datasets, tagging and classification of sensitive datasets, and the management of combined metadata stores underpinning technical observability and business formalization. The lineage schema is used as a foundation for augmented collection of operational metadata about the state and use of datasets to support impact analysis.

Access control and policy enforcement mechanisms are described, covering role-based and attribute-based access control; Unity Catalog permissions; policy orchestration across products and security levels; and maintenance of audit trails to establish accountability for data use and decision-making.

3.1. Reference Architecture for Unity Catalog

A reference architecture for Databricks Unity Catalog illustrates how its integrated components provide centralized governance for data management in multi-business-unit organizations. The architecture identifies the key components—catalogs, schemas, tables, metastore, and cross-workspace integration—and depicts the roles each component plays during the various stages of a data workflow: creation, maintenance, and usage of the associated data asset.

Databricks Unity Catalog, introduced in 2021, provides a cross-workspace implementation of a data catalog and metastore with advanced governance capabilities. A reference architecture illustrates how the integrated components support centralized governance for multi-business-unit enterprises, following the capability model. As with all implementation patterns within the enterprise data strategy, it remains agile and does not prescribe a rigid structure to fit every use case. However, applying these design principles will make future lifecycle and policy management easier to implement while limiting the risk of costly errors.

3.2. Data Lifecycle and metadata Management

Data lifecycle and metadata management processes—ingestion and curation, along with lineage tagging and management—are the backbone of governance. The quality and completeness of metadata determine the user experience, while observability, especially lineage, enables risk assessment and impact analysis for events (such as changes to upstream datasets, tables, or views) that involve sensitive data.

Data ingestion is the process of bringing data into the governed, central environment. Unlike legacy approaches, which often relied on silos for speed, ingestion is treated as a governance touchpoint. Datasets are ingested along with the associated metadata that will be used to assess sensitivity, criticality, and compliance, and to seed change management and quality profiling workflows. Ingestion includes tagging, for example with data stewardship labels that identify custodians and stewards.

Curated data is subject to further processing and validation. Lineage is traced at all stages—from ingestion through curation to consumption—and captured in a format suitable for automated analysis. Quality gates, profiles, and other characteristics are generated. Datasets deemed critical or sensitive are assigned for more comprehensive tagging activities. Retention policies are established, and non-essential data is disposed of according to rules aligned with industry regulations; all others are periodically refreshed and purged as necessary.

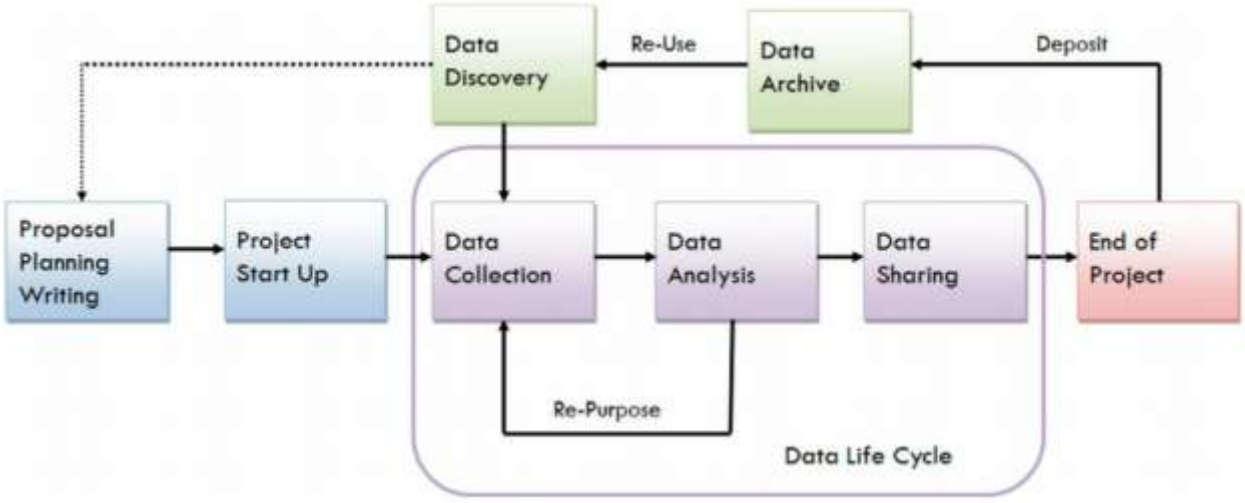


Fig 3: Metadata Life Cycles

3.3. Access Control and Policy Enforcement

Managing access control and policy enforcement in a multibusiness unit enterprise requires a risk-based approach. On one hand, fine-grained role-based access control (RBAC) can be cumbersome as the number of roles grows to satisfy specific data access needs. On the other hand, rule-based access control (ABAC) based on attribute tagging is difficult to maintain as the number of tags increases and intricate rules can conflict with each other. Using both RBAC and ABAC where they are most suitable minimizes the maintenance burden.

Unity Catalog introduces its own set of permissions and allows catalog administrators to assign them independently of workspace permissions. This adds an additional layer of policy management that, if properly synchronized with policy governance, enables a more complete use of the idea of a separation of duties. As permissions for different environments can be aggregated following the layered approach, workspace permissions become less critical and can rely more on environment structure than subtle fine-grain definition.

Policy as code complements access control. A policy is an expression of business rules formulated in a machine-readable manner, utilizing the declarative capabilities of the Databricks SQL platform to ascertain adherence to rules defined by the organization, and alert the designated roles when violations occur. A formalized repository of business rules can be assembled and integrated with the data in the data catalog, when available, to produce compliance dashboards that give insight into the current state of compliance.

