



Lakehouse in Action

Design Strategies, Common Pitfalls, and Real-World Gains

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Data & AI Architecture Sydney | 04 Mar 2026

The Lakehouse Isn't the Innovation Anymore — How You **Govern, Own, and Evolve** It Is

What We Actually Built — A Practitioner's Architecture

Consumption and Intelligence

Portal

Self-Service Analytics

Governed Reporting

Applications

AI Agents and Models

Platform
Quality
and
Operations

DevOps
and CI/CD

Monitoring and
Observability

SLOs and
Reliability

Cost
Management

Servicing — Semantic and Presentation Layer

Zero-copy federation — no data duplication

Data Marts

Certified Metrics

Reports and Dashboards

APIs

Lakehouse — Business Domain Data Models

Bronze

Silver

Gold

Organised by source

Organised by business domain

Stream Compute

Lake Compute

ML and Data Science

Integration and Exchange

Data Lake Storage

Hot Tier — Frequently Accessed Data

Warm Tier — Occasionally Accessed Data

Cold Tier — Rarely Accessed / Archive

Ingestion and Orchestration

Parameterised ELT

Event-driven triggers

Reusable pipelines

Self-service config

Real Time

Shortcuts

CDC

Mirroring

Event Stream

Source Systems

Operational databases

SaaS applications

Files and extracts

Cloud data Lakes

Streaming events

APIs

Domain
Ownership
(Data Mesh)

