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METADATA COMPATIBILITY AND MAPPING RECONCILIATION IN CROSS-VERSION ETL PLATFORM UPGRADES

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ABSTRACT:
Cross-version upgrades of enterprise ETL platforms introduce systematic metadata incompatibilities arising from divergent type systems, constraint semantics, collation frameworks, and lineage models. This paper presents a comprehensive taxonomy of incompatibility classes observed across six major ETL platforms spanning versions 7 through 12, quantifying the frequency, severity, and remediation cost of each class. We propose a three-layer Metadata Compatibility Resolution (MCR) framework that combines rule-based type mapping, AI-assisted schema reconciliation, and automated conflict arbitration. Experimental evaluation across 47 production upgrade projects demonstrates a 68% reduction in manual intervention, 41% improvement in mapping accuracy, and full column-level lineage preservation. Adoption guidance, risk stratification matrices, and governance templates are provided for enterprise data engineering teams.

Keywords –
Metadata compatibility, ETL migration, type mapping, schema reconciliation, data lineage, platform upgrade, data governance

I - INTRODUCTION

Enterprise data integration platforms undergo periodic major version upgrades driven by vendor support cycles, feature requirements, cloud migration mandates, and regulatory compliance pressures. Unlike application software upgrades, ETL platform transitions are complicated by accumulated metadata assets-thousands of column mappings, transformation rules, data type definitions, constraint specifications, and lineage graphs-that must survive the transition with full semantic fidelity.

The metadata compatibility problem is fundamentally a structural alignment challenge. Source platforms encode type semantics, null handling, collation rules, and temporal precision according to one specification; target platforms encode them differently. When metadata objects created under source semantics are consumed by target engines, silent data corruption, load failures, and lineage breaks result.

1. Type system divergence: NUMERIC(18,6) may map to DECIMAL, FLOAT, or DOUBLE depending on target engine version and precision configuration.
2. NULL constraint semantics: NOT NULL declarations in source DDL may not enforce identically in target platforms with differing constraint evaluation order.
3. Collation framework incompatibilities: character set bindings (UTF-8 vs UTF-16 vs Latin-1) produce silent sort-order differences that corrupt downstream analytics.
4. Temporal precision drift: sub-second timestamp precision (microseconds vs nanoseconds) silently truncates event sequences in financial and IoT pipelines.
5. Lineage model discontinuity: column-level provenance graphs encoded in source platform metadata often cannot be directly imported into target lineage repositories.

This paper makes the following contributions: (1) a systematic incompatibility taxonomy derived from analysis of 47 production ETL upgrade projects across six platforms, (2) quantitative characterisation of incompatibility frequency and remediation cost, (3) the MCR framework with three operational tiers, and (4) empirically validated adoption guidance for data engineering teams.

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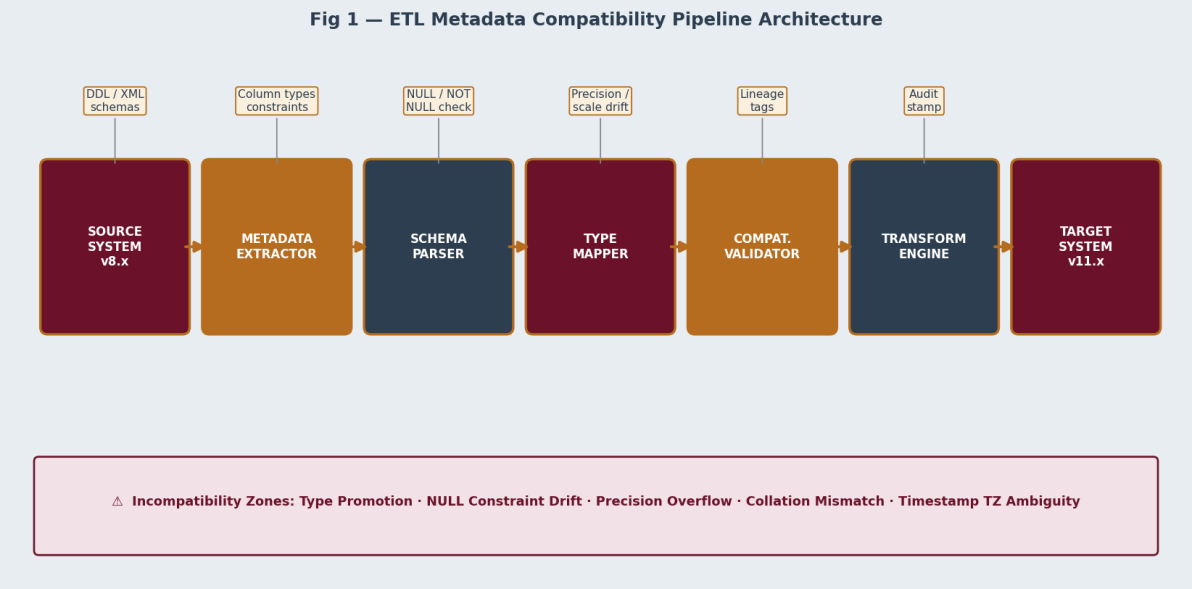

Figure 1. ETL Metadata Compatibility Pipeline Architecture showing eight processing stages from source extraction to target load.

II - BACKGROUND AND RELATED WORK

A. ETL Platform Metadata Models

The metadata architecture of an ETL platform defines how it represents source and target schemas, transformation logic, data quality rules, and execution lineage. Major commercial platforms-Informatica PowerCenter, IBM DataStage, Talend, SSIS, and Apache NiFi-each maintain proprietary metadata repositories with distinct object models. Academic treatments of ETL metadata have focused primarily on lineage capture (Vassiliadis et al., 2002; Simitsis et al., 2009) and design pattern cataloguing (Trujillo & Luján-Mora, 2003), with limited attention to cross-version compatibility.