Equation 3: Access Decision Function for RBAC + ABAC

A formal access decision can be written as:

$$\text{Permit}(u, r, o) = R(u, r) \wedge A(u, o) \wedge P(o)$$

where:

- u= user
- r= requested role / privilege
- o= object
- $R(u, r)$= user has required role
- $A(u, o)$= user/object attributes satisfy ABAC rules
- $P(o)$= object passes policy constraints

Step-by-step derivation

Step 1: In RBAC alone, access is granted if the user has the required role:

$$\text{Permit}_{RBAC} = R(u, r)$$

Step 2: In ABAC alone, access is granted if attribute rules are satisfied:

$$\text{Permit}_{ABAC} = \text{A}(\text{u}, \text{o})$$

Step 3: The paper says both should be used together, meaning both conditions must hold:

$$\text{Permit} = \text{R}(\text{u}, \text{r}) \wedge \text{A}(\text{u}, \text{o})$$

Step 4: The paper also emphasizes policy enforcement beyond access role logic, so add a policy-validity condition $\text{P}(\text{o})$:

$$\text{Permit}(\text{u}, \text{r}, \text{o}) = \text{R}(\text{u}, \text{r}) \wedge \text{A}(\text{u}, \text{o}) \wedge \text{P}(\text{o})$$

Step 5: Convert to binary notation if desired. Let each predicate be 1 if true, 0 if false. Then logical AND becomes multiplication:

$$\text{Permit}(\text{u}, \text{r}, \text{o}) = \text{R}(\text{u}, \text{r}) \cdot \text{A}(\text{u}, \text{o}) \cdot \text{P}(\text{o})$$

4. Objective of the Study

Developing and enforcing suitable policies requires detailed data classification schemes, which identify sensitivity levels, criticality tiers, retention rules, and labeling schemas, aligning with regulatory requirements such as GDPR, HIPAA, PCI-DSS, and local laws. Established Lineage governance ensures continuous capture of data lineage information and adequate usage for impact analysis concerning data quality, compliance, risk, and security.

The various actors of Data Stewardship—namely, data custodians, data stewards, data owners, and Data Governance committees—also fulfill essential roles for Data Quality, Data Security, Privacy, and Risk Management. Data custodians assign and enforce access controls on data assets according to company policies; Data stewards manage policies for data quality and observability; Data owners have the authority and accountability over data lineage, data classification, and data retention and disposal; and the Data Governance committee is in charge of Data Governance.

Governance-related data processes are continually cyclical and interwoven across the Data Lifecycle. The Data Governance objectives can be summarized in a few key questions: Are the data assets correctly named and documented? Are the data assets stored where they are expected to be? Are the access controls defined in line with the company policies? Is the data quality acceptable for its intended usage? Are the data-related regulations being followed? Is the localization of data assets in line with the defined residency controls? Is the data minimization principle being adhered to during data transfers?

Equation 4: Lineage Coverage Ratio

A direct metric is:

$$L = \frac{N_{\text{lineage-tracked}}}{N_{\text{total-assets}}}$$

Step-by-step derivation

Step 1: Let $N_{\text{total-assets}}$ be the number of tables / datasets in scope.

Step 2: Let $N_{\text{lineage-tracked}}$ be the subset whose lineage is captured.

Step 3: Coverage is "tracked over total":

$$L = \frac{N_{\text{lineage-tracked}}}{N_{\text{total-assets}}}$$

Step 4: If untracked assets are $N_{\text{untracked}}$, then

$$N_{\text{lineage-tracked}} = N_{\text{total-assets}} - N_{\text{untracked}}$$

Substitute:

$$L = \frac{N_{\text{total-assets}} - N_{\text{untracked}}}{N_{\text{total-assets}}}$$

Step 5: Simplify:

$$L = 1 - \frac{N_{\text{untracked}}}{N_{\text{total-assets}}}$$

4.1. Data Classification Schemes

Classification schemes underpin data governance. They comprise categories for sensitive data (for compliance), critical data (for risk management), retention periods (for data minimization), and labeling (for accessibility). Each catalogue in the Unity Catalog architecture has a sensitivity classification representing the most restrictive permission that any object in the scope can have. Therefore, it is often aligned with the classification of regulatory frameworks with which the enterprise interacts. Such schemes define objects that must be protected like PII and PHI. For example, If data has classification > 1 it must belong to a PII zone with access restricted to information security committee members and It must also be encrypted in transit and at rest.

When data is classified as critical, the data governance committee must estimate the data flow. It must determine what can be reused by other pipelines, what can be droped due to bad points, which points need an alert or some kind of remediation, and for every transformation that uses the participant at which point it will be transformed and at the end of the flow if some final table will be generated now or in the future. The classification also indicates for how long the data must be kept in the Data Lake and in other environments. Data that is in a some critical zone must have a creation date or some metadata that determine if it can be deleted or not. Every transformation must have at least a point that can determine if the data is still sensible to the business and should also track how many days of gap has between now and the last point.

The enterprise must have a schema for Unity Catalog that indicates which labeling system will be used (Red & Yellow or Bright & Dark). All the zone names of the Data Lake must follow a pattern that will facilitate the automation of the classification and labeling of the data. This help the data engineering team to facilitate access to the Data Lake environment separating data zones by which system they belong to even if there is isolation in access control.

