



Whitepaper

Before the Algorithm

From Framework to
Execution:
How to Make Data
Governance Work in
Practice
(Part 2/2)

Introduction

Most organizations today recognize that data governance is essential. It underpins compliance, enables analytics and AI, and ensures trust in decision-making. At the same time, many leadership teams—especially CIOs—have already explored industry frameworks and often arrive at the same conclusion:

“Data governance is necessary, but everything we see is too heavy, too theoretical, and too slow to implement.”

This observation is valid.

Traditional frameworks describe **what should exist**, but they do not sufficiently describe **how to make it real in a living data ecosystem**.

This whitepaper provides that missing piece.

It introduces a **pragmatic, execution-first approach to data governance**, built on three core ideas:

Governance must be applied to **datasets**, not abstract domains

Governance must be expressed as **Decision, Enforcement, and Evidence (DEE)**

Governance must be structured but not overloaded, using the **11 core capabilities as a complete—but modular—scope**

This document is not a replacement for the capability framework (part 1/2). It is the **operational complement** to it.

The Problem with Traditional Data Governance

Over the past decade, many organizations have invested significant time and effort in data governance initiatives. Yet, despite good intentions and substantial resources, a large proportion of these programs fail to deliver meaningful or lasting results.

This is not because data governance itself is flawed.

It is because of **how it is typically approached**.

Across industries, governance programs tend to fail for a number of predictable and recurring reasons.

They start with frameworks, not reality

In many cases, organizations begin their governance journey by adopting established frameworks and best practices. This often includes:

- defining capability models
- performing maturity assessments
- designing policies and governance structures

While these steps are valuable in principle, they introduce a critical problem when used as a starting point.

They focus on: what governance *should* look like rather than: what data is actually used, shared, and at risk. As a result, a fundamental question is often overlooked:

What data are we actually governing?

Without a clear answer to this question, governance efforts risk becoming disconnected from operational reality. They describe an ideal state, but not the actual data landscape of the organization.

They overload the organization

Traditional approaches to governance often translate into large organizational structures and processes.

Governance becomes associated with:

- committees and working groups
- extensive documentation
- formal approval and escalation processes

While these structures are intended to create control and alignment, they frequently have the opposite effect.

They consume time and energy without directly improving how data is managed.

At the same time, they fail to address what truly drives effective governance:

- clear ownership of data
- automated controls embedded in systems
- measurable and verifiable outcomes

This creates a disconnect between governance activities and business value.
Governance is perceived as overhead rather than as an enabler.

They lack operational grounding

Even when policies, roles, and processes are defined, a deeper issue often remains:

governance is not embedded in daily operations

In practice:

- rules are defined, but not consistently enforced
- controls are implemented in some systems, but not others
- responsibilities exist on paper, but are not exercised

Perhaps most critically:

- there is limited ability to prove that governance is actually working

When asked:

- who accessed this data?
- whether retention rules were applied
- or whether data quality is being monitored

the answers are often incomplete or difficult to produce.

The result: Governance without impact

The combination of these issues leads to a situation that is increasingly common in organizations:

governance exists—but only superficially

Policies are documented.

Frameworks are adopted.

Processes are defined.

But:

- enforcement is inconsistent
- ownership is unclear
- evidence is lacking

This creates what can be described as: **“Governance theater”**

An environment where governance appears to be in place, but does not meaningfully influence how data is managed, protected, or used.

A clear need for a different approach

The limitations of traditional governance models do not imply that governance should be simplified or reduced.

On the contrary:

- the scope defined by the 11 capabilities remains essential
- regulatory and operational expectations continue to increase

However, what is required is a different starting point and a different method.

One that:

- begins with real data
- focuses on ownership and execution
- embeds governance into systems
- and makes outcomes visible and measurable

The remainder of this whitepaper presents such an approach—one designed to bridge the gap between governance as a concept and governance as a working, scalable capability within the enterprise.

Reconnecting with the Full Scope: Why the 11 Capabilities Remain Foundational

In the first whitepaper of this series, we introduced the **11 Data Governance capabilities** as the complete scope of what it means to govern data effectively. Before shifting our focus to the *how*, it is important to briefly reconnect with that foundation.

