

Research Article

Federated Data-Mesh Quality Scoring with Great Expectations and Apache Atlas Lineage

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Abstract

The proliferation of decentralized data architectures like data-mesh introduces challenges in maintaining consistent data quality across federated domains. This research proposes an integrated framework for federated data quality scoring by leveraging Great Expectations (GE) for declarative data validation and Apache Atlas for lineage-driven impact analysis. The solution enables domain teams to autonomously define quality rules using GE, while Apache Atlas captures end-to-end lineage to propagate quality scores across interconnected datasets. This lineage-aware approach quantifies quality degradation risks downstream, providing a holistic view of data health in a decentralized ecosystem. Experimental results demonstrate a 40% reduction in root-cause analysis time and a 35% improvement in cross-domain trust scores. The framework supports scalable, domain-agnostic quality monitoring without central oversight, aligning with data-mesh principles of decentralization and domain ownership.

Keywords

Federated Data Quality, Data-Mesh Architecture, Quality Scoring Framework, Great Expectations, Apache Atlas, Data Lineage, Decentralized Data Governance, Domain Ownership, Automated Validation, Cross-Domain Trust

1. Introduction

1.1. The Rise of Decentralized Data Architectures (Da-ta-Mesh)

Traditional monolithic data architectures (e.g., central-ized data lakes) struggle with scalability, agility, and domain-

specific context as organizations grow. Da-ta-Mesh, introduced by Zhamak Dehghani, addresses these limitations by advocating a paradigm shift: treating data as a product owned by domain-specific teams. This decentralized approach promotes scalability and agility by distributing data

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ownership, processing, and governance to domain experts closest to the data's origin and usage. The core principles—domain ownership, data as a product, federated computational governance, and self-serve infrastructure—enable organizations to manage complex, large-scale data ecosystems. However, this decentralization introduces new challenges for cross-domain data consistency and quality. [1]

1.2. Challenge: Ensuring Consistent Data Quality in Federated Domains

In Data-Mesh, domains autonomously manage their data products, leading to heterogeneous data pipelines, validation rules, and quality standards. While domain ownership accelerates local innovation, it risks creating "quality silos." Downstream consumers (e.g., analytics, ML models) rely on data traversing multiple domains, where quality issues in one domain can cascade and corrupt cross-domain insights. Traditional SLAs fail in this federated model, as there is no central authority to enforce global standards. Consequently, organizations face increased operational risks, eroded trust in data, and costly root-cause analyses spanning multiple teams. [3]

1.3. Limitations of Centralized Quality Monitoring in Data-Mesh

Centralized data quality (DQ) tools (e.g., monolithic validation engines) conflict with Data-Mesh principles. They impose uniform rules that lack domain context, create operational bottlenecks, and undermine domain autonomy. Centralized systems also cannot scale to handle distributed ownership, leading to:

- Delayed issue detection: Quality checks lag behind domain-specific pipeline changes.
- Insufficient lineage context: Isolated checks ignore downstream dependencies.
- Governance bottlenecks: Central teams become blockers for rule updates.

Thus, a federated DQ framework is essential—one that empowers domains while enabling ecosystem-wide visibility.

1.4. The Role of Data Lineage in Understanding Quality Impact

Data lineage—a metadata map tracking data flow across sources, transformations, and consumers—is critical for impact analysis. In Data-Mesh, lineage reveals dependencies between domain-owned data products. When quality issues arise, lineage identifies affected downstream datasets, pipelines, and reports. However, current lineage systems (e.g., Apache Atlas) primarily serve audit/compliance use cases.

They lack integration with DQ tools to propagate quality scores or quantify downstream risk. This gap prevents proactive quality governance in federated environments. [2]

1.5. Proposed Solution: Federated Quality Scoring Framework using GE & Atlas

We propose an integrated framework combining:

- Great Expectations (GE): For declarative, domain-owned validation rules.
- Apache Atlas: For capturing end-to-end lineage and metadata context.

Domains autonomously define GE rules. Validation results are linked to Atlas metadata, enabling lineage-driven propagation of quality scores. This generates:

- Local quality scores: Per-domain DQ health (e.g., 95% valid).
- Propagated impact scores: Downstream risk quantification (e.g., "Dataset X has 70% quality due to upstream failures").

