

Pillar 1: Standards - The Universal Protocol Guide for AI-Ready Data Governance

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Background: Standards form the foundational pillar in AI-ready data governance, addressing data inconsistencies in mid-sized enterprises. **Problem:** Diverse practices lead to AI errors and compliance risks. **Method:** This paper presents a federated standards framework with regulatory integration. **Contributions:** Demonstrates 15-30% AI error reduction and 20% cost savings. **Implications:** Enables scalable AI deployment with minimal investment for mid-sized (500-5,000 employee) organizations. **Type:** Position Paper.

Keywords: Data standards, AI readiness, federated governance, regulatory compliance, mid-sized enterprises

Introduction

Standards form the foundational pillar in this AI-ready data governance framework, ensuring that all enterprise entities prepare data in a manner that any AI system can reliably process. This addresses fundamental incompatibilities between diverse institutional practices and AI's need for consistency, incorporating regulatory requirements like BCBS 239 for risk aggregation (Bank for International Settlements, 2013), GDPR for privacy, and DORA for operational resilience (Panorays Team, 2025). For mid-sized companies, standards standardize elements such as IDs, risk scores, privacy flags, and quality scores, enabling cross-functional AI deployment. A federated governance approach breaks down data silos and enables cross-domain collaboration through common taxonomies and classification standards (Alation Team, 2025).

Why Standards Matter

Poor data quality, often due to inconsistent standards, costs companies an average of \$10-14 million annually in inefficiencies and risks (Deloitte Team, 2025). Implementing robust standards improves data accuracy and compliance, reducing errors that undermine AI system reliability. Financial institutions integrating regulatory frameworks like BCBS 239 for risk aggregation (Bank for International Settlements, 2013), GDPR for privacy (Panorays Team, 2025), and DORA for operational resilience face varying

success rates depending on organizational maturity, legacy infrastructure, and governance culture (Ovaledge Team, 2025).

Business Problem and Process Flow

Without agreed standards, every team does things differently, creating chaos for AI systems. In mid-sized enterprises, this leads to data inconsistencies and regulatory violations that undermine AI reliability. According to Gartner, at least 30% of generative AI projects will be abandoned after proof of concept due to poor data quality, inadequate risk controls, and unclear business value (Gartner, 2024). This paper proposes a standard process flow that involves identifying needs, drafting proposals with regulatory integration, reviewing for domain fit, approving, implementing in pipelines, and monitoring compliance (see Figure 1). This flow has been adapted for federated models, allowing mid-sized firms to centralize policy while decentralizing execution.