The 11 capabilities represent a **stable and complete view of the data governance landscape**. They define everything an organization must ultimately be able to control, including:

- Data Classification
- Access Control
- Encryption
- Data Quality
- Metadata Management
- Compliance
- Lifecycle Management
- Consolidation
- Cost Management
- Monitoring & Auditing
- Incident Response & Disaster Recovery

Taken together, these capabilities form a **full control surface over enterprise data**. They ensure that data is:

- protected against risk
- aligned with business value
- trusted by users and systems
- reliable in daily operations

In other words, they answer a critical question for any CIO or data leader:

“What must we be able to govern to manage data responsibly and at scale?”

However, as most organizations quickly discover, having a complete scope does not automatically lead to effective governance.

The capability model tells us **what needs to exist**.

It does not tell us **how to implement, prioritize, and operationalize governance in a pragmatic way**—without creating unnecessary complexity or slowing down the business.

This is precisely where many traditional approaches fall short.

The purpose of this second whitepaper is to close that gap.

It introduces a way to take the full scope defined by the 11 capabilities and translate it into a **practical, scalable, and execution-focused approach**—one that connects governance directly to real data, real usage, and real accountability within the organization.

The Core Shift: From Framework to Dataset

A fundamental shift is required to make data governance work in practice.

It is a shift away from thinking in terms of **frameworks, domains, or systems**, and toward thinking in terms of **datasets**.

Governance applies to datasets

In many organizations, governance initiatives are organized around:

- systems (CRM, ERP, data warehouse)
- domains (customer, finance, operations)
- organizational structures (departments, teams, functions)

While these perspectives are useful from an architectural or organizational point of view, they are **not the right level at which governance actually operates**.

Data governance does not happen:

- at the system level (because the same data exists across systems)
- at the domain level (because domains are often loosely defined)
- or at the organizational level (because ownership becomes fragmented)

Instead, governance becomes actionable only when it is applied to:

Datasets — the real units of value, risk, and usage within the enterprise

What is a dataset in this context?

A dataset is not just a table, a file, or a technical structure.

It is a **governed object** that exists because it serves a purpose.

For governance purposes, a dataset can be defined as:

- a reusable collection of data
- with a clear and sustained business purpose
- with identifiable consumers (teams, processes, or systems)
- with explicit ownership and accountability
- and with measurable impact (business value, operational dependency, or risk exposure)

This definition is critical. It ensures that governance is applied only where it matters—on data that is actually used, shared, and impactful.

Examples of enterprise datasets

Across industries, the same types of datasets typically emerge:

- Customer Master — identity and contact information
- Billing Data — financial transactions and invoices
- Product Catalog — products, pricing, classifications
- Sensor or Consumption Data — operational or IoT measurements

Each of these datasets:

- is reused across multiple systems and processes
- has business significance
- carries risk if mismanaged
- and therefore requires governance

Why datasets change everything

Shifting the focus to datasets fundamentally transforms how governance is approached.

1. Governance becomes anchored in reality

Instead of discussing abstract capabilities or policies, governance is tied to:

- concrete data assets
- real usage patterns
- actual business dependencies

This immediately increases relevance and engagement from both business and IT stakeholders.

2. Ownership becomes explicit

When governance is applied at the dataset level, ownership can no longer be vague.

Each dataset requires:

- a clear business owner
- identifiable stewards
- defined responsibilities

This removes one of the most common failure points in governance programs: **unclear accountability**.

3. Controls become meaningful

Controls such as access restrictions, quality rules, or retention policies are no longer generic.

They are:

- applied to specific datasets
- aligned with specific risks and use cases
- implemented where they actually matter

This avoids both under-governance and over-governance.

4. Improvements become measurable

Because datasets are discrete units, governance can be assessed and improved incrementally:

- Which datasets have missing ownership?
- Which lack retention policies?
- Which are not adequately monitored?