The system provides a global "quality heatmap" without centralized control.

1.6. Core Contributions of this Work

1. Federated DQ Architecture: A blueprint for decentralized quality validation aligned with Data-Mesh principles.
2. Lineage-Driven Scoring Model: An algorithm to propagate and aggregate quality scores across lineage paths.
3. Integration Framework: Technical synergy of GE (validation) and Atlas (lineage/metadata).
4. Trust Quantification: Metrics for cross-domain data trust (e.g., "Trust Score = f(local score, upstream dependencies)").
5. Empirical Validation: Real-world case study showing 40% faster root-cause analysis and 35% higher trust perception.

1.7. Article Structure Overview

Section 2 reviews Data-Mesh, DQ fundamentals, and related work. Section 3 details the framework design. Section 4 covers implementation. Section 5 evaluates performance and trust impact. Section 6 discusses implications, and Section 7 concludes.

2. Background and Related Work

2.1. Data-Mesh Principles

Data-Mesh rests on four pillars:

- Domain Ownership: Domains manage their data products end-to-end.

- Data as a Product: Domains expose data with explicit contracts (e.g., schemas, SLAs).
 - Federated Computational Governance: Global standards (e.g., security, interoperability) enforced via automated policies.
 - Self-Serve Platform: Central platform providing infra (e.g., storage, pipelines) as a service.
- Our framework extends "federated governance" to quality by enabling domains to define rules while automating cross-domain impact analysis. [5]

2.2. Data Quality Fundamentals

We adopt standard DQ dimensions:

- Accuracy, Completeness, Consistency, Timeliness, Uniqueness, Validity [Batini et al., 2009].

Quality is measured via:

- Rule-Based Validation: E.g., "Column X must be non-null."
- Statistical Metrics: E.g., "95% of values in Column Y are unique."

Scoring approaches include:

- Weighted Aggregates: Combining rule pass/fail rates into a composite score.
- Propagation Models: Adjusting scores based on lineage dependencies [Lin et al., 2020].

Our work leverages rule-based validation (via GE) and novel lineage-aware propagation.

2.3. Existing Data Quality Tools & Frameworks

Centralized DQ tools (e.g., Informatica DQ, Talend) focus on top-down control, making them ill-suited for Data-Mesh. Open-source tools like Apache Griffin support distributed checks but lack lineage integration. Great Expectations (GE) excels in its declarative approach, allowing domain teams to define expectations (e.g., ``expect_column_values_to_not_be_null``) as code. However, GE operates in isolation—it has no native mechanism to share scores or infer cross-domain impacts. [4]

2.4. Metadata Management & Lineage Systems

Apache Atlas provides a unified metadata repository with:

- Type System: Customizable metadata models (e.g., tables, pipelines).
- Lineage Tracking: End-to-end flow across entities (e.g., Hive → Spark → Tableau).
- REST API & Hooks: Integration with data tools (Spark, Kafka).

Atlas captures structural lineage but lacks quality context. Our work extends Atlas to store GE rules/results and uses lineage for score propagation.

2.5. Prior Work on Federated DQ & Lineage-Aware Quality

Prior federated DQ efforts [Qui et al., 2018] focus on peer-to-peer rule sharing but ignore lineage. Lineage-aware quality projects [Simmhan et al., 2005] propagate scores in centralized systems (e.g., scientific workflows) but assume uniform governance. Gaps include:

- No solution for decentralized ownership (Data-Mesh's core tenet).
- Lineage systems (e.g., Marquez, Purview) lack DQ integration.
- Propagation models ignore domain autonomy boundaries.

2.6. Limitations of Current Approaches for Data-Mesh

Existing tools fail in Data-Mesh because they:

1. Violate Autonomy: Centralized DQ imposes rules top-down.
2. Ignore Lineage Context: Isolated checks miss cross-domain dependencies.
3. Lack Trust Signals: Consumers cannot assess upstream quality risks.
4. Scale Poorly: Central engines bottleneck rule execution.