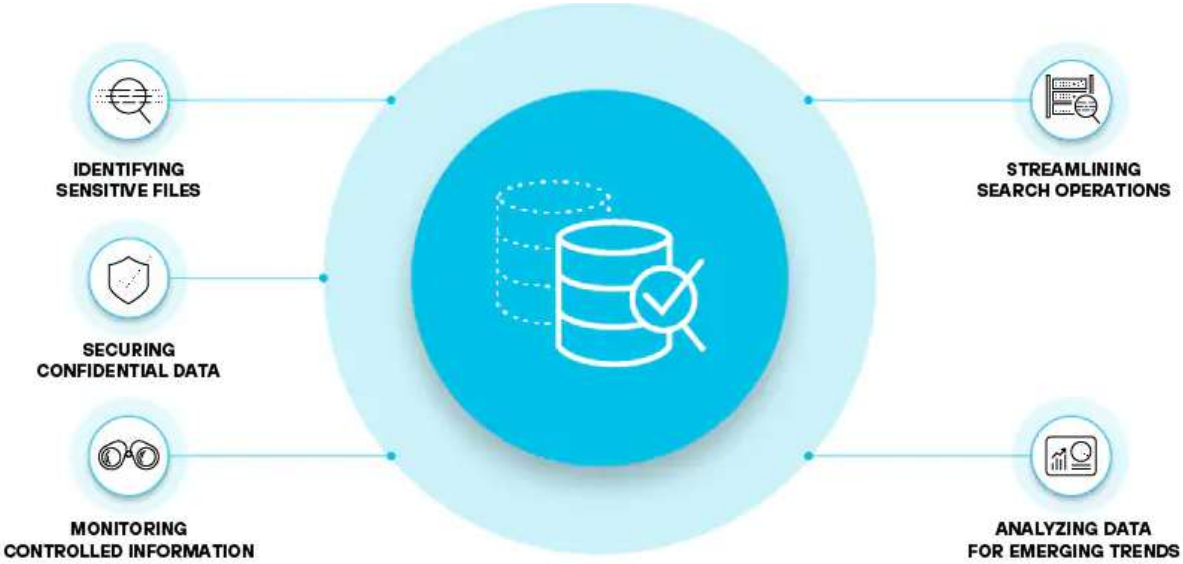


Fig 4: Data Classification Schemes

4.2. Lineage capture and Impact Analysis

Data lineage encompasses the discovery and visualization of data transformations across the entire data life cycle, from acquisition and extraction through compliance checks to appliance tables. It associates metadata with traceability, detectability, and understandability, enabling identification of data quality issues as well as the impact of the changes made to the source systems. Provenance serves as a historical footprint that provides an audit trail for surveillance by governing bodies. Lineage analysis accounts for information on the connections between datasets, hence data availability for analytics, regulatory compliance, or risk management.

Understanding how various systems, processes, and user interactions affect key datasets enables accurate assessment of risks to organizational performance. Tools for lineage enable building models to assess impact when changes occur, such as modifying the business logic of a key transformation or decommissioning an upstream data source. For both business and operational reasons, these assessments must happen formally and efficiently, particularly for data-intensive models that leverage thousands of file objects across several clusters, Calculate of test coverage area and evaluate test stability for both functional and performance test suites.

4.3. Data Stewardship Roles and Responsibilities

Data governance in a multi-business-unit environment demands that everyone be aware of their responsibilities in this context. Therefore, it is crucial to define the various data stewardship roles in the organization: custodians, data stewards, data owners, and a data governance committee. Clear definitions of each role, involving cross-BU collaboration, help clarify the handoffs and accountability for data-centric operations.

Data custodians are responsible for implementing the deployed architecture and procedures in accordance with the data stewards' specifications. Data stewards look after the data sets they manage and ensure they are accurate, reliable, timely, relevant, and secure for consumption. Data owners are responsible for the data's business fitness and thus its classification and retention policies. They remain accountable for the data supported by their areas of the business. With their cross-BU angle, the data governance committee identifies the right policy sets needed across the businesses, drives their adoption, and approves exceptions from the policy sets.

5. Methodology

The hierarchy of catalogs, schemas, and tables in Unity Catalog will vary depending on the enterprise's structure and data culture. It is crucial to develop a naming schema during the design phase to ensure deep scoping of datasets and unhindered access to high-volume shared resources during even the most demanding workloads. Partitioning at the schema and catalog levels can also be used to separate sensitive datasets and high-potential spillage datasets from other resources, which further mitigates the likelihood of inadvertent information leakage. Actual partitioning schemes may vary considerably across environments, business units, use cases, and even catalogs. Catalogs can also be scoped to specific domains such as commercial functions, product teams, technical functions, and financial functions; however, poor implementation of catalog scoping and naming should not impede the rollout or migration process.

Branding and naming conventions are important for all data governance components—they help to establish confidence and participation of stakeholders. Categories for governance touchpoints should reflect the sensitivity of the data and any privacy requirements. The naming of data quality and quality metrics and profiles should be based on marketing segmentation with respect to product support. White- label products are generally managed cross-locations and therefore these aspects of branding are amalgamated. Metadata profiles should address metadata and metadata quality for all stakeholders associated with the data throughout its lifecycle. Terms and conditions should harmonize across product and data categories. The definitions should be incorporated into a glossary. The glossary should account for all stakeholder-labeled terms. Automated testers should assess conformance with the glossary.

Equation 5: Policy Violation Rate

A suitable equation is:

$$V = \frac{N_{violations}}{N_{checks}}$$

Step-by-step derivation

Step 1: Suppose the system runs N_{checks} governance evaluations.

Step 2: Out of those, $N_{violations}$ fail.

Step 3: Violation rate is the fraction of failed checks:

$$V = \frac{N_{violations}}{N_{checks}}$$

Step 4: Compliance rate is the complement:

$$\text{Compliance} = 1 - V$$

Step 5: Substitute V:

$$\text{Compliance} = 1 - \frac{N_{\text{violations}}}{N_{\text{checks}}}$$

or equivalently,

$$\text{Compliance} = \frac{N_{\text{checks}} - N_{\text{violations}}}{N_{\text{checks}}}$$

5.1. Catalogs, Schemas, and Tables Hierarchy

A hierarchy of catalogs, schemas, and tables facilitates resource discovery and promotes consistency in resource naming and usage across the organization. Each catalog hosts multiple schemas, serving as logical containers of tables and enabling functional scoping and access isolation. A partitioning strategy prevents metadata from overwhelming analytic capabilities.

Naming conventions enforce cross-environment consistency, enabling easy identification of a resource's purpose relatedness based on its name. Resources are scoped and partitioned as needed to minimize unrelated user traffic while still supporting shared collaboration where beneficial.

Governance structures are established for the catalog/schema/table hierarchy, ensuring timely oversight and review of proposed changes. The same pattern is applied to other core governance capabilities: branding/naming/metadata standards, identity management with SSO, policy governance and auditing, data residency and residency control, data quality and observability, cross-workspace collaboration, CI/CD pipelines for data catalog artifacts, and training/change management.