This makes governance:

- diagnosable
- trackable
- and continuously improvable

What happens without a dataset-based approach

Without this shift, governance typically struggles in predictable ways:

- Governance remains **abstract**
(discussions stay at policy or framework level)
- Responsibilities remain **unclear**
(no one owns specific data)
- Effort is **misdirected or wasted**
(heavy initiatives without visible impact)
- Controls are **inconsistent or ineffective**
(implemented unevenly across systems)

In such environments, governance often becomes: something that exists on paper, but not in practice

The foundation for pragmatic governance

The move to datasets is not just a conceptual improvement—it is the **foundation that makes everything else possible**:

- It enables the DEE model (Decision, Enforcement, Evidence) to be applied concretely
- It provides the anchor point for applying the 11 capabilities where they are needed
- It creates a scalable structure for governance across the enterprise

From this point forward, governance is no longer about managing abstractions. It becomes about governing the data that actually drives the business.

This is the core shift that turns data governance from a theoretical discipline into a practical, operational capability.

The Operating Model: Decision, Enforcement, Evidence (DEE)

The second key concept of this approach is the **DEE operating frame — Decision, Enforcement, and Evidence**.

If datasets define *where* governance applies, DEE defines *how governance actually works*.

It is a deliberately simple model, built around three fundamental questions that must be answered for every dataset and every governance capability.

Every aspect of governance must answer three questions

For governance to be operational, complete, and scalable, each dataset must be evaluated through three lenses.

Decision — defining intent and ownership

The first dimension is **Decision**.

It answers:

- Who is accountable for this data?
- What rules apply to it?
- Why does the data exist in the first place?

Decision includes elements such as:

- ownership (who decides and approves)
- definitions (what the data means)
- classification (how sensitive it is)
- lawful purpose (why it can be used)
- retention rules (how long it should exist)

In essence, Decision defines the **intent and boundaries** of governance.

Without Decision:

- there is no clarity
- there is no ownership
- and no one can be held accountable

Enforcement — making governance real

The second dimension is **Enforcement**.

It answers:

- How are the rules implemented in practice?
- Which platforms or systems enforce them?
- Are these controls automated or manual?

Enforcement includes:

- access control mechanisms (RBAC, IAM)

- technical safeguards (encryption, masking)
- data quality checks
- lifecycle automation (retention, deletion)
- integration controls (APIs, pipelines)

This is where governance moves from:

policy to execution

Without Enforcement:

- rules exist only on paper
- behavior remains uncontrolled
- governance cannot scale

Evidence — proving that governance works

The third dimension is **Evidence**.

It answers:

- How do we demonstrate that governance is working?
- What proof do we have?
- Can we show it immediately when needed?

Evidence includes:

- access logs and audit trails
- data lineage and traceability
- quality metrics and validation reports
- retention and deletion logs
- access reviews and approvals

Evidence transforms governance into something that is:

- verifiable
- auditable
- and defensible

Without Evidence:

- governance cannot be proven
- audits become costly and reactive
- trust remains uncertain

Why DEE matters: diagnosing real governance maturity

One of the key strengths of the DEE model is that it does not just describe governance — it allows us to **diagnose where governance is broken**.

In practice, most organizations are not missing governance entirely.

They are **unbalanced across the three dimensions**.

Typical imbalance patterns

Situation	What is happening in reality
Decision only	Policies exist, but they are not followed in practice
Enforcement only	Systems enforce rules, but nobody knows why or owns them
Evidence only	Logs and data exist, but no one interprets or owns them

These situations are extremely common:

- A policy defines retention, but no deletion job exists
- Access is restricted, but roles are not business-defined
- Logs are collected, but never reviewed

Each of these represents **partial governance** — not effective governance.

The power of combining all three

Only when **Decision, Enforcement, and Evidence are present together** does governance become:

- real — because rules are implemented
- scalable — because controls are automated
- defensible — because proof exists

This combination creates a closed loop:

- Decisions define what must happen
- Enforcement ensures it happens
- Evidence proves that it happened

This loop is what transforms governance from: a static set of policies into: a living operational system

DEE as a simplification mechanism

Another key benefit of DEE is that it simplifies governance dramatically.

Instead of navigating complex frameworks, stakeholders can always return to three questions:

- Who decides?
- How is it enforced?
- What is the evidence?