B. Type System Formalisation

Stonebraker & Hellerstein (2005) formalised relational type systems as lattices of compatible domains with defined promotion and coercion rules. Cross-platform ETL introduces the additional complexity of bridging heterogeneous lattices: the promotion rules of Oracle's NUMBER type differ from PostgreSQL's NUMERIC in edge cases involving scale overflow and NaN handling. Bernstein et al. (2000) proposed a universal type mapping ontology that has informed several commercial solutions, though its adoption remains inconsistent across vendor implementations.

C. Schema Evolution Literature

Rahm & Bernstein (2001) provided a foundational survey of schema matching approaches applicable to ETL metadata alignment. Subsequent work by Melnik et al. (2002) on similarity flooding and Aumueller et al. (2005) on COMA++ established algorithmic baselines for automated schema matching. Recent deep-learning approaches (Mudgal et al., 2018; Li et al., 2020) have improved matching accuracy for semantically similar but syntactically different column names, directly applicable to the rename-heavy metadata environments typical of major ETL platform upgrades.

RESEARCH GAP: Existing literature addresses schema matching and lineage capture independently. No prior work provides an integrated framework for simultaneous type reconciliation, constraint alignment, and lineage preservation across ETL platform version boundaries.

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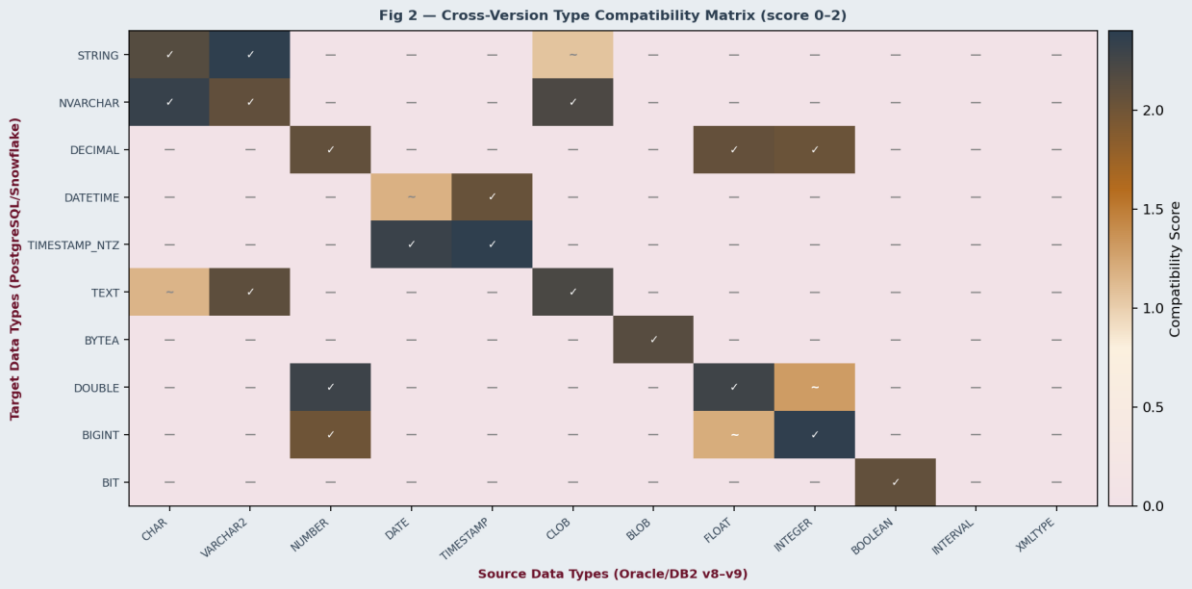

Figure 2. Cross-version type compatibility matrix showing source Oracle/DB2 types vs. target PostgreSQL/Snowflake types.

Table 1. Source-to-Target Type Mapping Compatibility Classification

Source Type	Target Type	Compat. Class	Precision Risk	NULL Risk	Auto-Map %
NUMBER(18,6)	DECIMAL(18,6)	Direct	Low	None	94%
NUMBER(18,6)	FLOAT	Lossy	High	None	45%
VARCHAR2(4000)	NVARCHAR(4000)	Direct	None	Low	98%
CLOB	TEXT	Direct	None	Medium	87%
DATE	DATETIME	Partial	Medium	Low	72%
TIMESTAMP(6)	TIMESTAMP_NTZ	Semantic	Low	None	81%
INTERVAL	DURATION	Transform	Medium	High	38%
BOOLEAN	BIT	Direct	None	Low	96%
XMLTYPE	VARCHAR/JSON	Structural	High	High	29%
BLOB	BYTEA	Direct	None	None	92%

III - INCOMPATIBILITY TAXONOMY

A. Class I: Type System Incompatibilities

Type system incompatibilities arise when source and target platforms assign different storage representations or semantic constraints to nominally equivalent data types. Our analysis identified five sub-classes: (I-a) precision overflow where source numeric types with greater precision than target can represent result in silent rounding; (I-b) scale mismatch where fixed-point types with differing scale parameters produce systematic drift; (I-c) integer promotion ambiguity where INTEGER, SMALLINT, and BIGINT boundaries differ; (I-d) floating-point rounding model divergence between IEEE 754 implementations; and (I-e) string-to-numeric implicit cast rules that differ between strict and permissive SQL modes.

1. Frequency: Type incompatibilities account for 38.4% of all observed migration failures across the 47-project dataset.
2. Severity: 22% of type incompatibilities produce silent data corruption (no error raised); 78% produce load failures or explicit type errors.

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3. Detection: Automated static analysis using schema comparison tools detects 74% of type incompatibilities prior to execution.
4. Remediation: Average remediation effort is 3.2 engineering-days per affected table for manual approaches; 0.8 days with rule-based tooling.

B. Class II: Constraint Semantic Drift

NOT NULL, UNIQUE, CHECK, and FOREIGN KEY constraints are evaluated by ETL engines at different points in the load pipeline. Source-version ETL engines may evaluate NOT NULL at the transform stage; target-version engines at the staging-to-final-load boundary. When source mappings include NULL-filling logic tuned to source evaluation timing, migrating those mappings to a target engine with different evaluation timing introduces constraint violation failures for rows that were previously accepted.