5.2. Branding, Naming Conventions, and Metadata Standards

A coherent strategy for data governance must be accompanied by quality metadata. Establishing a unified scheme of branding, naming conventions, controlled vocabularies, taxonomies, and data dictionaries limits confusion, enhances discoverability, and ensures consistency in both human communications and automated routines. Metadata quality requirements and monitoring strategies can provide end-users with confidence in the governance framework.

Branding and naming conventions apply to all datasets and assets in the organization. A unified look and feel, paired with a consistent scheme of logical naming, enhance usability and generate an impression of professionalism. Externally visible data must comply with detailed branding guidelines that include typographic and pictorial elements; any person responsible for an Organization unit sending data outside the organization must ensure these guidelines are observed. The presence of a common name across the different datasets made available to the external audience facilitates communication and exchanges.

A consistent and simple naming convention has been defined for the datasets. This convention enhances recognition and improves the avoidance of errors. The convention for naming datasets for countries and each language combined with the content of the dataset itself can avoid having to create maintenance lists. Taxonomies, data dictionaries, and controlled vocabularies manage the semantics. Shared definitions for various entities and descriptions allow systems from different BUs to interoperate better, for instance during a transition phase in a Data Lake consolidation or for data coming from external sources, such as market data. A common data dictionary helps to clarify the meaning of key variables. Validation is critical and should be automated. Dirty data should be tagged and routed for addressing, while clean data should pass through quality gates before being made accessible.

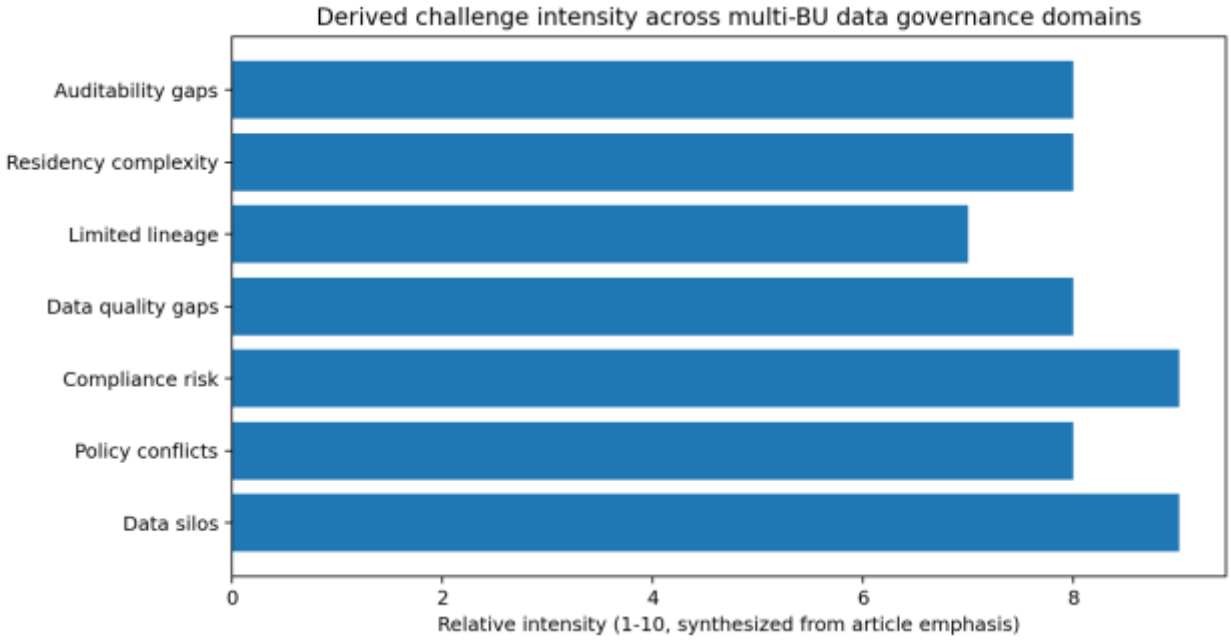
5.3. Cross-Workspace Collaboration and Isolation

Machine Learning Operations (MLOps) provides the approach, principles, and procedures for the lifecycle management of ML models, from initial conception to deployment and continuous maintenance. The deliverables of MLOps that must be managed include datasets, model training workflows, trained models, model inference endpoints (and the incoming and outgoing data), and dashboards to monitor the behavior of the deployed model. A modern MLOps implementation for enterprise ML development in Databricks

can leverage the guidelines in this paper for securing the supporting platforms and cloud infrastructure at enterprise scale.

Data and model artifacts can serve multiple purposes, and the corresponding work environments may cater for different audiences. Workspaces can therefore be organized with a shared-access-and-collaboration design pattern for experimentation and knowledge sharing (e.g. exploring a shared dataset to generate initial experiments) and an access-isolation design pattern for regulatory or ethical compliance. Environment scalability can be addressed with dedicated resources serving separate workspace groups that are scheduled based on usage patterns (e.g., burst of demand for training versus perpetual demand for model inference).

Synchronizing data, model, and inference layers across environment styles—whether shared or isolated—ensures timely access to the most up-to-date versions of artifacts without forcing additional coupling and maintenance work. Collaborative workspaces remain a popular design pattern for ML development as they harness the observability of ML producing and consuming entities, which is critical for ensuring model quality, safety, and performance during lifecycle advancements as the models are exposed for inference.



6. Result

Identity management for cross-workspace access is enabled through an Azure Active Directory identity provider that federates authentication to Databricks. Workspaces belonging to different business units can be integrated while preserving access boundaries, enabling collaboration across functional and geographic silos. Automated CI/CD pipelines manage resources and secrets in isolated and shared environments, providing predictable tooling and process support for rapid data ingestion, processing, and consumption. Data processing is shielded from platform-specific details.