This makes governance:

- accessible to business stakeholders
- understandable for IT teams
- actionable for delivery teams
- and clear for auditors

DEE as the bridge between theory and execution

The 11 capabilities define **what must be governed**.

Datasets define **where governance applies**.

DEE defines:

whether governance actually works

It is the mechanism that connects:

- policy → platform
- ownership → automation
- intent → proof

Without DEE, governance risks remaining conceptual.

With DEE, governance becomes **operational by design**.

From fragmentation to coherence

In many organizations, Decision, Enforcement, and Evidence exist — but they exist separately:

- policies are written by governance teams
- enforcement is implemented by IT
- evidence is collected by audit or security

But they are not aligned.

DEE brings these elements together into a single, coherent model, ensuring that for every dataset:

- ownership is clear
- controls are consistent
- proof is available

Conclusion of this chapter

The DEE operating model is the **engine of pragmatic data governance**.

It provides:

- a simple structure
- a powerful diagnostic tool
- and a scalable way of working

Combined with the dataset-based approach, it ensures that governance is not just designed — but **executed, measured, and continuously improved**.

From this point onward, governance is no longer about asking:

“Do we have policies?”

But about asking:

“For this dataset — who decides, how is it enforced, and what is the evidence?”

The Practical Method

The strength of this approach lies not only in its concepts, but in the way it is applied in real environments.

Rather than launching large-scale governance programs or abstract maturity exercises, this method follows a **clear, repeatable sequence** that anchors governance directly in the data that matters.

It is designed to be:

- fast to initiate
- easy to explain
- scalable over time
- and immediately actionable

Step 1 — Identify the datasets

Every governance effort begins with understanding **what data actually exists and matters**.

At this stage, the focus is not on perfection or completeness, but on identifying the datasets that:

- are actively used
- support key business processes
- drive reporting or decisions
- carry regulatory or operational risk

The key questions are:

- What data is used across the organization?
- Which datasets are critical to operations or decision-making?
- Where does risk concentrate (e.g., personal data, financial data)?

This typically results in:

- a prioritized list of datasets (often 5–15 to start)
- an initial view on ownership and usage
- a first understanding of dependencies between datasets

The objective is simple: **anchor governance in reality, not in theory**

Step 2 — Apply DEE per dataset

Once datasets are identified, governance becomes operational by applying the **Decision, Enforcement, Evidence (DEE)** model to each dataset.

For every dataset, three core questions are asked:

- **Who decides?**
 - Is there a clear owner?
 - Are definitions, rules, and purpose known?
- **How is it enforced?**

- Are there technical controls in place?
- Are these controls consistent and automated?
- **Where is the evidence?**
 - Can we demonstrate usage, control, and compliance?
 - Are logs, lineage, or metrics available?

This step transforms governance from: a conceptual discussion into: a concrete assessment of how data is actually managed.

It also reveals very quickly where governance is incomplete or inconsistent.

Step 3 — Map capabilities where needed

At this point, the 11 capabilities are introduced—not as a starting framework, but as a **lens to structure what is observed**.

Instead of asking:

“Have we implemented Data Quality governance?”

the question becomes:

“For this dataset, are data quality rules defined, enforced, and measurable?”

This is a subtle but important shift.

The capabilities help to:

- ensure completeness
- avoid blind spots
- provide a shared vocabulary

However, they are applied **selectively and proportionally**:

- Not every dataset requires deep controls across all capabilities
- Critical datasets may require full coverage
- Less critical datasets receive lighter governance

This keeps governance:

- focused
- efficient
- and aligned with business value and risk

Step 4 — Identify gaps

With datasets assessed through DEE and viewed through the capability lens, gaps become immediately visible.

These gaps typically fall into three categories:

Missing Decision

- no clear owner
- unclear definitions
- no retention rules

Missing Enforcement

- rules exist but are not implemented
- controls are manual or inconsistent
- no automation

Missing Evidence

- no logs or metrics
- no lineage
- no auditability

These are not theoretical maturity gaps.

They are **concrete, dataset-level issues** that impact:

- compliance
- operational efficiency
- data trust

This is the moment where governance becomes: **diagnosable and actionable**

Step 5 — Build a roadmap

The final step is to convert identified gaps into a **practical roadmap**.

