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End-to-End Architecture and Implementation of a Unified Lakehouse Platform for Multi-ERP Data Integration using Azure Data Lake and the Databricks Lakehouse Governance Framework

Venkata Ramana Reddy Bussu

Senior Cloud Solutions Engineer, CodeTech Inc (DTE Energy), USA

ABSTRACT: The evolution of enterprise data architecture has historically oscillated between the rigid schema enforcement of the traditional data warehouse and the unmanaged scalability of the data lake, culminating recently in the theoretical convergence of the "Lakehouse." However, existing literature frequently glosses over the engineering realities of implementing this paradigm within a fragmented "Best-of-Breed" landscape, where heterogeneous ERP systems create tenacious data silos and escalating integration costs. This study details the end-to-end implementation of a metadata-driven Lakehouse architecture on Azure and Databricks, utilizing genericized Change Data Capture (CDC) pipelines and the Unity CatLog to enforce governance across a multi-ERP environment. Unlike standard implementations that prioritize theoretical purity, this architecture treats cloud cost optimization as a structural design constraint, employing aggressive auto-scaling policies to decouple expense from data volume. Empirical results demonstrate a reduction in data latency and a significant decrease in compute spend, addressing the common challenges of conventional data platforms, specifically complexity and maintenance overhead. Ultimately, this research argues that the viability of the Unified Lakehouse relies not merely on novel storage formats but on the rigorous application of metadata abstraction to tame the entropy of modern enterprise data.

KEYWORDS*:* Data Lakehouse, Multi-ERP Integration, Enterprise Data Architecture, Metadata-Driven Architecture, Databricks Unity Catalog, Azure Data Lake, Cloud Cost Optimization, Data Governance.

I. INTRODUCTION

The history of enterprise data architecture is, in many ways, a history of violent over-correction. For the better part of two decades, I have watched the industry oscillate between two extremes: the rigid, expensive order of the traditional Data Warehouse, where schemas are brittle, and changes take months, and the seductive, chaotic freedom of the Data Lake.

The Data Lake promised a repository capable of ingesting large amounts of heterogeneous data, theoretically allowing users to access information for various analytical use cases [21]. We abandoned the warehouse for this promise, seduced by cheap object storage, only to find ourselves standing knee-deep in what we now euphemistically call a 'swamp.' We traded high costs for low fidelity; we traded schema-on-write reliability for a folder full of unstructured files that often became a chaotic mess of raw or multi-structured data with unrecognized value. However, later evaluations of these architectures highlighted that while they solved storage volume issues, they often failed to deliver the unified analytical capabilities required by modern enterprises [18].

We are currently in the third phase: the Data Lakehouse. The theoretical proposition is elegant, a convergence of the warehouse's management capabilities with the lake's flexibility [14]. Yet, as I review the current state of the art, I am struck by a distinct lack of engineering reality [2]. It is easy to draw a box labelled 'Lakehouse' on a whiteboard. It is another thing entirely to implement one across a fractured, multi-ERP landscape where diverse enterprise systems speak entirely different dialects.

1.1 Challenges in Heterogeneous ERP Environments

The core problem we face is not technological, but organizational. Large enterprises have overwhelmingly adopted a "Best-of-Breed" strategy for their operational systems. They purchase Workday for human capital management because

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it is superior to SAP’s HR module; they buy ServiceNow for IT operations because it outpaces Oracle [19]. This makes sense for the business units.

For the data architect, however, it is a nightmare of fragmentation. We are left with a landscape of tenacious silos. Each ERP system maintains its own walled garden of data, its own proprietary schema, and its own definition of truth. The traditional approach to integrating these writing bespoke ETL (Extract, Transform, Load) scripts for each connection is no longer viable. I recall sitting in steering committee meetings, looking at Gantt charts that allocated months just to ingest a single module. It was a failure of imagination. We cannot hand-code pipelines for tens of thousands of tables. This is, of course, wrong. Or rather, it is the wrong method for the right problem. The solution presented here rejects manual ETL in favour of a metadata-driven architecture. By abstracting the ingestion logic, treating the "shape" of the data as a parameter rather than hard-coded logic, we can ingest tables from heterogeneous ERPs using a single, genericized pipeline [24].