Management of data policy sets is delegated to a team within a designated Business Unit. Where policy violations are detected, details are stored in a compliant data repository to support forensics and rectification. Policy evaluation rules define the mechanism for risk-based detection of identity, access, and operational violations, including checks for illegitimate access, out-of-hours usage of analytics tooling, and data-processing activities that expose sensitive information-edited in a non-region-compliant manner. Activity logs are continuously evaluated against the defined rules, with violations recorded in an auditable format for downstream analysis and reporting.

Data residency control and minimization measures successfully identify the geographic location of all data store resources. Identity-based geography checks are applied to all new data stores and subsequently-negative test prior to data transfer. The data residency checks cover both primary storage and secondary-

regional-storage locations. Where data residency minimization rules have been broken, details are collected in a compliant location to help identify removed-minimization policies.

6.1. Identity Management and Single Sign-On

Users of the data platform must have accounts in the identity management service to access resources. The identity management service must be configured with the identity provider used for federated authentication, supporting single sign-on across multiple services and environments. A federation relationship is established between the identity management service and the cloud service used by the data platform. The identity provider must then provision and synchronize users' identities in the data platform on the relevant cadence and scope.

Enterprise data governance is demanding on organizations and their data provisioning support. The classical data management methodology treats data resources as static storage repositories, which in addition to its inadequacies, made it difficult to generate informative audit trails. Data needed to be handled as an information lifecycle issue with numerous touchpoints throughout the Lifecycle of the information within the Databricks Unity Catalog.

6.2. Policy Governance and Auditing

The establishment of effective policy governance involves the creation of logical policy groups related to various use cases. The detection of violent content in user-generated data serves as a prime example of automated policy enforcement in practice. The creation of a compliance-related policy set can be monitored over time to identify anomalies. An organization seeking to strengthen its commitment to the data protection of minors requires audit trails for the usage of sensitive data classes during data analytics. Policy governance must also consider data labeling and data orientation (e.g., public, internal, secret, confidential, etc.) rules that provide for a narrowing of the different exposure categories and density levels.

Policy violations must serve as triggers for proactive governance measures, and the fulfilment or non-fulfilment of labeled requirements must be reported in an understandable form to the relevant governance bodies, as violations of protective controls lead to a lack of compliance. In addition to the policy sets defined in the policy orchestration layer, which are automated by specific detections or transformations, different policies must be ensured in the environment so that controls that are sensitive to data processing legacy are not rendered ineffective (e.g., data residency) and warning thresholds for sensitive data processing are not reached.

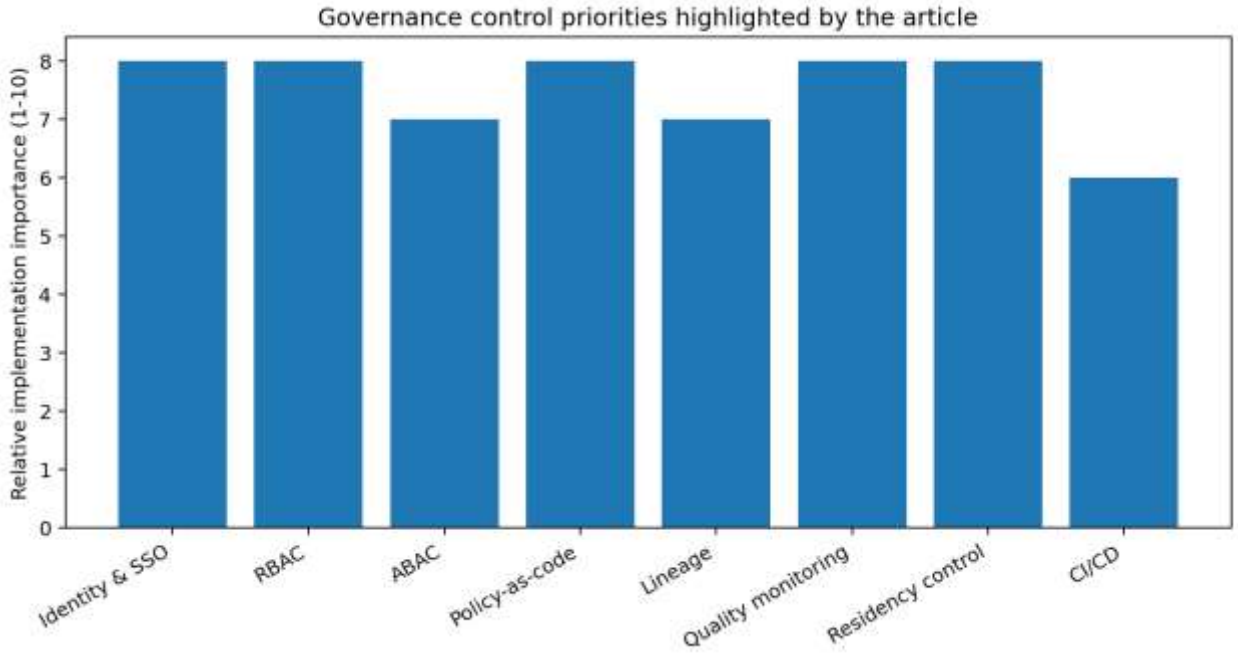
6.3. Data Residency, Residency Controls, and Data Minimization

Centralized governance offers enterprises the ability to enforce multi-region data residency mandates across their data landscape. Where business use cases do not require a particular data location, automated data minimization techniques can mitigate against data monetization and privacy risks.

Data residency policies specify the maximum or minimum location of data depending on business and regulatory requirements (e.g. GDPR, Local Data Laws, etc.). Enforcement may therefore include a mix of automated controls (e.g. refining policy checks) and mandatory checks for data-lifecycle events (e.g. data transfer). Unified Data Governance provides the ability to monitor data residency against expected location(s) to support compliance checks. Automated checks are essential where more than one of these policies applies to the same data store (which is the norm in multi-national, multi-legal data landscapes), especially when the policy decision is to minimize on economic grounds. Failure to do so increases the risk and magnifies the impact of a potential violation. Centralized Data Governance aims to unify policy and procedure across all Databricks workspaces. It provides a clear decision-making framework to assist confidential, private, and sensitive data monetization or transfer requests, while ensuring all other data is treated consistently regardless of which Data Engineer initiates the operation.