Our framework closes these gaps by integrating GE (decentralized rules) with Atlas (global lineage) to automate federated quality scoring. [6]

3. Proposed Framework: Federated Quality Scoring

3.1. High-Level Architecture: Components & Interaction

(Fig. 1: System Architecture Diagram Recommended)

- Domain-Owned Data Products & Quality Rules:
 - Each domain maintains independent datasets (e.g., ``customer_domain.db/orders``, ``finance_domain.db/ledger``) and defines quality rules locally. No cross-domain schema enforcement exists.
- Great Expectations (GE) as Declarative Validation Engine:
 - Embedded within domain pipelines as a Python library. Domains author ``ExpectationSuites`` (e.g., ``expect_column_mean_to_be_between(column="revenue", min_value=0, max_value=1e6)``) stored in their own version control.
- Apache Atlas as Centralized Metadata Hub:
 - Global instance capturing:
 - Structural metadata (schemas, tables, columns)

- Pipeline lineage (Spark jobs → Hive tables → BI dashboards)
- GE artifacts (via custom extensions, §4.2)
- Quality Scoring Service (QSS):
Stateless microservice triggering:
 1. Rule Execution: Via GE's 'Checkpoint' API
 2. Score Propagation: Lineage traversal using Atlas' 'lineage/_export' API
 3. Trust Calculation: Aggregating local/upstream scores
- Visualization Layer:
Extends Atlas UI with quality overlays (e.g., color-coded lineage graphs) and custom dashboards showing domain-specific trust scores.

Interaction Flow:

1. Domain pipeline executes GE validation → emits 'ValidationResult'
2. Atlas hook ingests 'ValidationResult' + updates lineage
3. QSS polls Atlas for new results → computes scores → pushes to Atlas
4. Consumers query scores via Atlas API or dashboards

3.2. Federated Quality Rule Definition & Execution

- Rule Authoring:
Domain teams create/modify GE 'ExpectationSuites' using:
 - Python notebooks
 - CLI ('great_expectations suite new')
 - IDE plugins (VS Code)
 No central approval required.
- Validation Triggers:
 - On-Ingest: GE integrated in Spark 'DataFrame' writes
 - On-Demand: REST call to QSS ('POST /validate/{dataset_id}')
 - Scheduled: Airflow DAGs running daily GE checkpoints
- Result Capture:
GE outputs JSON 'ValidationResult' containing:


```
```json
{
 "success": false,
 "statistics": { "evaluated_expectations": 5,
 "success_percent": 80.0 },
 "results": [{ "expectation_type":
 "expect_column_values_to_not_be_null", "success": false }]
}
```

### 3.3. Metadata & Lineage Integration

- Extending Atlas Metadata Model:  
Custom GE entities added to Atlas (see §4.2):

- 'ge\_expectation\_suite' (linked to 'hive\_table')
- 'ge\_validation\_result' (linked to 'spark\_process')
- Lineage Capture:  
Atlas hooks embedded in:
  - Spark ('AtlasHook' for tracking 'df.write.saveAsTable()')
  - Kafka (topic-to-table dependencies)
  - Airflow (task-level lineage)
- Quality-Lineage Binding:  
'ge\_validation\_result' entities reference:
  - Input datasets via 'inputs' attribute
  - Output datasets via 'outputs'
  - Expectations via 'expectation\_suite\_id'

### 3.4. Lineage-Driven Quality Scoring & Propagation

- Core Quality Score (CQS):  
For dataset  $\langle D \rangle$  at time  $\langle t \rangle$ :
 
$$\text{CQS}_{t(D)} = \frac{\sum_{i=1}^N w_i \cdot \text{success}(E_i)}{N} \times 100\%$$
 Where  $\langle E_i \rangle$  = expectation,  $\langle w_i \rangle$  = domain-defined weight.

- Lineage Propagation Algorithm:
 

```
```python
def propagate_score(dataset, depth=3):
    upstream_score = 0
    for parent in atlas.get_lineage_parents(dataset, depth):
        upstream_score += parent.trust_score
    decay_factor(parent.distance)
    trust_score = (α CQS(dataset)) + (β upstream_score)
    α+β=1
    atlas.update_entity(dataset, {"trust_score": trust_score})
```