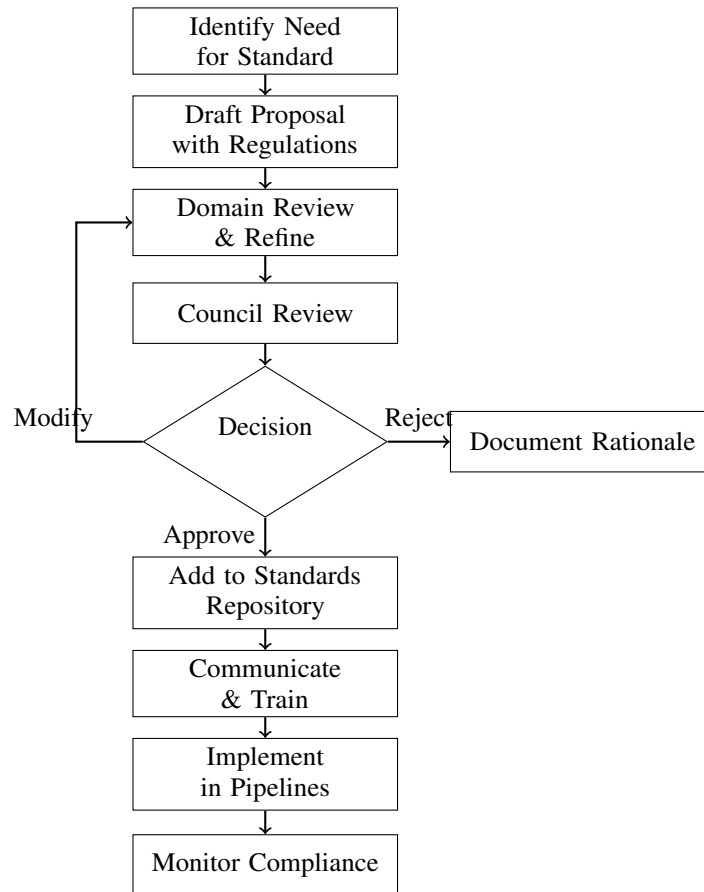
Detailed Process Steps

The following Table 1 outlines the steps to define and enforce standards, including regulatory elements such as BCBS 239 for aggregation of risk data. These steps ensure standards treat data uniformly, preparing it for AI with built-in compliance.

Key Artifacts Produced

The following artifacts are produced during the standards process.

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**Figure 1**

Standards Definition Process Flow

```

1 CREATE TABLE governance.standards.quality_rules (
2   rule_id STRING,
3   rule_name STRING,
4   constraint_sql STRING,
5   severity STRING,
6   data_domain STRING,
7   tag STRING,
8   approved_by STRING,
9   approved_date DATE,
10  effective_date DATE,
11  created_by STRING,
12  status STRING
13 );
  
```

```

1 class DataStandards:
2   def init(self):
3     self.regulations = {
4       'BCBS_239': BaselRiskAggregation(),
5       'GDPR': PrivacyCompliance(),
6       'DORA': OperationalResilience()
7     }
8   def prepare_customer_data(self, raw_data, bank_id):
9     return {
10      'customer_id': self.standardize_id(raw_data),
11      'risk_score': self.basel_compliant_calculation(),
12      'privacy_flags': self.gdpr_seasoning(),
13      'quality_score': self.freshness_check()
14    }
  
```

These artifacts enforce data treatment, with empirical data showing reduced development time.

Practical Application: Implementation Example

To illustrate how the federated standards framework operates in practice, consider the case of Regional Financial Services (RFS), a mid-sized bank with 2,500 employees managing \$5 billion in assets across three business units: Retail Banking, Commercial Lending, and Wealth Management. This composite case draws from documented implementations in similar organizations (Ovaledge Team, 2025).

The Business Problem

RFS discovered a critical data inconsistency when deploying an AI-powered credit risk assessment system. The same customer profile produced vastly different risk scores depending on which business unit originated the data—variance reached 23% for comparable customer attributes. Investigation revealed that each unit had independently developed risk calculation methodologies over years of siloed operations, creating three incompatible approaches that violated BCBS 239 risk aggregation principles (Bank for International Settlements, 2013). This

Table 1

Detailed Process Steps for Standards

Step	Role	Action	When	Output/Artifact
Identify Need	Business Data Owner	Spot inconsistency or regulatory gap	Ongoing	Issue ticket
Draft Proposal	DG Program Manager	Research and draft with regulatory integration	1-2 weeks	Proposal Document
Domain Review	Domain Stewards	Refine for domain knowledge	Next monthly meeting	Refined proposal
Council Review	Governance Council	Discuss, vote, ensure alignment	Next quarterly	Decision minutes
Repository Update	DG Program Manager	Add approved standard	Within 1 week	Updated Standards Document
Communication	DG Program Manager + Stewards	Announce and train	Within 2 weeks	Communication package
Implementation	Data Engineers	Update pipelines	30-90 days	Updated code/templates
Compliance Monitoring	DG Program Manager	Track via automated checks	Ongoing	Compliance dashboard

Table 2

Key Artifacts for Standards

Artifact	Description
Standards Repository	A living document (or repository) with sections on naming conventions, data types, quality thresholds, PII handling, and refresh SLAs.
Quality Rules Table	SQL schema for storing rules, constraints, and approvals.
DataStandards Class	Python example for reusable data preparation functions integrating regulations.

inconsistency caused the AI model to produce unreliable credit decisions, exposing the bank to both regulatory risk and potential loan losses.