While it is impossible to remove all risk of data distribution and associated privacy violations, the processes are designed to minimize both likelihood and impact when such an event occurs. It should also be noted that a nested-RBAC workflow is not practical for an operational governance process. Rather, strategic data minimization can be adopted, whereby legal, contractual, and economic principles are collectively applied

to determine if specific data at rest should be in the selected region. Failure of the review should result in removal of the Data Store.



7. Data Quality and Observability

Data Quality and Observability

Data quality and monitoring are mission-critical aspects of a data governance effort. Initiatives to assess data quality, provide monitoring capabilities, and infuse governance into data pipelines must rely on evidence-based definitions of data quality metrics and dimensions, scoring profiles that detail their acceptable levels, and observability solutions that visualize key performance indicators and warn interested parties of problems. Unity Catalog enables the integration of several open source and commercial tools that can continuously check for data quality, profile the data, and actually feed observability dashboards.

Quality metrics and profiles are established as part of the testing phase and adopted within the production environment. A small set of metrics is initially scoped, covering completeness, accuracy, consistency, and timeliness. The latter may be relaxed somewhat if the ingestion frequency of the data sets is also prone to variability. Automated checks are designed around these four metrics and implemented across the pipeline automations. For completeness, thresholds capture duplicate records, missing values, and expected distribution of categorical attributes. Profiling dynamically assesses the values of every attribute in the data sets and generates reports on key statistics, ranges, and unique value counts. Rules configured via the profiling tools refresh the reports periodically and alert if the values deviate from the established profiles. For accuracy, sample DataFrames are inferred by the quality tooling and compared against source queries or other reliable data sources. Checks for consistency surface data integrity violations, while delayed or missing ingestions trigger alerts.

7.1. Quality Metrics and Profiles

Quality is a foundational characteristic of reliable data. It determines whether the data can be safely used in day-to-day operations, applied in compliance contexts, or trusted for high-impact decisions such as mergers or strategic shifts. As previously stated, detection of low-quality data is an important basis for mitigating risk, yet it raises operational complexity and costs. The investment burden can be reduced by establishing a set of explicit quality rules for each dataset, checking only the changes to the data over time, and incorporating the cost of failure into the analysis.

For each dataset in the catalog, relevant quality metrics are defined and monitored to ensure that the data remains valid and trustworthy. Completeness is checked against data retention policies. Accuracy is evaluated for a sample of records against an authoritative source. Consistency checks verify that minimum and maximum values comply with allowed distributions. Timeliness verifies that data from third-party suppliers can be trusted based upon past performance. Profiles of historical data quality metrics are maintained to enable change detection and threshold definition.
In addition to quality checks, an exploratory analysis system can be built to automatically profile datasets based upon user-defined profiles. The profilers detect outliers and other potentially interesting anomalies such as shifts in correlation. Both the metric check and the profiling system are integrated into a data quality gate for automatic approval or reprovisioning of data.

7.2. Data Quality Gates and Monitoring

Automated data quality gates verify the correctness of sensitive data arriving in the data operations center, and ensure that required sanity and integrity checks are performed on new data. Each data sink should be equipped with a corresponding gate that reflects its data quality profile. The gates evaluate incoming data against a series of threshold rules (e.g., null counts, cardinality ratios) that signal a potential data quality issue. When a potential issue is encountered, remediation workflows are triggered to help the data operation and support teams investigate and resolve the problems. Remediation workflows enable notifying the respective data operations custodian and that data operations team that an automated check has failed, and that assistance may be required. Completion of the remediation workflow normally results in one of the following actions being performed:
Data observability provides an operational view of selected KPIs without details around incident resolution, allowing the data operations and support teams to monitor data assets that require special attention.

7.3. Observability Dashboards and Alerts

Automated observability dashboards present key performance indicators collected from various business units in a unified format that adheres to established visualization principles. These dashboards follow a clearly defined structure that allows stakeholders to interpret them quickly and easily. Business users receive alerts when key performance indicators trigger defined thresholds or require human intervention.
Data Observability Dashboard: KPIs that inform data governance, end users, and organizational affairs are visually represented in a common format across business units, enabling stakeholders to compare their position within the enterprise and identify areas requiring improvement. Each dimension of data quality can be represented in a dedicated dashboard configured to data governance requirements. For example, a data lineage observability dashboard that tracks the endianness of all data lineage diagrams available within the catalog (as a percentage of total tables using a lineage diagram); a completeness observability dashboard that highlights the percentage of tables, at a column level, validated for completeness; and a timeliness observability dashboard that presents the percentage of systems that adhere to published timing rules.
Alerts: Data observability dashboards define KPIs that trigger alerts when threshold levels are breached. Alerts can be routed through existing enterprise channels via already established alerting tools. Automated workflows ensure that dedicated data stewards for a given dimension of data quality are immediately informed about data quality problems.

8. Operationalization and Change Management

Migration to a centralized data governance model requires preparation, adoption, and support for the new way of working. A phased approach allows gradual transition and risk reduction. A pilot implementation, with selective monitoring and governance of key resources, demonstrates the desired capabilities on a limited scale. Success encourages broader adoption, while evidence of shortfalls promotes corrective action. Specialized CI/CD pipelines enable automated testing and deployment of catalog primitives. Finally, stakeholders are prepared through appropriate training, with Change Champions facilitating knowledge transfer and community building.

Transitioning to a centralized data governance framework represents a significant alteration to the entire organization's way of working with data. Structured preparation—concerned with both willingness to change and the operationalization of the change—therefore requires careful definition. Defining a migration strategy helps determine the required set of modifications to processes, patterns, and technology, along with appropriate executive communication and leadership visibility. A phased rollout of the transition helps reduce the impact and risk of the change. On a smaller scale, stakeholders can hone the new approach on a limited basis before embarking on wider adoption. A proof-of-concept pilot that includes active monitoring and governance of critical resources confirms that the desired outcomes can indeed be achieved. Demonstrated success encourages wider rollout; adverse evidence prompts appropriate corrective action.