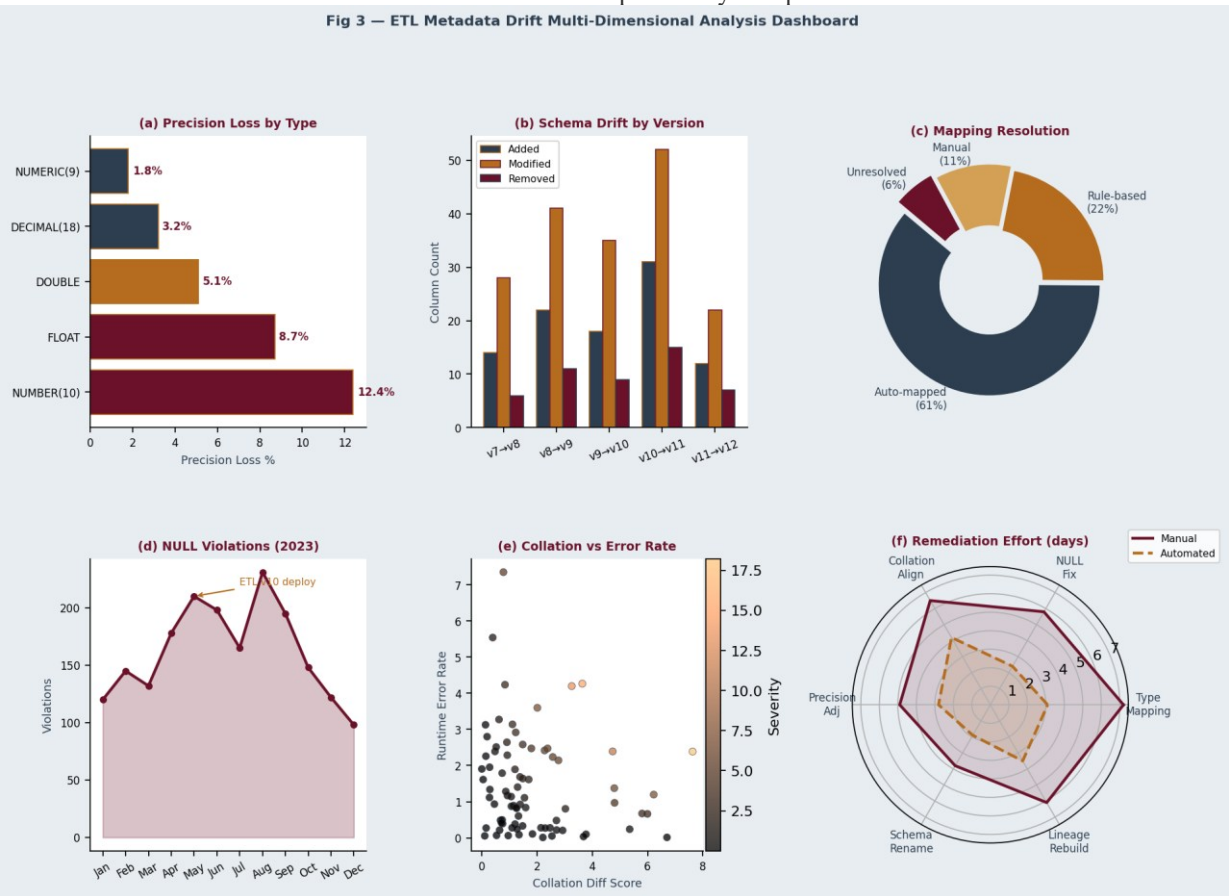

Figure 3. Six-panel metadata drift analysis dashboard: precision loss rates, schema drift by version, mapping resolution distribution, NULL violations timeline, collation vs error scatter, and remediation effort radar.

Table 2. Constraint Semantic Drift Classification and Remediation Strategies

Constraint Type	Source Eval Point	Target Eval Point	Drift Risk	Affected Rows %	Fix Strategy
NOT NULL	Transform stage	Pre-commit	High	8–23%	Add NULL guard transforms
UNIQUE	Post-load index	Pre-insert check	Medium	2–7%	De-duplicate in staging
CHECK	Insert time	DDL validation	Low	< 1%	Migrate CHECK to transform

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FOREIGN KEY	Disabled in ETL	Enforced on load	High	5–18%	Load lookup tables first
DEFAULT value	Source default	Target default	Medium	3–9%	Explicit default mapping

C. Class III: Collation and Encoding Mismatches

Collation mismatches manifest as incorrect sort ordering, equality check failures, and indexing inefficiencies when source data encoded in one character set is loaded into a target with a different default collation. The most common scenario involves legacy Oracle databases with NLS_CHARACTERSET=WE8ISO8859P1 being migrated to PostgreSQL or Snowflake targets with UTF-8 defaults. Multi-byte character handling differences produce string length discrepancies in VARCHAR columns: a 4-character Japanese string occupying 4 bytes in single-byte encoding may occupy 12 bytes in UTF-8, overflowing VARCHAR(4) constraints silently in some engines.