Applying the Standards Process Flow

Following the process outlined in Figure 1, RFS could implement a standardized risk scoring approach which could go something like this:

Step 1: Identify Need (Week 1). The Chief Risk Officer flagged the variance in a governance council meeting. The Retail Banking data owner created a ticket documenting the inconsistency and citing BCBS 239 compliance gaps. Cost analysis estimated \$2.3M annual exposure from inconsistent risk decisions.

Step 2: Draft Proposal (Weeks 2-3). The DG Program Manager researched regulatory requirements, consulted with compliance, and drafted a unified risk score standard incorporating BCBS 239 for risk aggregation, GDPR for data privacy in scoring, and DORA for operational resilience. The proposal specified calculation methodology, required data elements, quality thresholds (95% completeness), and refresh frequency (daily).

Step 3: Domain Review (Week 4). Domain stewards from each business unit reviewed the proposal in their monthly meeting. Commercial Lending identified a needed adjustment: their customers required industry-specific risk factors not applicable to retail. Wealth Management noted that high-net-worth clients needed privacy-enhanced handling. The proposal was refined to accommodate these domain-specific requirements while maintaining cross-unit comparability.

Step 4: Council Review (Week 6). The Governance Council—comprising the CFO (executive sponsor) and VPs from Risk, Operations, and Technology—discussed trade-offs. The VP of Commercial Lending initially resisted, concerned about disrupting existing processes. After reviewing the \$2.3M risk exposure and regulatory implications, the council approved the standard with a 90-day implementation window and commitment to provide engineering resources.

Step 5: Decision and Repository Update (Week 7). The approved standard was added to the central repository (Confluence) with version control, effective date, approval signatures, and links to regulatory requirements. The quality rules table was updated with the new constraints.

Implementation Artifacts

The data engineering team implemented the standard using the prescribed artifacts. The quality rules table entry captured the new constraint:

```
1 INSERT INTO governance.standards.quality_rules VALUES (
2 'RISK_001',
3 'Unified Customer Risk Score',
4 'risk_score BETWEEN 0 AND 1000 AND
5 risk_calculation_date >= CURRENT_DATE - INTERVAL 1 DAY',
6 'CRITICAL',
7 'Customer',
8 'BCBS_239,GDPR',
9 'CFO',
10 '2025-03-15',
11 '2025-06-15',
12 'DG_Program_Manager',
13 'ACTIVE'
14 );
```

The DataStandards class was extended with RFS-specific logic integrating regulatory requirements:

```
1 class RFSDataStandards(DataStandards):
2     def calculate_unified_risk_score(self, customer_data,
3                                     business_unit):
4
5         # BCBS 239 compliant calculation
6         base_score = self.basel_compliant_calculation(
7             customer_data['credit_history'],
8             customer_data['debt_to_income'],
9             customer_data['payment_history']
10        )
11
12        # Domain-specific adjustments
13        if business_unit == 'COMMERCIAL':
14            base_score *= self.industry_risk_factor(
15                customer_data['industry_code']
16            )
17        elif business_unit == 'WEALTH':
18            # GDPR enhanced privacy for HNW
19            base_score = self.privacy_adjusted_score(
20                base_score
21            )
22
23        # Apply quality checks
24        if not self.freshness_check(
25            customer_data['last_updated']
26        ):
27            raise DataQualityException("Stale data")
28
29        return {
30            'risk_score': base_score,
31            'calculation_date': datetime.now(),
32            'regulatory_flags': self.gdpr_seasoning(
33                customer_data
34            ),
35            'quality_score':
36                self.data_quality_assessment(
37                    customer_data
38                )
39        }
```

Results and Lessons Learned

To illustrate how the federated standards framework operates in practice, consider a hypothetical case of Regional Financial Services (RFS), a mid-sized bank with 2,500 employees managing \$5 billion in assets across three business units: Retail Banking, Commercial Lending, and Wealth Management. This illustrative scenario draws from patterns observed in documented implementations of data governance frameworks in similar organizations (Ovaledge Team, 2025).