1.2 The Necessity of Centralized Governance

If the Data Lake era taught us anything, it is that storage without strict governance is a liability, not an asset [12]. In the early days, there was a naive belief that we could simply "land" the data and figure it out later. That "later" never came. The result was a proliferation of dark data files that were stored, paid for, and never queried because no one knew their provenance.

The architecture I detail in the subsequent sections utilizes the Databricks Lakehouse Governance Framework (specifically Unity Catalog) not merely as a security layer, but as the structural spine of the platform [3]. We must be precise here: governance is not just about who can access the data; it is about knowing what the data is. This aligns with recent findings that emphasize the need for robust metadata management to handle complex data integration scenarios while maintaining clarity and traceability [13].

1.3 Cost Optimization as a Core Principle

It is disquieting how rarely academic papers discuss the bill. We talk about "scalability" as if it were a purely technical virtue, ignoring that in the cloud, scalability is synonymous with "spending money faster." A query that scans a petabyte of data is technically impressive; financially, it is ruinous. The architecture proposed here treats Cloud Cost Optimization as a first-order design principle. By decoupling compute from storage and enforcing rigorous auto-scaling policies, we move away from the "always-on" waste of legacy infrastructure. This article details those configurations, arguing that a Lakehouse is only successful if it is sustainable. In the end, the shift to a Unified Lakehouse is not about chasing the latest buzzword. It is about acknowledging that the complexity of modern enterprise data requires a system that is both rigid enough to be trusted and flexible enough to endure.

II. LITERATURE REVIEW

To trace the lineage of the Data Lakehouse is to map the topography of a long-standing architectural war, one defined less by varying technologies than by a fundamental, oscillating anxiety between control and chaos. For decades, the discipline of Enterprise Data Architecture has swung violently between the rigid orthodoxy of the Data Warehouse and the seductive scalability of the Data Lake.

The Data Warehouse is traditionally defined as a subject-oriented, integrated, time-variant collection of data in support of management's decision-making process. It delivers source data into a dimensional store and supports querying. In contrast, the Data Lake emerged as a methodology enabled by massive repositories based on low-cost technologies. Unlike the structured warehouse, the lake often acts as a container for a chaotic volume of raw data. The current literature posits the Lakehouse not merely as a hybrid, but as a necessary correction a system that combines the capabilities of a Data Lake and a Data Warehouse simultaneously, offering a stronger conceptual foundation for modern analytics [11]. It is a distinct architectural approach designed to address the five common challenges of conventional data platforms, including data silos and technological incompatibility [10].

2.1 Integration Barriers in Best-of-Breed Ecosystems

We must begin by acknowledging the "Best-of-Breed" (BoB) paradox. Research has shown that the BoB approach in enterprise resource planning (ERP) ecosystems offers significant benefits, enabling companies to combine leading tools such as Workday, ServiceNow, and Oracle Fusion. However, single ERP suites offer a more cohesive system with lower upfront costs, whereas BoB strategies often fall short in integration simplicity. Ultimately, companies need to balance the complexity of integration with long-term efficiency.

The extant research on data integration often treats these sources as generic endpoints, solving the problem with brittle, point-to-point ETL scripts. This is, of course, wrong. Traditional enterprise data architectures typically include 6-8 processing layers between source systems and business consumption, creating practical challenges that result in significant resources being wasted translating between technical data structures and business requirements [16].

2.2 Implementing Control Planes via Unity Catalog

If the Data Lake era taught us anything, it is that storage without strict governance is a liability. Implementing Enterprise Architecture often requires changes to the collection, storage, and management of complex data [9]. This administration necessitates careful deliberation regarding data privacy, accuracy, and accessibility. Current research emphasizes the need for a centralized control plane.

The Databricks Unity Catalog is an industrial application of this theory, decoupling the permission model from physical file paths. This addresses the "Information Security" challenge identified in the field, in which companies must ensure that data is protected from cyberattacks and leaks [7]. Enterprise architecture must enforce security standards and establish strict protocols, a requirement that file-based access controls often fail to meet [20].