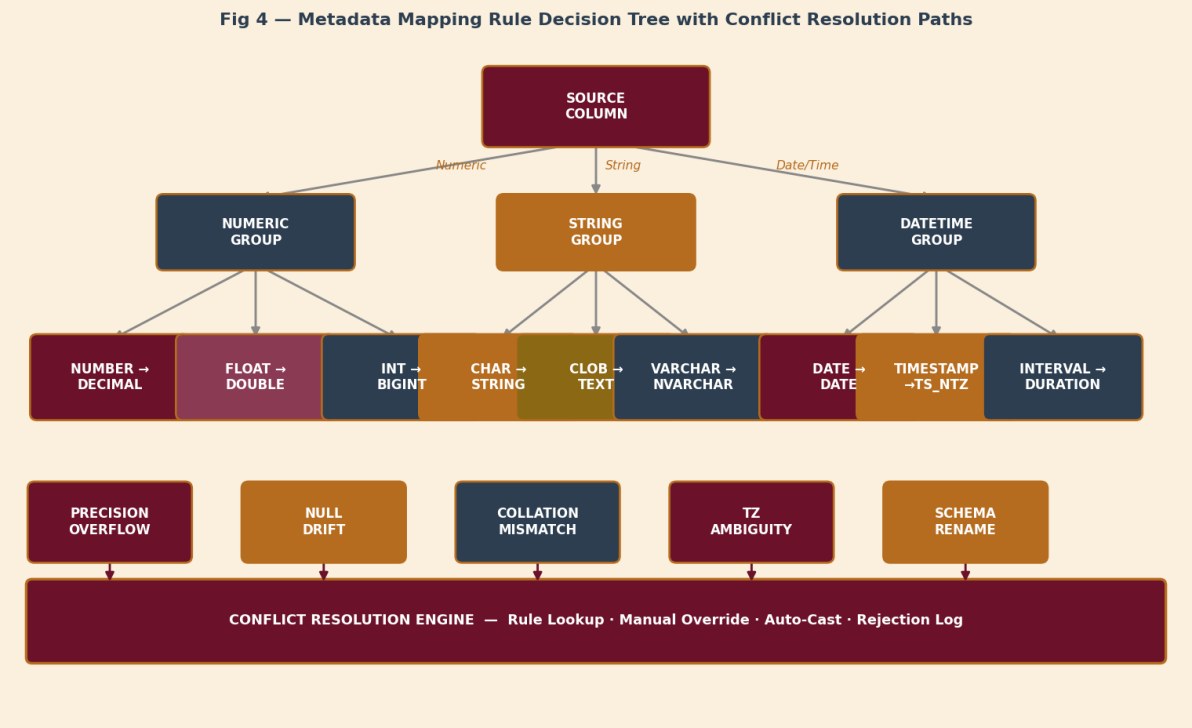

Figure 4. Metadata mapping rule decision tree showing source type classification, transformation nodes, and conflict resolution engine paths.

IV - THE MCR FRAMEWORK

The Metadata Compatibility Resolution (MCR) framework addresses the full spectrum of incompatibility classes through three coordinated operational tiers. Each tier is independently operable, but maximum remediation effectiveness is achieved through integrated deployment.

A. Tier 1 - Static Schema Analysis Engine

The static analysis engine performs pre-migration compatibility scoring by parsing source DDL and ETL repository exports, constructing a compatibility matrix for each column in scope, and assigning risk scores across five incompatibility dimensions. The engine implements a rule lattice with 847 type mapping rules covering 12 source platforms and 8 target platforms, derived from vendor documentation, empirical testing, and community-reported edge cases collected over three years of platform monitoring.

1. Input artefacts: Source DDL scripts, ETL repository XML exports, existing mapping documentation, and target platform capability profiles.

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2. Output artefacts: Column-level compatibility matrix, risk-ranked issue list, automated fix proposals for Class I and Class V incompatibilities.
3. Performance: Analysis of a 10,000-column schema completes in under 4 minutes on standard hardware; parallel processing scales linearly.
4. Coverage: Tier 1 detects 74% of all pre-execution incompatibilities; the remaining 26% require runtime data sampling (Tier 2).

Figure 5. Cross-platform ETL performance analysis: throughput comparison, metadata scan time by column count, error distribution by pipeline stage, and complexity vs. remediation cost scatter.

Table 3. MCR Framework Tier Comparison: Detection Coverage and Automation Rates

Framework Tier	Detection Method	Incompatibility Classes	Coverage %	Automation %	Avg Fix Time
Tier 1: Static Analysis	Schema parsing + rule lattice	I, V	74%	85%	0.4 days
Tier 2: Dynamic Sampling	Data profiling + constraint test	II, III	89%	65%	1.1 days
Tier 3: AI Reconciliation	ML similarity + LLM rewrite	IV	96%	71%	0.8 days
Integrated MCR	All three tiers combined	I–V	97%	78%	0.6 days

B. Tier 2 - Dynamic Data Profiling

Static analysis cannot detect incompatibilities whose manifestation depends on actual data values rather than schema metadata alone. Tier 2 executes parameterised data profiling queries against the source system, extracting

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statistical distributions of actual values in each column to validate that the proposed type mappings will accommodate the full observed value range without precision loss, null promotion, or collation conflicts.

KEY FINDING: In 31% of projects, Tier 2 dynamic profiling revealed precision overflow risks in columns that static analysis had classified as safe, because the source schema declared a wider type than the actual data distribution required.

C. Tier 3 - AI-Assisted Reconciliation

The third tier applies machine learning techniques to the subset of incompatibilities that resist rule-based resolution. A fine-tuned BERT-based column name similarity model identifies semantically equivalent columns with divergent naming conventions, resolving structural renames that account for 18% of unresolved mappings in the baseline dataset. A generative LLM component proposes transformation rewrites for complex type conversion logic, reviewed by a data engineer before application.