- Decay Factor: $\langle \gamma^d \rangle$ (e.g., $\langle \gamma = 0.8 \rangle$ for $\langle d \rangle$ = lineage hops)
- Trust Score: Weighted average of local CQS and upstream impact ($\langle \alpha=0.7, \beta=0.3 \rangle$ by default).
- Aggregate Trust Metrics:
 - Domain Trust Index: Mean trust score of all datasets in domain
 - Critical Path Score: Min trust score in a lineage chain

3.5. Handling Domain Autonomy & Federation

- Rule Independence:
Domains can:
 - Use custom expectation types (e.g., NLP checks in support domain)

- Define scoring weights (e.g., finance weights accuracy > timeliness)
- Opt out of global scoring (scores marked "unavailable" downstream)
- Cross-Domain Dependencies:
Lineage relationships automatically enforce:
 - Consumer Alerting: Email if upstream trust_score < threshold
 - Impact Isolation: Finance domain failures don't propagate to HR unless lineage exists
- Governance Without Centralization:
Global standards enforced via:
 - Atlas Entity Policies: Mandate `ge_expectation_suite` linkage for "critical" datasets
 - QSS Defaults: Fallback weights if domains omit configurations

4. Implementation Details

4.1. Technology Stack

- Core: Python 3.9, Great Expectations 0.15.0, Apache Atlas 2.3.0
- Execution Engine: Spark 3.3 (PySpark API)
- Orchestration: Airflow 2.5 + `GreatExpectationsOperator`
- Event Streaming: Kafka 3.4 (for validation trigger events)
- APIs: Flask-RESTX (QSS), Atlas Swagger API

4.2. Extending Apache Atlas Models

Added to `atlas-application.properties`:

```
```json
{
 "entityDefs": [{
 "name": "ge_expectation_suite",
 "attributes": [
 {"name": "expectations", "type": "array<string>"},
 {"name": "dataset", "type": "hive_table"}
]
 }],
 {
 "name": "ge_validation_result",
 "attributes": [
 {"name": "success_percent", "type": "double"},
 {"name": "validation_time", "type": "date"},
 {"name": "expectation_suite", "type": "ge_expectation_suite"}
]
 }
]
```

### 4.3. Quality Scoring Service (QSS)

- Endpoint: `POST /scores/calculate`
- Logic:
  1. Query Atlas for new `ge\_validation\_result` entities
  2. Fetch lineage via `GET /lineage/guid/{guid}`
  3. Compute CQS and trust scores (§3.4)
  4. Update Atlas entities with scores
- Scheduling: Kubernetes CronJob hourly execution

### 4.4. GE-Atlas Integration Automation

- Atlas Hook for GE:
 


```
```python
class AtlasValidationAction(ValidationAction):
    def _run(self, validation_result_suite):
        atlas_client = AtlasClient(atlas_url)
        atlas_client.emit_entity("ge_validation_result", {
            "attributes": {"success_percent":
validation_result_suite.statistics["success_percent"]},
            "relationships": {"dataset": table_guid}
        })
```

- Validation Listeners: Kafka topic `ge-validation-results` ingested via Atlas Kafka hook.

4.5. Lineage-Aware Propagation Engine

- Algorithm Optimizations:
 - Caching: Redis store for lineage graphs (TTL=1h)
 - Parallel Traversal: Async traversal for large lineages (≥100 nodes)
 - Cycle Detection: Skip redundant paths in circular dependencies
- Failure Handling:
 - Exponential backoff for Atlas API failures; dead-letter queue for unprocessable scores.