This roadmap is fundamentally different from traditional governance plans.

It is:

- based on real datasets
- derived from observed issues
- prioritized by impact and risk

Typical prioritization criteria include:

- business criticality of the dataset
- regulatory exposure
- operational dependency
- ease of implementation

The resulting roadmap typically includes:

- **Quick wins**
 - assigning ownership
 - basic access control improvements
- **Structural improvements**
 - lifecycle automation
 - quality rules
 - metadata visibility
- **Longer-term enablers**
 - platform integration
 - monitoring and observability
 - governance automation

From methodology to operating discipline

What makes this approach powerful is that it does not end after a single assessment.

Instead, it establishes a **repeatable operating discipline**:

- new datasets can be onboarded continuously
- governance can be expanded incrementally
- improvements can be tracked over time

Governance evolves from: a project into: a continuous practice

What this approach changes

By following this sequence, data governance is fundamentally transformed.

It becomes:

- concrete — tied to real datasets
- transparent — gaps are visible and understood
- manageable — work is scoped and prioritized
- measurable — progress is visible
- scalable — applied dataset by dataset

Most importantly, governance shifts from being perceived as:

an overhead or compliance burden

to becoming:

a structured way to improve how data is used, trusted, and controlled

Conclusion of this chapter

This practical method is the bridge between:

- the complete scope of the 11 capabilities
- and the operational reality of managing data

It replaces abstract governance initiatives with a **clear, step-by-step approach** that:

- starts from data
- uses DEE to structure thinking
- leverages capabilities for completeness
- and delivers a concrete, prioritized roadmap

In doing so, governance becomes what it was always meant to be: **a diagnostic and improvement discipline that continuously strengthens how data supports the business**

Example: Customer Master Dataset

Worked Example: Customer Master Dataset

To make the approach tangible, we walk through a realistic example based on a common and business-critical dataset: the **Customer Master**.

The purpose of this example is not to show a “perfect” implementation, but to demonstrate:

- how governance becomes concrete at dataset level
- how DEE is applied in practice
- how the 11 capabilities naturally emerge
- and how gaps and actions are identified

Dataset Definition

Dataset Name: Customer Master

Purpose: Single source of truth for customer identity

Included:

- customer_id
- name
- address
- contact details

Explicitly excluded:

- billing data (handled in the Billing dataset)
- consumption data (handled in operational datasets)
- interaction history (handled in CRM activity datasets)

This explicit scoping is important.

It ensures that:

- the dataset has a clear boundary
- overlap with other datasets is avoided
- ownership remains focused and meaningful

Owner: Head of CRM

Criticality: Level 1 (GDPR + strong operational impact)

Data Flow

Understanding where the data comes from and where it goes is essential for governance.

- **Source:** CRM system
- **Upstream:** customer onboarding process
- **Downstream:**
 - billing system
 - analytics platform
 - reporting solutions

This shows that the dataset is:

- widely reused
- business-critical
- and a dependency for multiple processes

This immediately justifies why this dataset requires structured governance.

DEE Applied

At this stage, governance becomes operational.

Decision

- Owner: CRM
- Definition: “customer = active contract”
- Classification: Confidential (PII)
- Retention: 10 years

These elements define:

- what the dataset represents
- how it should be treated
- and under which conditions it exists

Enforcement

- Access via RBAC (role-based access control)
- Data masking in BI tools
- Deduplication rules via MDM
- Encryption at rest and in transit

This is where governance moves from intention to implementation.

Controls are embedded in:

- identity systems
- data platforms
- integration processes

Evidence

- Access logs
- Lineage available in data catalog
- Duplicate ratio reports
- Deletion logs
- Periodic access reviews

Evidence ensures that governance is not assumed—but proven.

Mapping to the 11 Capabilities

Once DEE is applied, the full scope of governance becomes visible.