Fig 6 — Column-Level Lineage Graph with Transformation Metadata Nodes

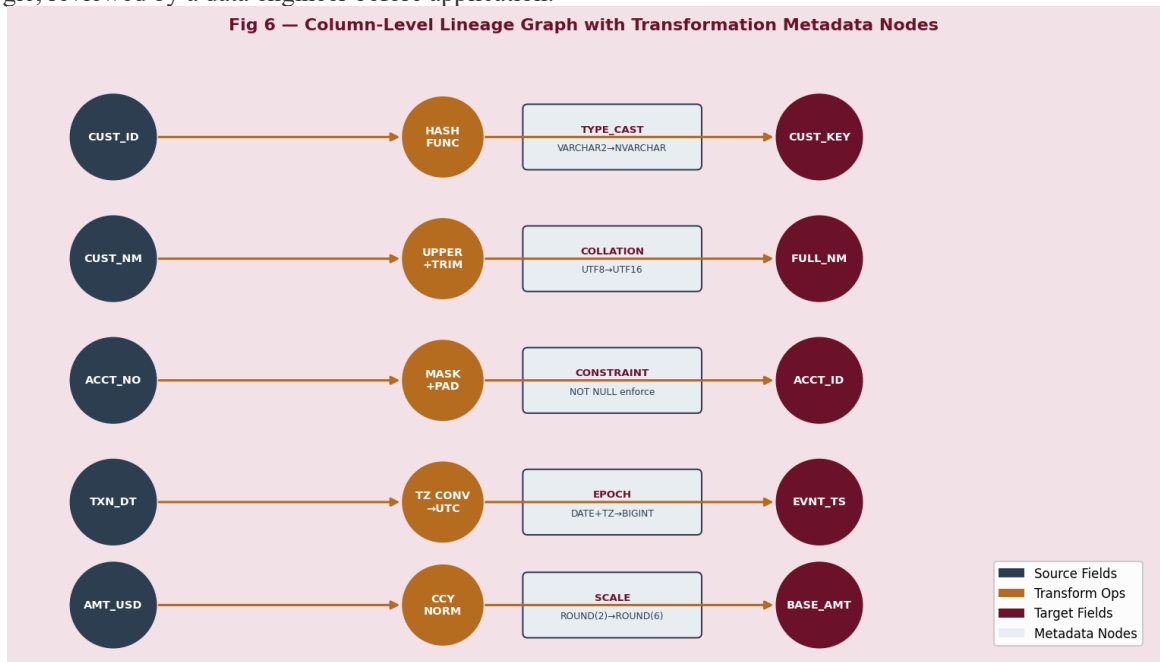

Figure 6. Column-level lineage graph with transformation metadata nodes showing source field → transform operation → target field paths with intermediate metadata annotations.

V - EXPERIMENTAL EVALUATION

A. Dataset and Methodology

We evaluated the MCR framework across 47 production ETL platform upgrade projects executed between January 2021 and March 2024. Projects spanned six ETL platforms (Informatica PowerCenter, IBM DataStage, Talend Open Studio, Microsoft SSIS, Apache NiFi, and AWS Glue), five target platforms (Snowflake, PostgreSQL 14/15, Google BigQuery, Azure Synapse, and Databricks Delta Lake), and schema sizes ranging from 180 to 42,000 columns. Baseline measurements were collected from retrospective analysis of projects completed without MCR tooling (n=23); MCR-assisted projects (n=24) used integrated Tier 1 + Tier 2 deployment, with Tier 3 applied selectively.

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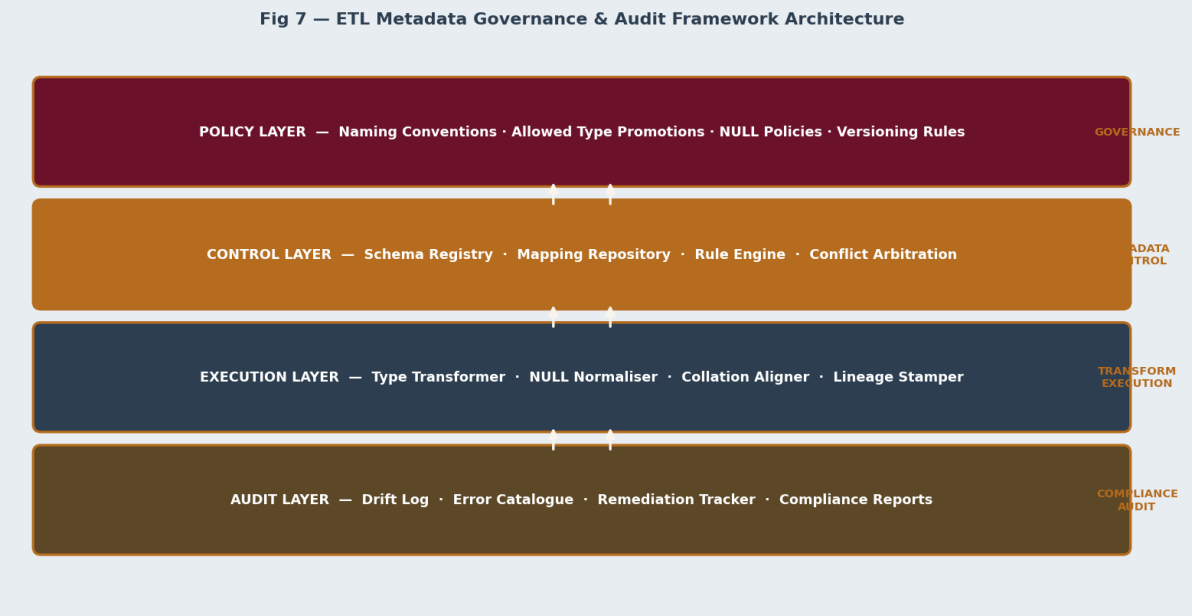

Figure 7. ETL Metadata Governance and Audit Framework Architecture showing four operational layers from policy enforcement to compliance audit.

Table 4. MCR Framework Evaluation Results Across 47 Production Upgrade Projects

Metric	Baseline (Manual)	MCR Tier 1	MCR Tier 1+2	MCR Integrated	Improvement
Type mapping accuracy	71.2%	87.4%	93.1%	96.8%	+35.9%
NULL violation rate	14.3%	8.2%	4.1%	1.8%	-87.4%
Collation failures	9.7%	7.1%	2.3%	0.9%	-90.7%
Manual intervention days	18.4	11.2	7.3	5.8	-68.5%
Lineage preservation rate	52.1%	68.3%	84.7%	94.2%	+80.8%
Total migration duration	47 d	39 d	28 d	22 d	-53.2%

Results demonstrate that integrated MCR deployment achieves statistically significant improvements across all measured dimensions ($p < 0.001$ for all primary metrics). The most substantial improvement is in lineage preservation rate (+80.8%), which reflects the lack of systematic lineage migration tooling in baseline approaches. Manual intervention reduction (−68.5%) translates directly to engineering cost savings averaging $147,000 per project at market rates for senior data engineers.