Responsibility area	Custodian	Steward	Owner	Gov. committee
Access controls	Primary	Support	Approve	Oversight
Data quality rules	Support	Primary	Approve	Oversight
Classification & labeling	Implement	Support	Primary	Approve exceptions
Retention & disposal	Implement	Support	Primary	Oversight
Lineage visibility	Implement	Primary	Accountable	Oversight
Cross-BU policy harmonization	Support	Support	Support	Primary

Table: Stewardship responsibility matrix

8.1. Migration Strategy and Phased Rollout

A phased rollout strategy for Unity Catalog governance is proposed to mitigate the significant risks of governance transformation. Unity Catalog is an addition to the existing Databricks Lakehouse environment and continued use of an earlier metastore, which contains one-off datasets, is envisaged for those multi-business unit solutions with effectively continuous development cycles. The migration strategy incorporates a pilot phase involving a single business unit, a second data-and-system combination from the catalog production area with a broader scope, and the consideration of a JEESH4Like flag. Successful completion of these phases would open up for the company much of its historical data for transformation supply under best practice guidelines while further ramping up for further production builds. The pilot phase deployment of business unit identity provider-based federated authentication is set to guarantee single sign-on across environments without enabling additional detail discovery.

Assessments against criteria for success during each phase of the rollout would indicate readiness to proceed to the next stage of the pipeline. Pre-approved rollback criteria ensure that if new attempts unexpectedly break, there is a strong basis for halting it on that condition and returning to a previously working state. Governance deployment is also flexible enough to support and mitigate new underlying issues in earlier produced datasets. Even the absence of any pilot run would not be a show-stopper. It is envisaged that a CI/CD pipeline that allows for the catalog artifact definitions to be treated in a standard software delivery model will be deployed shortly and forms an enabler hurdle for approval and security function teams. Given the anticipated large number of requirements to drive its use, a subsequent migration to a production-style landing zone and helpdesk-based service process administration should flow almost as a matter of course thereafter.

8.2. CI/CD for Data Catalog Artifacts

To establish CI/CD for data catalog artifacts, Unity Catalog nomenclature requires versioning, and deployment calls must be automated to ensure testing before promoting to production. Changes may occur in metadata definitions (identity provider mappings, catalog, schema, or table definitions), governance policies, or data quality rules. Automated tests validate naming conventions. Separate environments are used to enforce distinct development and operational cycles.

Data catalog artifact definitions, rules, and configurations reside in a version-controlled repository. Calls to the feature pipeline create, alter, or drop artifacts in the Unity Catalog, applying any changes detected since the last deployment. Within the governance landing zone, a code branch triggers remediative workflows should data quality gates not be passed.

8.3. Training, Adoption, and Stakeholder Engagement

Robust training programs and sustained stakeholder engagement are vital to Unity Catalog adoption and data stewardship enablement. A cross-business-unit team of analytics change champions cultivates interest, shares knowledge, and promotes behavioral transformation.

New ways of working do not just happen; people need training and support. Training builds capability and confidence. It prepares users and stewards of the governance model to execute their day-to-day activities in the new operating model. The skill uplift covers data access and discovery, stewardship duties, and compliance obligations. Surveys identify specific needs, and curricula are tailored accordingly. Longer lead times are needed for technical and compliance training. Regular courses are scheduled for other topics.

Different people have different interests. A grassroots change-engagement program gets analytics practitioners talking about the changes. Data changes may create friction points—particularly in shared spaces where unit-level roles and responsibilities are blurred. Analytics practitioners explore solutions and resolve issues in the cross-unit discussions. They surface issues for development teams, highlight training needs, and help to manage broader stakeholder relationships.

9. Governance Economics and Cost Management

Libraries, products, and environments consume resources that have a financial impact. Therefore, it is prudent to assess the financial implications of any proposed controls, while acknowledging that costs are only one consideration, and that the costs of uncontrolled risk are often immeasurable. A high-level model estimating the cost of operating Databricks Unity Catalog is presented, covering licensing, storage, compute, and governance tooling, as well as migration costs. The model is not intended to be definitive and must be adapted to local contexts, but it demonstrates the feasibility of such assessments.

Governance economics modeling aims to ascertain the total cost of Unity Catalog governance adoption and operation, enabling comparisons with the anticipated benefits, although costs must not be the sole consideration. Investigated costs include license fees, governing tooling, compute resources required for governance functions, and associated storage. A brief outline of a migration strategy is also proposed.

Two additional areas of cost management require attention. First, careful resource consumption discipline during operations may deliver significant savings for a large governance operation. Second, the automated tiering, retention, and de-identification (or other privacy-minimization) techniques being implemented inside Unity Catalog can have a transformative impact on the real cost of data privacy.

The financial implications of adopting Unity Catalog will depend on the degree to which it is utilized and on the cost structure of local environments. For example, maintaining a single, logically-modular cross-BU environment could have very different cost considerations to a multi-environment operating model, where data residency is a prime consideration.

9.1. Cost Modeling for Unity Catalog

Planning for the costs of deploying Databricks Unity Catalog provides a context for the associated benefits and supports approving the initiative and investing in its governance throughout the application and service life. Important cost categories cover Databricks managed services—license charges, storage costs, and compute resource costs for outcome data hosted in Databricks—as well as governance tooling deployed in the corporate environment, costs incurred when working on the Unity Catalog implementation (including

contracts with external consulting teams), and ongoing costs tied to continually governing, enhancing, and expanding the usage of the Unity Catalog.
Establishing a full cost model represents a significant body of work, possibly beyond the scope of a single initial analysis. Therefore, prioritizing the completion of major cost areas and capturing them in a management report provides appropriate coverage. A database could then be created to flesh out additional costs in a comprehensive manner. Subsequent analyses could focus on the other cost categories identified above, while important points in ROI considerations would also merit a dedicated business case, as the eventual return will positively influence the decision to invest in Unity Catalog from many perspectives, including human resources, vendor MarkLogic technology, and Momentum ETL platform.