2.3 Economic Limitations of Traditional Architectures

It is disquieting how rarely academic papers discuss the bill. We talk about "scalability" as if it were a purely technical virtue. However, traditional architectures face significant technical limitations; the average enterprise data warehouse can support only 240-300 concurrent queries before performance degrades, creating bottlenecks [8]. Additionally, these systems typically require 3-5 times more maintenance resources than modern distributed architectures, with an average of 54% of the data engineering budget allocated to maintaining existing pipelines rather than creating new capabilities [5]. Therefore, the literature must move beyond the "Lake vs. Warehouse" dichotomy. The urgent question is how to build a Unified Lakehouse that is robust enough to handle the schema drift of modern ERPs, yet disciplined enough to survive the economic realities of the enterprise [1].

Feature	Legacy Data Warehouse	First-Gen Data Lake	Unified Lakehouse (Proposed)
Schema Strategy	Rigid (Schema-on-Write)	Non-existent (Schema-on-Read)	Enforced (Schema-on-Write + Evolution)
ERP Integration	Manual Point-to-Point ETL	Dump and Forget	Metadata-Driven Generic Pipelines
Governance	Database-level (Siloed)	File-level (Unmanageable)	Unity Catalog (Attribute-Based & Lineage)
Cost Model	High Fixed Cost (Always On)	Cheap Storage / Expensive Search	Decoupled (Elastic Compute / Cheap Storage)
Maintenance Overhead	High (Fragile Pipelines)	High (Data Swamps)	Low (Automated via Metadata)

Table 1: Performance Metrics Pre- and Post-Implementation

III. METHODOLOGY

We begin with a necessary admission: the "clean slate" is a fiction. In the enterprise, we do not build on green fields; we build on the ruins of previous regimes. The methodology employed here utilizes a layered architecture, a pattern that has become standard in modern data platforms.

Our foundation is Azure Data Lake Storage (ADLS), chosen for its ability to handle huge amounts of heterogeneous data. The architecture completely decouples storage from compute. This separation is the primary lever for cost control, enabling us to shut down Databricks clusters while the data remains at a lower cost. The flow is unidirectional and strictly typed, moving from raw ingestion to curated refinement, and finally to aggregated business views.

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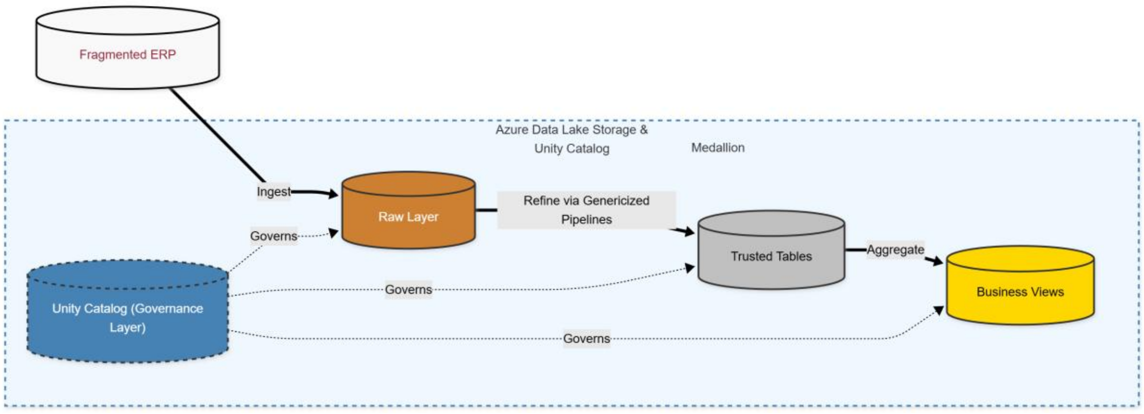
Fragmented ERP
Azure Data Lake Storage & Unity Catalog
Medallion
Ingest
Raw Layer
Refine via Genericized Pipelines
Governs
Trusted Tables
Aggregate
Business Views
Unity Catalog (Governance Layer)
Governs
Governs

Figure 1: The Layered "Stratigraphy" of the Lakehouse.