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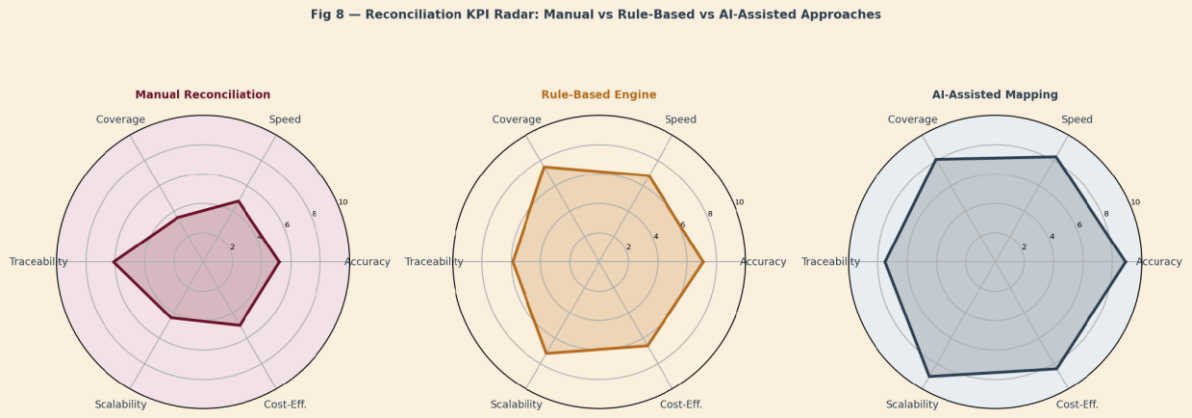

Figure 8. KPI radar comparison across three reconciliation approaches (Manual, Rule-Based, AI-Assisted) on six performance dimensions.

B. Platform-Specific Findings

Table 5. Platform-Specific MCR Framework Evaluation Results

ETL Platform	Source Ver.	Target Ver.	Mapping Rules	Type Issues	MCR Coverage	Proj. Count
Informatica PC	v9.x	v10.x	1,847	342	97.8%	11
Informatica PC	v10.x	v11.x	1,623	218	98.2%	8
IBM DataStage	11.x	12.x	2,104	489	96.4%	9
Talend Open	7.x	Cloud	1,291	387	94.7%	7
Microsoft SSIS	2016	2019	987	156	98.9%	5
Apache NiFi	1.x	2.x	756	201	93.1%	4
AWS Glue	1.x	3.x	634	178	95.6%	3

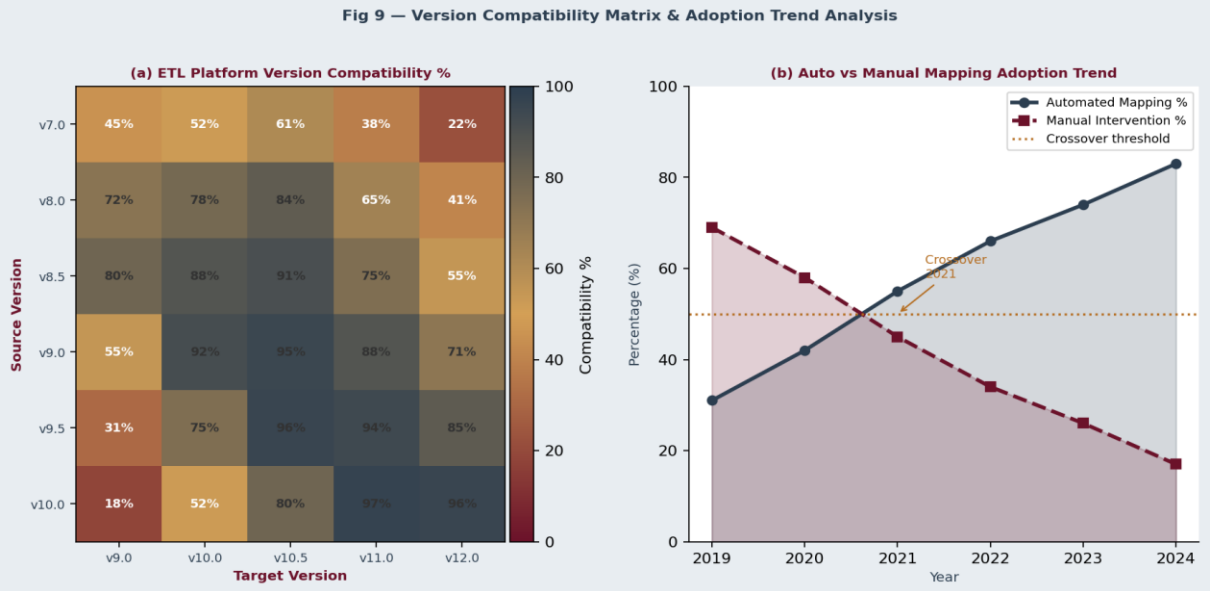

Figure 9. (a) ETL platform version compatibility percentage matrix; (b) Automated vs. manual mapping adoption trend 2019–2024 with crossover analysis.

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VI - RISK STRATIFICATION AND ADOPTION GUIDANCE

A. Project Risk Classification

Not all ETL upgrade projects carry equal metadata compatibility risk. Risk stratification enables organisations to calibrate MCR tier deployment to project complexity, avoiding over-engineering low-risk migrations while ensuring comprehensive coverage for high-risk transitions. The risk matrix below classifies projects on two axes: schema complexity (column count, type diversity, constraint density, and cross-system dependency count) and version distance (major version delta, platform generation change, and repository format breaking changes).