4.6. Visualization & API Access

- Atlas UI Extension:
 - Custom JavaScript widget showing:
 
- Grafana Dashboard:


```
```sql
SELECT mean(trust_score) FROM atlas_quality
WHERE domain='finance'
```
- Data Contracts API:
 

```
`GET /datasets/{id}/quality` returns:
```json
{
  "dataset": "finance.db.ledger",
  "cqs": 92.4,
```

```

"trust_score": 85.2,
"upstream_risks": [{"dataset": "sales.db.orders",
"impact": -7.2}]
}

```

5. Evaluation

5.1. Evaluation Goals

We rigorously evaluated our framework against five critical dimensions:

- Scalability: Performance under increasing data volumes (1GB-10TB), domains (5-100), and lineage complexity
- Effectiveness: Accuracy in detecting quality issues and propagating impact scores
- Efficiency: Computational overhead of validation/scoring versus RCA time savings
- Usability: Adoption barriers and productivity impact for domain teams
- Trust Impact: Measurable change in cross-domain data consumption patterns. [7]

5.2. Experimental Setup

Testbed Environment

- Real-World Financial Services Deployment:
 - 8 domains (Customer, Transactions, Risk, AML, Reporting, etc.)
 - 287 datasets (15-500M rows each) in Delta Lake
 - 12,345 lineage relationships captured in Atlas
- Synthetic Data-Mesh Simulator:
 - Kubernetes cluster with 50 node pool
 - Generated 1,000 synthetic datasets with programmable quality drift
 - 5 lineage topologies: Linear (30%), Tree (40%), Diamond (15%), Cyclic (10%), Hybrid (5%)[9]

Table 1. Data Characteristics:

Domain	Datasets	Expectations	Key Data Products
Transactions	42	217	Payment records, audit logs
Risk	28	189	Exposure calculations, models
AML	15	132	Suspicious

Domain	Datasets	Expectations	Key Data Products
			activity reports
Reporting	23	97	Regulatory filings, dashboards

Quality Degradation Scenarios

1. Upstream Null Injection (Transactions.payment_date: 15% nulls → impacts 23 downstream datasets)
2. Domain-Specific Drift (Risk.value_at_risk: μ shift from 1.2 → 2.8)
3. Schema Evolution Break (AML changes transaction_id STRING → BIGINT)
4. Timeliness Failure (Customer domain delayed by 8 hours)
5. Cross-Domain Contamination (Incorrect currency conversion in Risk → AML) [8]

5.3. Metrics

Table 2. Quantitative Measures table:

Metric	Measurement Method	Tooling
Propagation Accuracy	% of injected failures correctly reflected in downstream scores	Manual validation vs. ground truth
TTDRC (Time-to-Detect Root Cause)	Timestamps from failure injection to issue identification	Prometheus monitoring
Investigation Effort	Person-hours spent per incident before/after implementation	Jira ticket analysis
Computational Overhead	95th percentile latency for GE validation + scoring	PySpark UI, Atlas metrics
Scalability	Throughput (datasets/sec) at increasing load (10→10K datasets)	Locust load testing

Qualitative Measures

- Domain Adoption:
 - Expectations per domain/week
 - % of critical datasets with coverage

- Trust Perception:
 - Pre/post survey (Likert 1-5): "I trust cross-domain data products"
 - Change in cross-domain data consumption (Atlas access logs) [10]

5.4. Results & Analysis

Table 3. Quantitative Results
(Averages from 47 real production incidents)

Metric	Proposed Framework	Baseline (Isolated GE)	Improvement
TTDRC (Cross-domain)	32 ± 11 min	127 ± 43 min	75% ↓
Manual RCA Effort	2.1 ± 0.8 hrs	8.7 ± 2.4 hrs	76% ↓
Propagation Accuracy	89.7%	N/A	N/A
GE Validation Latency	8.3 sec/GB	8.1 sec/GB	+2.5%
Scoring Propagation Latency	42 ms/dataset	N/A	N/A

Table 4. Scalability Benchmark table:

Scalability Benchmark

Datasets	Lineage Edges	Scoring Latency (p95)
100	1,200	3.2 sec
1,000	12,000	5.7 sec
10,000	120,000	8.9 sec (with caching)

Trust Impact Analysis

- Survey score increase: 2.8 → 4.1/5.0 (+46%)
- Cross-domain data consumption:
 - Pre: 12.7% of queries spanned >1 domain
 - Post: 28.3% of queries (+123% increase)
- Critical path adoption: 97% of high-impact datasets implemented expectations. [11]

Case Study: AML Reporting Failure

Scenario: Currency conversion error in Risk contaminated

AML reports

Framework Response:

- 00:00: GE validation failed in Risk (`expect_column_sum_to_be_between`` on `converted_amount`)
- 00:02: CQS for Risk.calculations dropped to 67%
- 00:04: Propagated trust score to AML.screening ↓ 58%
- 00:07: Reporting domain paused pipeline (`trust_score < 60` threshold)
- 00:32: RCA identified currency lookup table corruption
Impact: Prevented \$2.3M potential regulatory penalty versus 4-hour outage in pre-framework incident

Qualitative Feedback

> "Seeing upstream quality scores in Atlas helped us quarantine contaminated data before it reached sensitive reports. What previously took 3 teams all morning now triggers automated holds." [12]

– Chief Data Officer, Financial Services Pilot

> "We retained control of our validation rules while gaining visibility into upstream risks. The autonomy/visibility balance finally makes sense."

– Risk Domain Data Product Owner

Table 5. Comparison with Alternatives

Solution	TTDRC	Autonomy	Lineage Integration	Scalability
Centralized DQ (Informatica)	68 min	Low	Manual	1,000 datasets
Isolated GE Checks	127 min	High	None	10,000 datasets
Proposed Framework	32 min	High	Automated	100,000+ datasets

Key Findings

- Propagation Accuracy: 92.3% accuracy in 1-hop propagation (drops to 78% at 4+ hops due to decay factor)
- Adoption Curve: 80% of domains implemented expectations within 4 weeks (vs. 6 months for centralized DQ)
- False Positive Rate: 5.7% (versus 22% in centralized tools due to domain context)
- Resource Overhead: 12% increase in pipeline latency, but 76% reduction in firefighting effort
- Trust Catalyst: Domains exposing quality scores saw 3.2x more cross-domain consumption

6. Discussion

6.1. Interpretation of Evaluation Results

The experimental results validate our core hypothesis: federated quality scoring with lineage propagation significantly enhances trust while maintaining domain autonomy. The 75% reduction in TTDR demonstrates that lineage-contextualized scores enable precise impact analysis - a critical capability in decentralized environments where issues span multiple domains. The modest 12% latency overhead is offset by a 76% reduction in manual effort, representing a favorable tradeoff for operational efficiency. Notably, the trust score increase (46%) and higher cross-domain consumption (123%) indicate that quantitative quality transparency fundamentally changes consumption behaviors, transforming quality from a compliance requirement to a value driver. [13]

6.2. Advantages of the Proposed Framework

- Scalability Through Federation: By distributing rule execution to domains, the system handles 10,000+ datasets without central bottlenecks
- Autonomy Preservation: Domain-specific rule customization (weights, expectation types) respects Data-Mesh's core principle
- Holistic Quality View: Combines local validation with global lineage context for true ecosystem visibility
- Proactive Impact Assessment: Trust scores predict downstream impacts before failures occur (e.g., AML case study)
- Self-Correcting Governance: Higher consumption of high-trust datasets creates market incentives for quality.[14]

6.3. Limitations & Challenges

1. Lineage Completeness: Gaps in captured lineage (observed in 15% of production datasets) cause underreported propagation impacts
 - Mitigation: Augment Atlas with OpenLineage standards
2. Rule Standardization: Heterogeneous expectation rigor across domains complicates score comparison
 - Solution: Develop domain calibration indices
3. Schema Evolution: Breaking changes invalidate 23% of column-level expectations
 - Approach: Version expectation suites with schema snapshots
4. Performance Tradeoffs: Deep lineage traversal (4+ hops) adds 300-800ms latency
 - Optimization: Configurable depth limits with risk-based prioritization

5. False Positives: Decay factor oversimplification caused 12% false impact alerts
 - Improvement: Context-aware decay incorporating semantic distance

6.4. Applicability Beyond Data-Mesh

The framework extends to:

- Data Fabrics: As quality scoring layer for logical governance
- Multi-Cloud Architectures: Standardized scoring across heterogeneous platforms
- Regulated Ecosystems: Financial services consortiums with federated data sharing
- IoT Networks: Edge-to-cloud quality propagation in hierarchical topologies

Core Value Proposition: Any decentralized system needing local autonomy with global quality awareness

6.5. Governance Implications

The framework enables:

- Automated Compliance: Atlas policies enforce minimum quality thresholds
- Accountability Tracing: Lineage maps quality issues to responsible domains
- Incentive Alignment: Public trust scores create reputational motivation
- Gradual Standardization: Domains adopt common expectations organically

This operationalizes "federated computational governance" - establishing quality as an emergent property rather than centrally mandated control. [15]

7. Related Work (Revisited)

Table 6. Comparison of Approaches and Our Framework's Advancements

Approach	Key Capabilities	Data-Mesh Limitations	Our Framework's Advancements
Centralized DQ Tools (Informatica, Talend)	- Unified rule management - Executive	- Violates domain autonomy- Single-point	- Federated rule ownership- Lineage-

Approach	Key Capabilities	Data-Mesh Limitations	Our Framework's Advancements
	dashboards[16]	bottlenecks-Ignores lineage context	aware scoring- No central execution bottleneck
Apache Griffin	- Batch/stream support-Metrics aggregation	- Centralized rule repository-No cross-domain propagation[17]	- Domain-owned rule storage-Lineage-based impact quantification
P2P Quality Contracts(Quiet al.)	- Bilateral quality agreements-Negotiation protocols	- Manual coordination overhead-Doesn't scale beyond dyads	- Automated propagation-N-way dependency handling-Zero negotiation latency
Lineage-Aware DQ(Simmhan et al.)	- Workflow quality propagation-Accuracy estimation	- Assumes centralized control-Academic prototypes only	- Decentralized control planes-Production-ready integration-Trust quantification
OpenLineage	- Standardized lineage capture-Extensible metadata	- Quality metric gap-Passive observation only	- Active quality injection-Scoring as first-class lineage concept

8. Conclusion and Future Work

8.1. Summary

This work addresses the critical challenge of maintaining data quality in decentralized architectures through:

- A novel federated scoring framework combining GE (validation) and Atlas (lineage)
- Lineage-propagation algorithms quantifying cross-domain impact
- Production-grade implementation respecting domain autonomy
- Trust metrics correlating with 123% increased cross-domain consumption

8.2. Key Contributions

1. Architectural Blueprint: First federated quality system fully aligned with Data-Mesh principles
2. Propagation Model: Mathematically-grounded quality decay across lineage paths
3. Trust Quantification: CQS and trust score metrics validated in production
4. Open Integration: GE/Atlas extensions available as open-source modules
5. Empirical Validation: 75% RCA reduction demonstrated in financial services case

8.3. Practical Significance

For organizations adopting Data-Mesh, this framework:

- Reduces cross-domain incident resolution from hours to minutes
- Increases trust in decentralized data products
- Lowers governance overhead through automation
- Provides migration path from centralized DQ tools

8.4. Future Work

1. Adaptive Rule Recommendations: ML-driven expectation suggestions based on:

- Dataset profiling statistics
 - Similar domains' practices
 - Historical failure patterns
- $$\text{RuleRec} = f(\text{column_stats}, \text{domain_type}, \text{failure_history})$$

2. Cost-Benefit Optimization: Quantifying tradeoffs between:

- Rule execution cost (compute/storage)
 - Failure prevention value
 - Trust impact
- $$\text{EnforcementROI} = (\text{DownstreamRiskReduction} - \text{ExecutionCost})$$

3. Policy-Driven Automation: Integration with Open Policy

Agent for:

```
python
if trust_score < threshold:
    execute_policy("quarantine_dataset")
```

4. Advanced Visualization:

- 3D lineage quality heatmaps
- Impact simulation sandbox
- Trust score forecasting

5. Streaming Extension: Real-time trust scoring for:

- Kafka/Pulsar pipelines
- Stateful stream processing
- Dynamic score adjustment

6. Cross-Domain Calibration:

- Standardized score normalization
- Domain complexity indices
- Inter-domain benchmarking

7. Alternative Backends:

- OpenLineage integration
- Cloud-native (AWS Glue/Azure Purview)
- Graph-native (Neo4j/TigerGraph)

Final Perspective: This work transforms data quality from a centralized policing function to a federated value-creation mechanism - essential for realizing Data-Mesh's promise of scalable, agile, and trustworthy decentralized analytics.

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