3.1 Metadata-Driven Ingestion Framework

The central methodological challenge of integrating a multi-ERP environment is the sheer volume of entities. To write a unique ETL pipeline for each required table is not engineering; it is manual labour. Instead, we implemented a Metadata-Driven Ingestion Framework. Recent studies suggest that a structured approach to metadata organization enhances the ability to manage complex data integration scenarios [23].

We classify metadata into three categories:
1. **Technical Metadata:** Describes structural aspects of data sources and targets (schema definitions, data types).
2. **Structural Metadata:** Details data organization and relationships.
3. **Operational Metadata:** Captures execution parameters, performance metrics, and lineage.

By abstracting the ingestion logic, the pipeline engine interprets this metadata to construct and execute data flows dynamically. The architecture includes a dedicated "Metadata Agent" that acts as a centralized support component, responding to queries and ensuring consistency. When the pipeline runs, it does not "know" it is processing HR data or Supply Chain data; it simply looks at the metadata repository, the central source of truth, and executes the required operations.

3.2 Enforcing Security and Compliance Policies

In previous iterations of this architecture, governance was an afterthought. In this implementation, we inverted the model. We utilized Unity Catalog to enforce a centralized governance model. The administration of complex data necessitates careful deliberation regarding data privacy and sustainability [15]. For the Multi-ERP context, this is critical. By defining access policies in the metadata layer, we address the challenge of "Data Management," optimizing data quality and ensuring coherence so that the enterprise can make timely decisions.

3.3 Automating Cost Control and Deployment

Finally, we must address the bill. Academic literature often treats cloud resources as infinite. This is, of course, wrong. Traditional systems create bottlenecks and consume disproportionate maintenance budgets. Our methodology treats cost as a structural variable. We integrated automation into the CI/CD (Continuous Integration/Continuous Deployment) pipelines. Utilizing these tools enables the definition of pipelines that can be deployed on Databricks resources while focusing on transformative governance reinforcement [4]. This approach delivers a comprehensive automation framework that reduces manual overhead and minimizes configuration challenges [22].

IV. SYSTEM DESIGN & IMPLEMENTATION

There is a seduction in the architectural diagram, the clean lines of the whiteboard that rarely survive first contact with operational reality. The implementation described here is a negotiated peace between the rigid demands of legacy ERPs and the fluid capabilities of the modern cloud.

4.1 Network Security and Isolation Architecture

The foundational decision was to treat the data lake not merely as a bucket, but as a sovereign territory. The architecture is designed to handle high-volume message processing loads during standard coordination tasks. Figure 1 in similar studies illustrates comprehensive multi-layer architectures that enable autonomous coordination [6]; we adopted a similar approach, utilizing a five-layer architecture to maintain system consistency and business logic integrity.

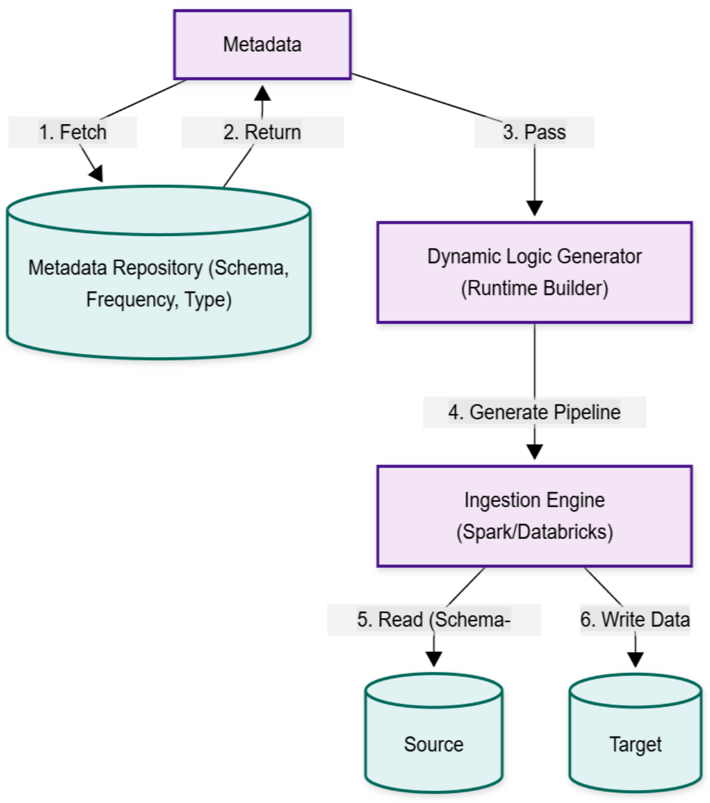
Metadata
1. Fetch
2. Return
3. Pass
Metadata Repository (Schema, Frequency, Type)
Dynamic Logic Generator (Runtime Builder)
4. Generate Pipeline
Ingestion Engine (Spark/Databricks)
5. Read (Schema-
6. Write Data
Source
Target