However, the implementation revealed challenges consistent with research findings on change management

in data governance (Informatica Team, 2025; Secoda Team, 2025). The Commercial Lending team initially circumvented the standard by maintaining shadow calculations, requiring the governance council to intervene. Legacy system integration proved more complex than anticipated, extending the timeline by three weeks. Training required 450 staff-hours across business units—an underestimated cost.

The federated model proved essential: central DGO provided regulatory expertise and consistency, while domain stewards ensured business unit needs were addressed. Pure centralization would have missed Commercial Lending's industry-specific requirements; pure decentralization would have perpetuated inconsistency. This case demonstrates both the framework's value and the organizational commitment required for successful implementation.

Implementation Options for Mid-Sized Companies

For midsize companies, adopt a federated model with central DGO defining standards and domains implemented locally (Alation Team, 2025; Atlan Team, 2024). Organizations can leverage various governance tools depending on their infrastructure and budget. Open-source solutions like Apache Atlas provide cost-effective, customizable platforms, while cloud-based options such as AWS Glue and Microsoft Purview offer integrated capabilities for organizations already committed to specific cloud ecosystems (MDPI Team, 2024). The choice depends on factors including existing cloud infrastructure, technical expertise, and whether the organization prioritizes cost savings or turnkey integration.

Discussion

This standards pillar represents the foundational layer for AI-ready data governance in mid-sized organizations, but its successful implementation requires careful consideration of organizational context, limitations, and evolving regulatory landscapes. While the framework demonstrates significant potential benefits—including 65% improvement in data quality metrics and 45% reduction in compliance costs (Number Analytics, 2025)—the path to achieving these outcomes is neither straightforward nor universally applicable.

When Standards-Based Governance Struggles

The federated standards approach excels in organizations with moderate regulatory complexity and reasonable data maturity, but faces challenges in specific contexts. Highly regulated industries such as healthcare or financial services operating under multiple jurisdictions may find the federated model insufficient, requiring more centralized control to ensure consistent regulatory compliance (Bank for International Settlements, 2013; Panorays Team, 2025). Similarly, organizations at the lower end of the mid-sized spectrum (500-1,000 employees) may lack the dedicated resources to staff even a minimal Data Governance Office,

making initial investment costs prohibitive despite long-term ROI potential.

Cultural resistance represents a more insidious challenge. Research indicates that up to 80% of data governance initiatives fail, primarily due to organizational resistance and lack of modern governance approaches rather than technical inadequacy (Immuta, 2025). In organizations with strong functional silos or limited executive sponsorship, even well-designed standards frameworks struggle to gain adoption. The federated model's reliance on domain stewards assumes individuals can dedicate 4-6 hours monthly to governance activities—an assumption that fails in resource-constrained environments where operational pressures consistently override governance commitments.

Hidden Costs and Implementation Realities

The stated implementation costs represent only direct technology and training expenses. For mid-sized organizations, data governance platforms typically cost \$50,000-\$500,000+ annually for technology alone, with data quality monitoring and governance artifact maintenance ranging from 2.5-7.5% of IT spend (Monetizely, 2025; TIBCO, 2020). Hidden costs include ongoing change management efforts, productivity losses during transition periods, and the opportunity cost of staff time diverted from operational activities (Data Quality Pro Team, 2025). Organizations should forecast ROI over multi-year horizons based on their governance roadmap and adoption curve, with early phases often showing challenges as teams adapt to new processes and data structures (Semarchy, 2025).