9.2. Optimization Strategies and Cost Controls

Modeling costs for Unity Catalog deployment highlights several potential areas for cost optimization. The software licensing is of primary concern, since the various editions of Databricks Unity Catalog and support for multiple cloud services at various levels is critical to the successful deployment of the centralized solution. Cost consideration of other components such as storage, compute engine (especially for the Colab) infrastructure supporting the different BUs, together with monitoring and alteration actions of the policies related to data policies should guide the organizations to maintain the overall expenses in accordance with the provisions.
Appropriate assignment of governance roles is fundamental, aiming to provide an adequate level of automation and integration into the cloud architecture while remaining within the expected governance budget. The achieved critical mass of workloads in a shared governance architecture justifies investing in governance tooling for Cloud and Data-as-a-Service solutions. Still, sufficient prudence is required to avoid excessive monitoring and enforcement of policies across staging, testing, development, and sandbox environments, leading to delays in the iterative improvements of business solutions compared to isolated governance structures. Maintaining policy monitoring alerts per environment allows a tailored threshold to avoid the alert fatigue phenomenon.
Using tiered Cloud and governing the entire environment's resource and life cycle based on usage by multiple BUs is advisable. Analytical environments' tiers could be adapted for new products, risks, or regulations considered a premium and mostly used for a shorter period. Data in multiple BUs with overlapping lives could follow a different cloud residency based on usage or latency venue requirements. At different life stages of the data, the localization can be balanced according to costs and compliance rules. Policies could be created in such a way that sensibility labeling derives from the business environments that mostly use the data at a given time period, ensuring minimum movement of data across regions while meeting the overall governance objectives.

9.3. ROI Considerations

The prospective ROI from deploying centralized governance tooling depends on the cost of the tools, the reduced risk of non-compliance, and the reduced costs of the deltas that are being managed. Better data in areas of regulation and compliance, such as data residency and data privacy, will also mitigate risk. However, quantifying this improvement is not straightforward and will likely take the form of a qualitative statement along the lines of "failure to secure a significant improvement in these areas would present an unacceptable level of risk." In the world of cloud computing, the cost of storage and compute are largely controllable. Controlling the demand for cloud resources used in analysis, especially around idle workloads (e.g., spurious resource allocation requests during holiday weeks, weekends, overnight, etc.) will go a long way toward managing costs. There are additional levers available, such as tierring frequently used data and using cheaper tiers for cool / archive data. For data lifecycle management, re-testing delta data quality automatically (especially for temporal deltas), and moving to delete as soon as the data has no further usefulness will help reduce data bloat, thereby controlling cloud costs.
For the major parts of Unity Catalog's sourcing costs such as Data Quality, Correctness, and Lineage there is an expectation for a positive return. This is because these areas of Governance produce data that is being used in downstream processes—these are not delta processes—these are core data used for critical decision

making within the organization. Any opportunity to inject even small improvements into the three core pillars should be sought. Important Transformation processes should also be kept under continuous review. For Delta processes—either for data quality or governance—an expectation is that a pay-back period of less than 12 months should generally be obtained, noting that in some areas any level of data quality should be seen as an improvement to the quality of the outcome.

10. Conclusion

Legacy data governance implementations often lack centralization in access control, policy enforcement, and metadata management. These deficiencies expose organizations to operational and compliance risks, especially when business-unit-centric setups evolve into enterprises with multiple business units. A review of Databricks Unity Catalog highlights its role as a unified metadata layer that provides essential governance planks for the Databricks platform. When applied to governance, Unity Catalog delivers a framework catering to identity management, policy oversight, access boundaries, data-quality engineering, observability measures, data-steel, and data-classification needs. Support for metadata management functions—such as tagging and lineage tracing—further enriches the offering. Implementation is slated for a phased approach, commencing with an initial pilot phase.

Enterprises with multi-business-unit (BU) setups encounter challenges in data governance, especially when different BUs launch individual governance initiatives. These setups often lack centralized governance for data classification, data stewardship, regulatory compliance, risk, and security. In the absence of cross-BU policy harmonization and centralized management of access control, policy enforcement, metadata quality, and data quality, the prospects of regulatory breaches or difficulties in forensic analysis multiply. Burgeoning data volumes add to the pressure.

11. List of important References

Addressing the challenge of fragmented data governance across multiple-bu business environments using Databricks Unity Catalog, which provides centralized data-management capabilities such as data classification and data quality management, data lifecycle management, access management, and auditability. Addressing these governance aspects allows the implementation of best practices for data management in the data and analytics domain. The research culminates in a technical design of Databricks Unity Catalog and recommends a reusable reference architecture. It consists of multiple business catalogs hosted in separate Databricks workspaces yet sharing data assets for tenant mutualization. The implementation design is formulated using the example of Azure Data Lake Storage Gen2, where default permissions at Shopify, Azure Active Directory, and Storage levels are provided using role-based access control.

A multi-business-unit enterprise consists of several business units that operate independently and pursue their unique business objectives. Each of them typically has its own cloud tenants and operates in separate environments. However, many business units share the data from their data and analytics solutions for tenant mutualization. A consequence of this architectural independence is the lack of consistency across these infrastructures, leading to conflicts in data policy implementations; for example, retention and data-locations policies can differ from one environment to another, impacting compliance and risk processes. Furthermore, conflicts and gaps in policies for data observability can hinder any end-to-end trust in the analytics delivered by these solutions. A deployment or architectural design approach is desired that fosters harmonized data governance for auto-discovery and automatic-policy implementation across these multi-business-unit environments that leverage a common design in their data and analytics solutions. Such an architecture marketing strategy also enables business catalogs in a single governance framework, wherein data products are supplied by resident business units for other consumers.

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