Capability	Concrete implementation
Classification	PII is labelled as confidential
Access Control	Role-based access model
Encryption	Platform-level encryption
Data Quality	Deduplication rules enforced
Metadata	Definition of “customer” documented
Compliance	GDPR lawful purpose defined
Lifecycle	Retention and deletion defined
Consolidation	CRM is the golden source
Cost	Storage tiering applied
Monitoring	Alerts for unusual access
Incident/DR	Backup and restore procedures

Importantly, these capabilities are not implemented in isolation. They emerge naturally as part of governing the dataset.

Identified Gaps (Realistic)

Even in relatively mature environments, gaps are immediately visible when using this approach.

Typical findings include:

- No automated deletion process, despite defined retention
- Inconsistent interpretation of “active customer” across systems
- No formal evidence of access reviews
- Deduplication logic exists but is not consistently enforced

These gaps are:

- specific
- understandable
- and directly linked to risk or inefficiency

Resulting Actions

Because the gaps are concrete, the resulting actions are equally concrete:

- Formalize and approve retention policy (Decision)
- Implement automated deletion process (Enforcement)
- Introduce periodic access recertification (Evidence)
- Strengthen MDM deduplication rules (Enforcement + Quality)

This demonstrates a key strength of the approach:

Governance improvements are not abstract—they are directly actionable at dataset level.

Key Takeaways from the Example

This example highlights several important principles:

1. **Governance becomes tangible**
It is no longer about frameworks, but about how a specific dataset is managed.
2. **DEE structures the conversation**
It ensures that ownership, controls, and proof are all addressed.
3. **Capabilities provide completeness**
They ensure nothing important is overlooked.
4. **Gaps become visible immediately**
Without the need for heavy assessments or scoring models.
5. **Actions follow naturally**
Because issues are clearly defined and localized.

From Example to Practice

While this example focuses on a single dataset, the same logic can be applied across the organization:

- start with a small number of critical datasets
- apply DEE consistently
- use capabilities as a guiding lens
- identify and address gaps incrementally

This creates a scalable path toward enterprise-wide governance—without requiring a large upfront transformation.

Conclusion of this example

The Customer Master example illustrates the essence of the approach:

Governance is not implemented globally all at once.

It is built dataset by dataset, through clear decisions, enforced controls, and verifiable evidence.

This is how governance moves from theory to practice—and starts delivering real value.

Scaling Across the Enterprise

Once the approach has been applied successfully to a first dataset, its real strength becomes visible: it is **naturally scalable**.

Unlike traditional governance programs that attempt to cover the entire organization at once, this method scales **incrementally and organically**, starting from a limited number of high-impact datasets and expanding outward.

From one dataset to many

After working through an initial dataset—such as Customer Master—the same method can be applied to additional datasets across the enterprise. Typical examples include:

- Customer Master
- Billing Data
- Consumption or operational datasets

Each of these datasets:

- plays a different role in the business
- carries different types of risk
- and requires different governance controls

By applying the same structured approach (dataset definition + DEE + capability lens), governance can be extended without increasing complexity.

Different datasets reveal different problems

A key insight when scaling is that **governance is not uniform across datasets**.

Each dataset exposes a different type of weakness.

Customer Master (identity & compliance-driven)

Typical issues:

- unclear definitions (e.g. “active customer”)
- retention and deletion gaps
- ownership ambiguities

Focus areas:

- compliance
- lifecycle
- metadata
- access control

Billing Data (financial & operational integrity)

Typical issues:

- overly broad access (too many users with sensitive financial access)
- inconsistencies between systems
- unclear ownership between finance and IT

Focus areas:

- access control
- data quality
- reconciliation
- auditability

Consumption or Sensor Data (volume & operational data)

Typical issues:

- missing or incomplete data
- inconsistent formats
- weak validation rules
- high storage and processing costs

Focus areas:

- data quality
- lifecycle management
- cost management
- monitoring

Why this matters

This diversity is exactly why governance cannot be solved with a one-size-fits-all approach.

Instead:

- each dataset reveals its own governance profile
- and requires targeted improvements

This ensures that effort is:

- focused where it matters
- aligned with real business impact
- and not wasted on unnecessary controls

From dataset insights to enterprise patterns

As more datasets are assessed, patterns begin to emerge.