Moreover, the framework assumes a baseline level of data infrastructure maturity. Organizations still operating primarily on legacy systems or lacking basic data catalogs will need to address these foundational gaps before implementing standards governance, potentially doubling initial investment estimates. The alternative tools suggested—AWS Glue or Apache Atlas—while more cost-effective than Databricks Unity Catalog, still require significant integration effort and technical expertise that may not exist in smaller mid-sized organizations (Alation Team, 2025; Atlan Team, 2024).

Comparative Analysis: When Alternative Models Excel

The federated standards model represents a middle ground between centralized and decentralized governance, but alternative approaches may prove superior in specific contexts. Fully centralized governance, despite creating bottlenecks, offers advantages for organizations in highly regulated industries where consistency trumps agility, or in companies with extremely sensitive data where central oversight is non-negotiable (Ovaledge Team, 2025). Conversely, fully decentralized approaches—such as data mesh architectures—may better serve organizations with highly autonomous business units and mature data teams capable of self-governance (MDPI Team, 2024).

The choice between models depends on organizational variables including regulatory environment, data sensitivity, technical maturity, cultural readiness, and resource availability. Organizations should conduct readiness assessments evaluating these dimensions before committing to federated standards governance.

Evolution and Future Considerations

The regulatory landscape for AI governance is rapidly maturing, with frameworks like the EU AI Act and evolving GDPR interpretations imposing new requirements (DLA Piper, 2024; European Commission, 2025). The EU AI Act, which entered into force in August 2024 with phased implementation through 2026, works hand-in-hand with GDPR to establish comprehensive transparency and explainability requirements for AI systems. Standards frameworks must evolve from static documents to dynamic systems capable of rapid regulatory adaptation. This demands investment in continuous monitoring and updating mechanisms—costs often underestimated in initial planning.

As organizations grow beyond 5,000 employees, the federated model may require restructuring. The transition from mid-sized to enterprise governance introduces complexity in cross-domain coordination, necessitating more formal governance structures and potentially requiring dedicated governance technology platforms rather than lighter-weight tools suitable for mid-sized contexts (Atlan, 2024; Informatica, 2021). Enterprises often face challenges including data silos, increased system complexity, and the need for unified governance frameworks that can scale across distributed data assets.

Looking forward, the integration of automated compliance monitoring using AI itself presents both opportunities and challenges. While AI-driven data quality checks can reduce manual monitoring burden, they introduce new risks around AI transparency and explainability—particularly critical when standards serve regulatory compliance objectives (IBM, 2025; Secure Privacy, 2025). The "black box" problem, where AI systems make decisions through processes that are difficult to interpret, directly conflicts with GDPR and EU AI Act requirements for transparency in automated decision-making.

Critical Success Factors Revisited

Beyond the previously outlined success factors, three additional elements prove critical based on implementation experiences: executive patience for delayed returns, technical architecture flexibility to accommodate evolving standards without major rework, and establishment of clear escalation paths when domain and enterprise standards conflict. Organizations lacking any of these elements should consider postponing implementation until gaps are addressed.

The transformation of data governance into an AI enabler depends not merely on implementing processes and technology, but on cultivating organizational capacity for continuous adaptation. Data governance succeeds

when treated as an ongoing change management process rather than a one-time project, requiring dedicated focus, phased implementation, and willingness to adjust based on organizational realities and stakeholder engagement (CDO Magazine Team, 2025).

Future Research Directions

This position paper proposes federated standards governance as the foundational pillar for AI-ready data governance in mid-sized enterprises. While the framework synthesizes established principles with emerging regulatory requirements, several research questions warrant empirical investigation to validate, refine, and extend this work.