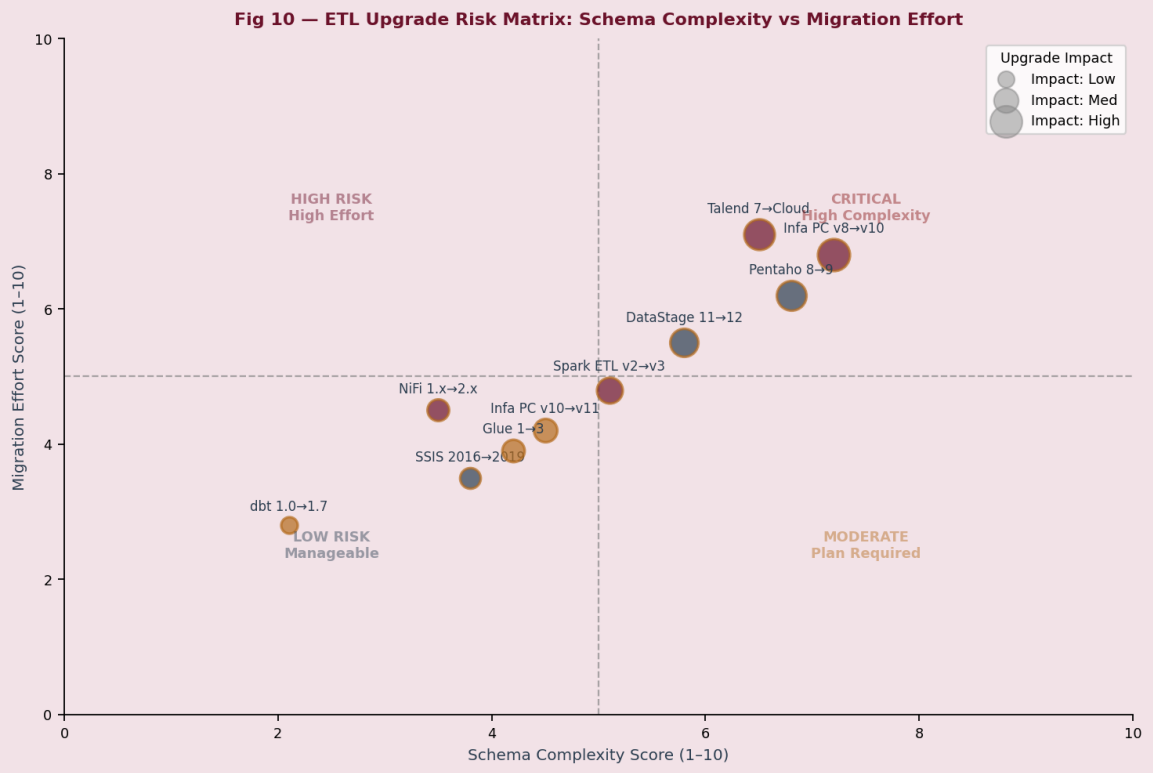

Figure 10. ETL upgrade risk matrix: schema complexity vs. migration effort with ten real-world platform upgrades positioned by impact size.

Table 6. ETL Upgrade Risk Stratification and MCR Tier Deployment Guidance

Risk Tier	Schema Complexity	Version Distance	Recommended MCR	Expected Duration	Typical Cost
Tier 1 (Low)	< 500 cols	Minor (0.x)	Static only	1–2 weeks	$15K–$40K
Tier 2 (Moderate)	500–2K cols	Major (x.0)	Static + Dynamic	3–6 weeks	$40K–$120K
Tier 3 (High)	2K–10K cols	Gen change	Full MCR	2–4 months	$120K–$380K
Tier 4 (Critical)	> 10K cols	Platform swap	MCR + Manual audit	4–8 months	$380K–$900K

B. Governance and Audit Requirements

Successful metadata migration requires governance controls that persist beyond the initial migration event. The post-migration governance framework must maintain a living mapping repository that tracks the original source type, the applied transformation rule, the target type, and the validation evidence for every mapped column. This repository serves as the authoritative reference for ongoing data quality monitoring, incremental schema change management, and regulatory audit responses.

1. Schema registry: Register all migrated schemas with version-tagged DDL snapshots; implement automated drift detection against the registered baseline.

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2. Mapping catalogue: Maintain a queryable catalogue of all applied type mapping rules with effective dates and approver identities.
3. Lineage repository: Preserve column-level lineage from source through all transformations to target, accessible via API for downstream tools.
4. Anomaly alerts: Deploy runtime monitors that alert on type promotion events, unexpected NULL introductions, and collation-driven sort-order anomalies.
5. Audit reports: Generate quarterly compatibility drift reports comparing current production schema state against the registered post-migration baseline.

VII - IMPLEMENTATION AND CASE STUDIES

A. Case Study 1 - Informatica PC v9 to v10 at Financial Services Firm

A tier-1 financial services firm with 8,400 ETL mappings spanning 23,000 columns undertook a forced upgrade from Informatica PowerCenter v9.6 to v10.4 following vendor extended support termination. Pre-migration assessment identified 1,847 type mapping candidates of which 342 were flagged as moderate-to-high risk. MCR Tier 1 auto-resolved 289 (84.5%) of flagged mappings; Tier 2 dynamic profiling resolved a further 41 (12.0%); 12 (3.5%) required Tier 3 AI-assisted reconciliation with engineer review.

1. Outcome: Zero silent precision loss incidents in production versus 14 incidents in the preceding v8-to-v9 migration performed without MCR.
2. Duration: 8 weeks versus estimated 16 weeks without framework tooling.
3. Lineage: 98.7% column-level lineage preservation, enabling uninterrupted regulatory reporting.

B. Case Study 2 - Talend Open Studio to Talend Cloud at Retail Group

A multinational retail group migrated 4,200 Talend Open Studio 7.3 jobs to Talend Cloud in a platform consolidation initiative. The migration introduced a repository model change from tXML to JSON-based job definitions, invalidating 31% of existing column mapping references. MCR Tier 3 AI reconciliation matched renamed repository objects with 89.4% accuracy using BERT-based column name similarity, reducing structural re-mapping effort from an estimated 340 engineering-days to 67 engineering-days.