For example:

- multiple datasets may lack clear ownership → Decision gap
- several datasets may have no deletion process → Lifecycle gap
- access reviews may be missing across the board → Evidence gap

At this stage, governance insights move from: individual datasets to: cross-cutting organizational themes

Aggregating into capability-level priorities

This is where the 11 capabilities re-enter the picture at an enterprise level.

Individual dataset findings are **rolled up** into capability-level insights.

For example:

- If many datasets lack retention enforcement → Lifecycle Management becomes a priority
- If access is inconsistent → Access Control becomes a focus area
- If definitions are unclear across datasets → Metadata Management needs attention

This aggregation creates a **clear and defensible prioritization**.

Instead of stating: “We should improve data quality”, you can state: “6 out of 10 critical datasets have data quality issues affecting reporting and operations”

This level of specificity is critical for:

- CIO decision-making
- investment prioritization
- stakeholder alignment

Building a scalable governance roadmap

At this point, governance moves from dataset analysis to **enterprise improvement planning**.

The roadmap becomes structured along two dimensions:

1. Dataset-specific actions

- fix deduplication in Customer Master
- restrict access in Billing Data
- improve validation in Consumption Data

2. Cross-cutting capability improvements

- implement retention automation across platforms
- introduce standardized access review processes
- deploy metadata/catalog solutions

This ensures that governance evolves:

- both locally (per dataset)
- and structurally (across the organization)

Incremental expansion: a controlled rollout

Scaling does not mean expanding everything at once. Instead, organizations typically follow a phased approach:

- Start with 5–10 critical datasets
- Apply DEE and identify gaps
- Deliver initial improvements
- Expand to additional datasets
- Refine and standardize controls

This creates:

- fast initial results
- manageable scope
- continuous momentum

Creating a governance baseline

Over time, as more datasets are onboarded, the organization builds a **governance baseline**:

- most critical datasets have ownership
- core controls are implemented consistently
- evidence is available for key processes
- major risks are addressed

At this stage, governance shifts from: reactive to: proactive and structured

From scaling to operating model

Once the approach is embedded, scaling becomes part of the normal operating model.

New datasets are:

- identified early
- onboarded into governance
- assessed using DEE
- integrated into existing controls

Governance becomes:

- repeatable
- standardized
- yet still flexible per dataset

Conclusion of this chapter

Scaling data governance is not about expanding a framework across the organization. It is about expanding a **way of working**.

By applying the same simple structure dataset by dataset:

- governance remains grounded in reality
- complexity is kept under control
- improvements are targeted and measurable

And most importantly: The organization gains a clear, data-driven view of where its governance strengths and weaknesses truly lie.

This is what enables governance to grow from isolated efforts into a **coherent, enterprise-wide capability**.

Why This Approach Works

One of the most important questions for any CIO or data leader is not *what* data governance should look like—but whether it will actually work in their organization. The approach described in this whitepaper works because it is grounded in a small set of principles that directly address the common failure points of traditional governance programs. It is designed to be practical, scalable, and aligned with how data is actually used.

It starts from reality

This approach does not begin with frameworks, maturity models, or policies.

It starts with **real data as it exists and is used in the organization**.

By focusing on datasets that:

- drive operations
- support reporting
- or carry regulatory risk

governance is immediately connected to:

- business processes
- operational dependencies
- and actual usage patterns

This ensures that governance discussions are not theoretical, but **relevant and actionable from the start**.

It creates ownership

A major reason why governance initiatives fail is the absence of clear accountability.

This approach solves that problem structurally:

- every dataset has a defined owner
- that owner is responsible for decisions about the data
- stewardship responsibilities are clarified

This establishes a simple but powerful principle:

if a dataset matters, someone owns it

Ownership is no longer abstract or shared across committees.

It becomes **explicit, visible, and actionable**, enabling faster decision-making and clearer responsibility.

It enables automation

Governance cannot scale if it relies on manual processes.

By structuring governance through DEE (Decision, Enforcement, Evidence), this approach ensures that:

- rules are translated into **technical controls**
- controls are embedded into **platforms and pipelines**
- repetitive governance tasks are **automated**

Examples include:

- automated access provisioning
- lifecycle and retention jobs

- data quality validations

This shifts governance from: manual control to: **systematic enforcement at scale**

It is evidence-driven

In many organizations, governance exists—but cannot be demonstrated.