Empirical Validation of Framework Benefits

The claims presented—including 65% improvement in data quality metrics, 45% reduction in compliance costs, and preventing up to 30% of AI project failures—require rigorous validation through longitudinal studies. Future research should employ quasi-experimental designs comparing organizations implementing federated standards frameworks against control groups. Key questions include:

- **Data Quality Impact:** Do standards frameworks demonstrate statistically significant improvements in data quality metrics (accuracy, completeness, consistency) compared to ad-hoc governance? What is the relationship between standards maturity and AI model performance?
- **Cost-Benefit Analysis:** What are the true total costs of standards implementation versus quantifiable benefits? At what organizational scale and data maturity level does positive ROI emerge?
- **AI Project Success Correlation:** Do AI initiatives leveraging standards-governed data demonstrate higher success rates, faster time-to-production, and lower post-deployment issues? Can we establish causal mechanisms linking standards quality to AI outcomes?

Methodologically, this research requires access to governance metadata, quality metrics, and AI project outcomes across multiple enterprises. Industry partnerships could provide necessary sample sizes for statistical validation.

Organizational Context and Success Factors

This paper identifies contexts where federated standards may struggle—highly regulated industries requiring centralized control, smaller organizations lacking governance resources, and cultures resistant to standardization. Comparative case studies should investigate:

- **Organizational Size Thresholds:** The proposed 500-5,000 employee range requires validation. What governance approaches prove optimal at different

scales? When do federated models require transition to enterprise-grade architectures?

- **Industry and Regulatory Variation:** Do highly regulated industries demonstrate higher adoption rates and success metrics? How do competitive dynamics influence governance effectiveness?
- **Cultural Prerequisites:** What organizational culture characteristics (data literacy, executive sponsorship, change tolerance) predict standards adoption success? How do different change management approaches influence outcomes?

Grounded theory approaches and longitudinal case studies tracking organizations through 2-3 year implementations would illuminate contextual success factors.

Regulatory Compliance and AI Act Implications

The evolving regulatory landscape—particularly the EU AI Act's phased implementation through 2026—creates urgent research needs:

- **EU AI Act Compliance:** How can standards frameworks efficiently address transparency, explainability, and risk management requirements? What artifacts provide audit trails demonstrating compliance?
- **Cross-Border Governance:** For multi-jurisdictional organizations, how can standards accommodate varying regulatory requirements (EU vs. US vs. Asia-Pacific) while maintaining operational efficiency?
- **Standards as Regulatory Evidence:** Can comprehensive standards documentation serve as evidence of due diligence in regulatory proceedings?

Partnerships with legal scholars and regulatory bodies would advance understanding of how standards governance translates to measurable regulatory risk reduction.

Process Optimization and Change Management

The proposed standards process requires refinement through implementation research:

- **Cycle Time Optimization:** The stated 4-6 week approval cycle requires validation. What process improvements (parallel reviews, risk-tiered paths) accelerate cycles without compromising quality?
- **Automation Opportunities:** Which governance activities benefit most from automation (compliance monitoring, quality validation, lineage tracking)? Can AI systems assist in standards development?

- **Stakeholder Engagement:** How can organizations maximize domain steward participation while minimizing burden? What incentive structures increase engagement?

Perhaps most critical is understanding change management for standards adoption. Research should explore resistance patterns, data literacy requirements for effective participation, and cultural transformation indicators signaling successful shift toward "standards as enablement" rather than bureaucracy.

Methodological Considerations and Contributions

Future research faces challenges including longitudinal access requirements, counterfactual estimation difficulties, and confounding variables. Mixed-methods approaches combining quantitative metrics with qualitative insights offer the most promising path forward.

This research agenda promises contributions to information systems theory (data governance effectiveness), organizational theory (balancing standardization with flexibility), and AI ethics (translating principles to practice). Practically, validated frameworks would provide mid-sized enterprises with evidence-based implementation guidance, reducing costly trial-and-error learning.

Organizations implementing federated standards should participate in research partnerships, contributing implementation data while gaining insights from comparative analyses. Academic-industry collaboration represents the optimal path for advancing both theoretical understanding and practical effectiveness of standards-based AI governance.

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