Domain teams
own
data products

Self-serve
ingestion

Federated
governance

Data Governance Foundation

Data Quality

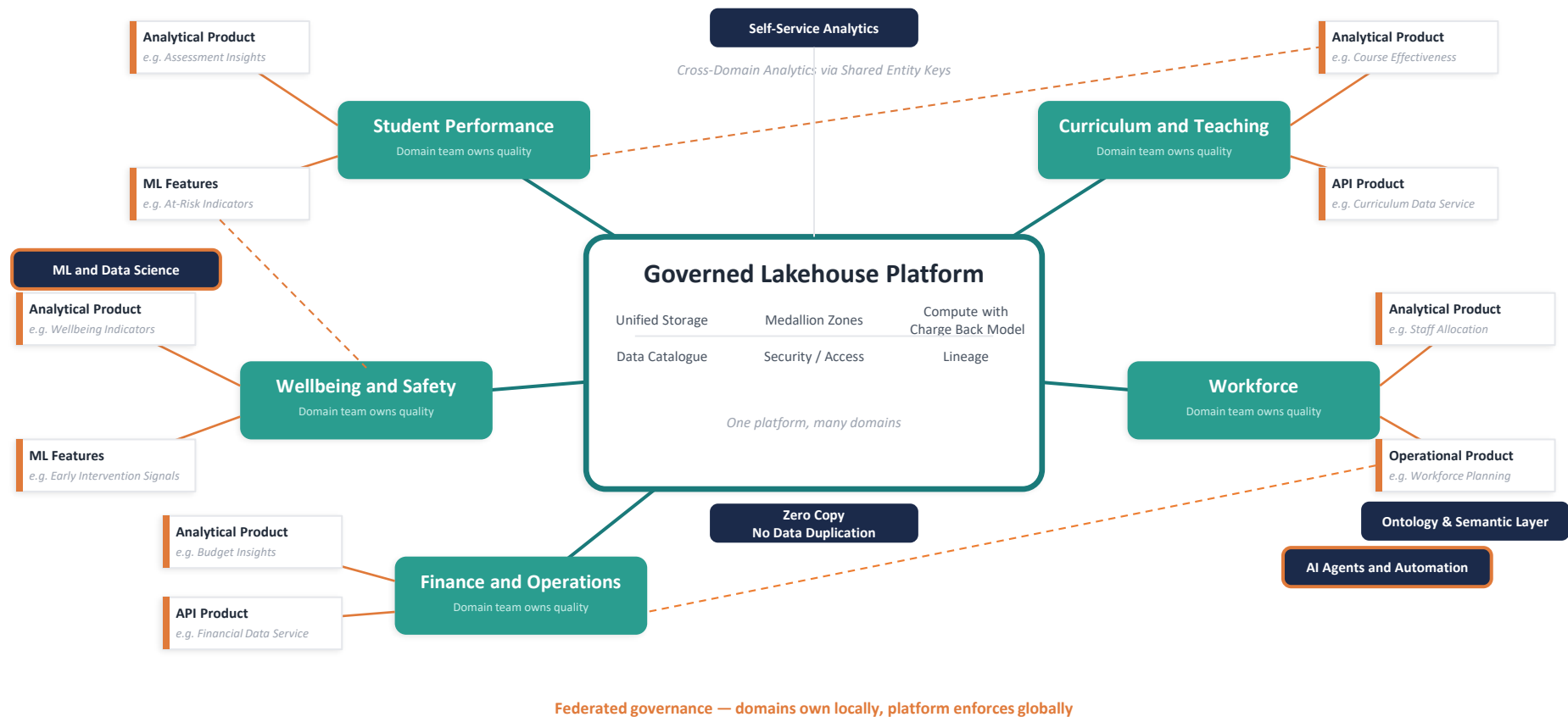
Access Management

Metadata Management

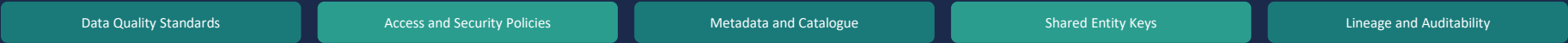
Master Data Management

Lineage

From Central Lake to Domain Ownership — The Mesh Operating Model



Federated Governance Framework



Six Decision Areas That Define Lakehouse Success

ORGANISATIONAL ARCHITECTURE

1



Business-aligned use case sequencing

2



Data ownership and product boundaries

3



Governance by design

OPERATIONAL ARCHITECTURE

4



Performance and reliability architecture

5



Trusted consumption and semantic layer

6



AI-readiness as a design requirement

Organisational Architecture: Sequencing, Ownership, Governance



1

Use case sequencing

Start where the pain is, not where the engineering is easy. Prove value in 2–3 domains, then expand.



2

Data ownership

Domain teams own data as products with SLAs — not a central team bottleneck. Mesh is an operating model, not a technology.



3

Governance by design

Embed from sprint one. Classification, access control, lineage, auditability. Retrofitting costs 5–10x more.

Architect: Ownership boundaries and control-point decisions

Business: How you avoid the platform becoming a queue

Operational Architecture: Performance, Trusted Consumption, AI-Readiness



4

Performance & reliability

Design for operational SLOs, not reactive tuning. Workload isolation, compaction, observability from day one.



5

Trusted consumption & semantic layer

Bridge the gap between technical schemas and business concepts. One vocabulary for analysts and AI agents.



6

AI-readiness

Governed data + business ontology = foundation for safe, scalable AI. A design requirement, not a future concern.

BUSINESS CONCEPTS

"Attendance rate" · "At-risk student" · "Course improvement"



SEMANTIC LAYER / ONTOLOGY

Maps business language to technical assets and metrics



TECHNICAL ASSETS

Tables · Columns · Pipelines · Certified datasets

The Translation Gap

What Breaks in Practice

These are the patterns that repeatedly create delays, performance issues, and trust erosion.

Pitfalls: Migration Thinking, Late Governance, Wrong Metrics

PITFALL



Treating lakehouse as a technology migration

Lift & Shift or Uplift?



Governance implemented too late



Success = data landed, not data trusted

CONSEQUENCE

Same bottlenecks, new platform.
6–12 months rework.

5–10x retrofit cost. Security friction. Lost confidence.

High ingestion, low adoption.
Investment without value.

PREVENTION



Hybrid approach — Retire legacy fast and reduce risks

Modernize incrementally with new patterns



Redesign ownership — not just pipelines.

Governance from sprint one.



Track certified outputs, usage, and decision-use cases.

Pitfalls: Reactive Performance, Building Ferraris for Push-Bike Riders

PITFALL



Performance treated as tuning, not architecture

CONSEQUENCE

User trust declines faster than engineers expect.

PREVENTION



Design for SLOs, observability, compaction from day one.



Building a Ferrari when users are on push bikes

High capability, low adoption.
Platform nobody uses.



Meet users where they are.
Invest in onboarding, ontology and enablement alongside engineering.

PLATFORM CAPABILITY

USER READINESS

THE GAP

Four Lenses for Communicating Lakehouse Value



Risk & Trust

Governance and security posture

"Months to weeks" for access approvals



Delivery Agility

Faster onboarding of new sources

"Weeks/months to days/weeks" for time-to-market



Adoption & Confidence

Business trust and platform usage

"Data as value enabler, not cost to justify"



AI-Readiness

Governed foundation for safe AI

"Agents grounded in governed, semantic data"

From Data Landed to Data Trusted — and AI-Ready

BEFORE

Data seen as a cost to justify

Cross-domain questions require weeks of analyst work

AI pilots build their own data pipelines

“How much data is in the lake?”



AFTER

Data seen as a value enabler

Cross-domain questions answerable through semantic layer

AI agents query governed, certified data products

“How much data is trusted, consumed, and informing decisions?”

What Success Looks Like

A successful lakehouse is **not defined by ingestion or data volume**

It is defined by **trusted consumption, governed scale, and operational reliability**

Its long-term value is realised when it becomes a **foundation for faster delivery and AI-readiness**

THREE TAKEAWAYS

1

Start with decision frameworks, not vendor features

2

Design governance and operability from day one

3

Build for the user you have today, not the user you wish you had

Questions + Discussion

“How is your organisation measuring lakehouse success beyond data landed?”

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