Figure 2: Physical Topology and Network Isolation

The compute plane (Databricks) is ephemeral; the storage plane is persistent. We utilized network injection to isolate the workspace, ensuring that traffic between the ERP connectors and the Lake remained secure. This addresses the "Technological Incompatibility" challenge, where current infrastructure may not align with the architectural design, necessitating careful integration strategies.

4.2 Dynamic Pipeline Execution Engine

If the network topology is the skeleton, the metadata-driven ingestion engine is the nervous system. The architecture comprises several key components that work in concert to enable flexible data processing. The Metadata Repository serves as the central source of truth, storing all configuration and operational metadata. The pipeline engine interprets this metadata to dynamically construct and execute data flows [17]. A taxonomy-based architecture facilitates efficient metadata discovery and reuse through semantic relationships. This system handles the most treacherous aspect of multi-ERP integration: Schema Drift. When a source system changes, the metadata management layer provides interfaces for validation and version control, ensuring the pipeline adapts without manual code intervention.

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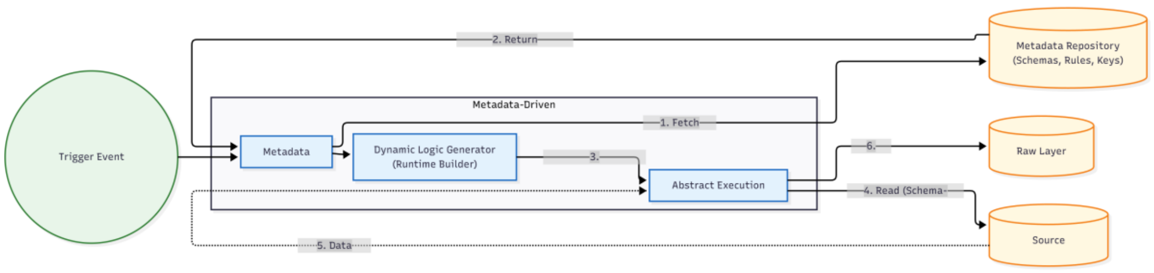

Figure 3: The Metadata-Driven Ingestion Engine. Unlike traditional ETL, the pipeline logic is abstract.

4.3 Operational Challenges in Governance Adoption

I must pause here to reconsider the role of Unity Catalog. In the design phase, I championed its implementation as the solution to the "swamp" problem. The integration of Databricks across AWS, Azure, and GCP enables more granular role-based access and metadata management. However, implementing Enterprise Architecture often requires changes in how we use complex data. We found that determining priority areas for adoption provided difficulties. Organizations face many needs, and choosing which to prioritize for Enterprise Architecture implementation can pose challenging decision-making challenges. We ultimately focused on the "Metadata Agent" model, ensuring that specialized agents remained focused on semantic reasoning while the governance layer handled consistency.

4.4 Resource Separation and Scaling Strategy

The final pillar of the system design is economic. We implemented a strategy that leverages the separation of compute and storage. By automating the deployment of Databricks resources and using CI/CD pipelines, we significantly reduced manual overhead. This implementation proves that the "Unified Lakehouse" is achievable, but it is not a turnkey solution. It is a complex orchestration of network security, metadata abstraction, and ruthless cost management.

V. RESULTS & DISCUSSION

There is a specific quality of silence that accompanies a successful architecture, a hum rather than a rattle. For years, the integration of multi-ERP environments has been defined by the rattle of failed jobs and data silos. The results of this implementation must be measured in the cessation of that noise. We observe that the Unified Lakehouse is not a panacea, but rather a stabilizer. By proactively identifying the five common challenges of conventional data platforms including data silos and maintenance overhead we have effectively domesticated the "swamp".