This approach ensures that governance is **provable by design**:

- access is logged and traceable
- lineage is visible
- quality metrics are measured
- retention and deletion are documented

As a result:

- audits become simpler
- compliance is easier to demonstrate
- trust in data increases

Governance is no longer based on assumption.

It is based on **evidence that can be produced at any moment**.

It scales incrementally

Rather than attempting a large, organization-wide transformation, this approach scales **dataset by dataset**.

This has several advantages:

- it allows for a **focused starting point** (5–10 critical datasets)
- it creates **quick, visible results**
- it limits risk and complexity
- it builds momentum over time

Each dataset governed:

- improves the overall governance posture
- reinforces patterns and practices
- contributes to enterprise-wide maturity

This results in a **controlled and repeatable scaling model**, instead of a disruptive transformation program.

Putting it together

What makes this approach effective is not a single element, but the combination of all five principles:

- starting from real data
- establishing clear ownership
- embedding controls through automation
- proving governance through evidence
- and scaling incrementally

Together, they transform data governance into **a practical, sustainable capability that evolves with the organization**. Instead of being perceived as a heavy initiative or compliance burden, governance becomes:

- manageable
- measurable
- and directly linked to business value

This is why the approach works—and why it can be successfully adopted across a wide range of organizations and maturity levels.

Conclusion

Data governance has long been recognized as a critical capability for modern organizations. It is essential for managing risk, ensuring compliance, enabling analytics and AI, and building trust in data-driven decision-making. Yet, despite this recognition, many governance initiatives fail to deliver lasting impact. They remain theoretical, overly complex, or disconnected from the realities of how data is actually used.

This whitepaper has outlined a different approach—one that retains the completeness of established governance thinking, while making it **practical, operational, and scalable**.

At its core, a successful data governance strategy must meet four essential criteria.

First, it must be **complete**.

The 11 Data Governance capabilities define the full scope of what an organization needs to control. They ensure that all aspects of data—security, quality, compliance, lifecycle, cost, and resilience—are addressed. Without this completeness, governance will inevitably leave gaps that introduce risk or limit value.

Second, it must be **pragmatic**.

Governance cannot start from frameworks alone. It must be applied to **real datasets**, where value is created and risk is concentrated. By focusing on datasets, organizations ensure that governance efforts are aligned with actual business usage, and that time and resources are invested where they matter most.

Third, governance must be **operational**.

Rules and policies only create value when they are translated into **enforcement mechanisms**. This means embedding controls into platforms, systems, and processes—so that governance is applied automatically, consistently, and at scale. Without this operational layer, governance remains theoretical and ineffective.

Fourth, governance must be **verifiable**.

In a modern data environment, it is not enough to assume that governance is in place. Organizations must be able to **prove** it. Through logs, lineage, quality metrics, and audit trails, governance becomes transparent, auditable, and trustworthy. Evidence transforms governance from intention into fact.

When these four dimensions come together—completeness, pragmatism, operationalization, and verifiability—data governance becomes fundamentally different.

It is no longer:

- a compliance exercise
- a documentation effort
- or a theoretical framework

Instead, it becomes:

- a structured way of managing real data

- a mechanism for aligning business and IT
- and a continuous improvement discipline

Most importantly, it becomes a **capability that delivers tangible value**.

The approach presented in this whitepaper enables organizations to make this transition.

By:

- starting from datasets
- applying the Decision, Enforcement, Evidence model
- and using the 11 capabilities as a guiding structure

governance becomes:

- understandable for business stakeholders
- actionable for technical teams
- and defensible for auditors and regulators

It scales incrementally, adapts to different levels of maturity, and remains flexible as the data landscape evolves.

Ultimately, this approach transforms data governance from:

a theoretical requirement into a practical, scalable capability that enables innovation, trust, and control

It allows organizations to build a governance foundation that not only protects them from risk, but also empowers them to use data with confidence—unlocking its full potential as a strategic asset.

In a world where data is central to every business decision, this shift is not optional. It is the difference between managing data as a liability—and leveraging it as a true driver of value.