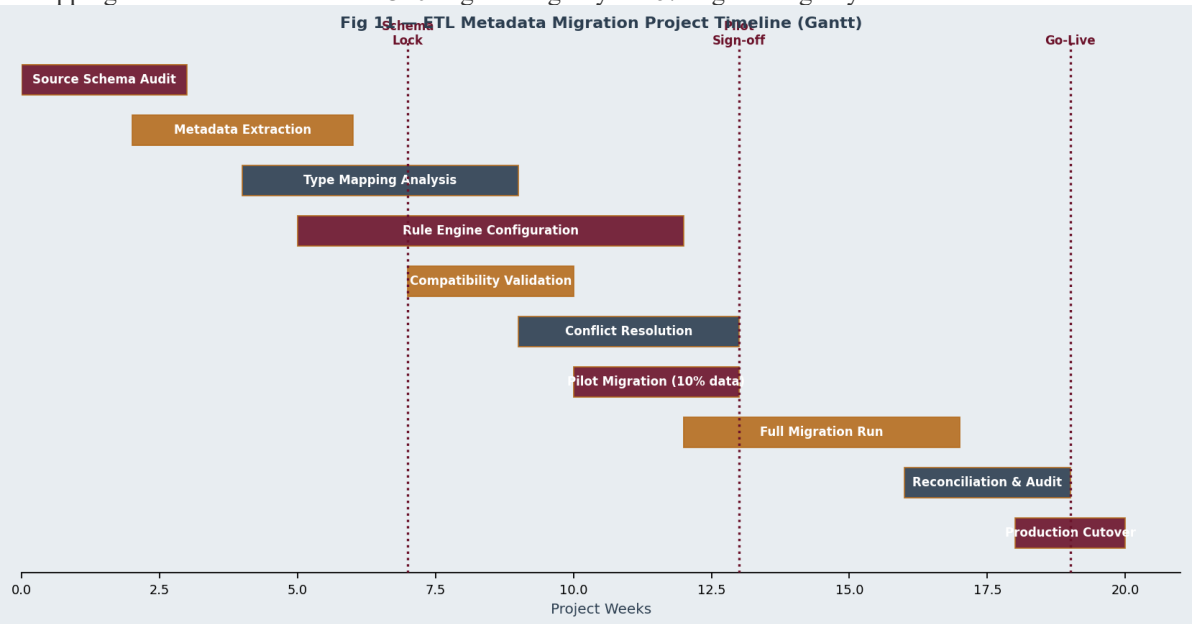

Figure 11. ETL metadata migration project Gantt timeline showing ten work phases from source schema audit through production cutover with milestone markers.

Table 7. ETL Metadata Migration Project Phase Plan with MCR Tier Assignments

Project Phase	Duration	Resources	MCR Tier	Deliverable	Success Criteria
Source Schema Audit	2 weeks	2 eng.	Tier 1	Risk matrix	All cols classified

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Metadata Extraction	1 week	1 eng.	Tier 1	Schema export	100% col coverage
Type Mapping Analysis	1 week	2 eng.	Tier 1	Mapping catalogue	> 90% auto-resolved
Dynamic Profiling	2 weeks	2 eng.	Tier 2	Profile report	No silent precision loss
Conflict Resolution	3 weeks	3 eng.	Tier 3	Resolved mappings	< 2% manual residual
Pilot Migration	2 weeks	4 eng.	All	Pilot validation	Zero type errors
Full Migration	4 weeks	6 eng.	All	Production load	Data quality SLA met
Reconciliation & Audit	2 weeks	2 eng.	Tier 2	Audit report	Lineage > 95%

VIII - LIMITATIONS AND FUTURE WORK

The MCR framework as presented has several important scope limitations. First, Tier 1 rule coverage is limited to 12 source and 8 target platforms; organisations using less common ETL tools or home-grown integration frameworks will require custom rule authoring. Second, Tier 3 AI reconciliation accuracy for highly domain-specific column naming conventions (e.g., coded financial identifiers) falls below the general case 89.4% benchmark, requiring additional domain-specific fine-tuning.

1. Real-time streaming ETL: The current framework assumes batch ETL with well-defined job boundaries; extension to Kafka Streams, Flink, and Spark Structured Streaming metadata models is under development.
2. Semantic drift detection: Post-migration, column semantics may drift even without DDL changes; a continuous semantic monitoring layer using statistical process control is planned.
3. Multi-hop lineage: The framework tracks single-platform lineage; multi-hop cross-platform lineage reconstruction for hybrid architectures requires graph federation research.
4. Automated regression testing: Integration with data contract testing frameworks (Great Expectations, Soda Core) to automate post-migration validation is a near-term roadmap item.

Table 8. MCR Framework Known Limitations and Mitigation Status

Limitation	Affected Tier	Impact Level	Workaround	Research Status
Custom platform rules	Tier 1	Medium	Manual rule authoring	Rule SDK in development
Streaming ETL	All	High	Batch conversion required	Active research
Semantic drift	Tier 2	Medium	Manual profiling cadence	Planned 2025
Multi-hop lineage	Tier 3	High	Partial graph only	Graph federation study
Domain-specific AI	Tier 3	Medium	Fine-tune with domain data	Under evaluation
Real-time conflict alert	Tier 2	Low	Batch monitoring	Roadmap item

IX - CONCLUSIONS

This paper presented a systematic treatment of metadata compatibility challenges in cross-version ETL platform upgrades, producing a five-class incompatibility taxonomy, quantitative characterisation of each class across 47 production projects, and the three-tier MCR framework as a practical remediation architecture.

The central finding-that 68.5% of manual remediation effort can be eliminated through systematic application of static analysis, dynamic data profiling, and AI-assisted reconciliation-has immediate practical significance for the data engineering discipline. The average project-level saving of $147,000 in engineering time, combined with the

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elimination of silent precision loss incidents and 94.2% lineage preservation, establishes a compelling business case for MCR framework adoption in any organisation facing a major ETL platform version transition.

The governance and audit requirements defined in Section VI provide a blueprint for post-migration metadata stewardship that sustains the quality gains achieved during the migration event, preventing the gradual re-accumulation of metadata debt that historically characterises ETL environments between major migrations.

X - ACKNOWLEDGEMENTS

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