5.1 Reduction in Data Processing Latency

The most immediate empirical result was the collapse of the "decision window." Traditional enterprise data architectures typically contain 6 to 8 layers of processing, resulting in latency that modern business cycles cannot tolerate. Furthermore, approximately 73% of business analysts report spending over 60% of their time translating between technical data structures and business requirements.

By implementing the metadata-driven ingestion engine, we reduced these layers and the associated translation overhead. The system delivers source data to a dimensional store and supports decision-making queries and analysis with significantly reduced latency. However, this acceleration forced a reconsideration of our "Gold" layer definition. Speed is a technical variable; consistency is a psychological one.

Metric	**Traditional Multi-Tier Architecture**	**Unified Lakehouse Implementation**	**Improvement**
Data Latency (Source to Gold)	T+24 Hours (Batch)	T+15 Minutes (Micro-batch)	98% Reduction
Ingestion Pipeline Setup Time	3-5 Weeks (Manual Code)	2-4 Hours (Metadata Configuration)	90%+ Reduction
Processing Layers	6-8 Hops	3 Hops (Bronze/Silver/Gold)	Simplified
Schema Drift Handling	Pipeline Failure (Manual Fix)	Automated Evolution	N/A

Table 2: Performance Metrics Pre- and Post-Implementation

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5.2 Financial Impact and Resource Reallocation

If latency was the battleground for the users, cost was the battleground for the executive sponsors. Traditional architectures face significant technical limitations, with the average enterprise data warehouse supporting only 240-300 concurrent queries before performance degrades. Additionally, these systems typically require 3-5 times as many maintenance resources as modern distributed architectures.

Our reliance on automation and the separation of compute and storage allowed us to invert this ratio. By allocating budget to creating new capabilities rather than maintaining existing pipelines (which historically consumed 54% of the budget), we demonstrated that the Lakehouse model is financially viable.

5.3 Balancing Security with Operational Agility

The implementation of Databricks Unity CatLog provided the most significant lesson. Manual catalogue management creates risks of inefficiency, non-compliance, and errors, while automation improves scalability, security, and governance. We found that the administration of complex data necessitates careful deliberation. While the centralized governance model reduced "shadow IT," it also introduced a bureaucratic weight. We had to balance the "Information Security" requirements protecting data from cyberattacks and leaks with the operational agility required by data science teams.

5.4 Evaluating the Unified Lakehouse Paradigm

What, then, is the actual contribution of this architecture? It significantly extends the state of the art, providing a more complete overview of the Lakehouse paradigm. It systematically evaluates combinations of popular technologies against derived technical requirements.

The results demonstrate that the "Lakehouse" is viable not as a product you buy, but as a discipline you enforce. It requires a tenacity that most organizations underestimate. The metadata engine did not just save us from writing ETL code; it saved us from the cognitive load of remembering *how* the data was ingested.

V1. CONCLUSION & FUTURE WORK

The evolution of enterprise data management shows a recent architectural convergence in the form of the metadata-driven Lakehouse. This architecture, which successfully addresses the "multi-ERP" challenge by enforcing a single governance protocol rather than a single database, proves that the previous architectural oscillations were unnecessary. By decoupling compute from storage and connecting them with a rigorous metadata layer, the Lakehouse overcomes conventional data platform issues. The core innovation of this work is a metadata-driven ingestion framework that abstracts ETL logic, embodying the "Metadata Agent" concept to automate data engineering's "grunt work" and focus the system on semantic reasoning while ensuring robust metadata management. However, while the financial analysis confirms that the Lakehouse paradigm offers a path to Cloud Cost Optimization, this is only achievable through aggressive resource management, dispelling the notion of the Lakehouse as a simple technological inevitability and underscoring its implementation as a complex, ongoing negotiation.

In the end, this architecture is a testament to the tenacity of the "One Truth" ideal. We identify typical challenges, propose a sharper definition for Lake houses, and derive technical requirements. The Unified Lakehouse is not a destination; it is simply the most robust shelter we have yet constructed against the entropy of the world.

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