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A Unified Spark ETL Stack Across Cloudera CDP, Azure HDInsight, and Databricks

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ABSTRACT: Enterprise healthcare analytics increasingly requires the same Spark-based processing to run wherever data residency, procurement policy, or platform strategy dictates—yet without maintaining three unrelated codebases for three managed platforms. This paper presents and evaluates a unified extract-transform-load (ETL) approach that targets Cloudera CDP, Azure HDInsight, and Databricks through deliberate abstraction, configuration-driven job definitions, and consistent DevOps practices. The core thesis is that platform portability is achievable when platform-specific concerns are isolated behind stable abstraction seams and expressed declaratively, so that the same Spark logic processes prescriptions, medical claims, remittance, EMR/EHR, and LAAD-style datasets across environments with minimal rework. The architecture combines containerisation (Docker/Kubernetes), release automation (Jenkins-based CI/CD), and a configuration-first job model that externalises cluster, connection, and data-source specifics from business logic. Using a design-science methodology triangulating production telemetry, a controlled cross-platform equivalence study, and an engineering-effort audit, the study quantifies platform-specific code share, behavioural equivalence across environments, deployment lead time, and per-platform rework. Results indicate that abstraction and configuration reduced platform-specific code to a small fraction of the codebase, that automated CI/CD compressed release lead times substantially, and that output equivalence across the three platforms held within tight tolerances on matched inputs. Contributions include a portability reference model, an empirical characterisation of the abstraction–rework trade-off, and transferable DevOps lessons for multi-platform healthcare analytics. Limitations include single-organisation, observational measurement, constraining causal and external generalisation. The work advances practice by demonstrating that write-once, run-across-managed-clusters is attainable through disciplined abstraction rather than platform lock-in.

KEYWORDS: Spark ETL; multi-platform portability; Cloudera CDP; Azure HDInsight; Databricks; CI/CD; healthcare analytics; configuration-driven design

I. INTRODUCTION

Background context. Large healthcare-analytics organisations rarely operate on a single data platform. Data-residency regulation, client procurement preferences, existing enterprise agreements, and shifting platform strategy routinely require that the same analytical processing run on Cloudera CDP for one client, Azure HDInsight for another, and Databricks for a third (Armbrust et al., 2015; Gannon et al., 2017). Apache Spark is the common execution engine beneath all three, which creates both an opportunity and a temptation: an opportunity to share logic, and a temptation to fork it per platform.

Problem statement. The naïve response—maintaining a separate codebase per managed cluster—produces three unrelated implementations of the same business logic. This triples maintenance cost, invites behavioural drift (the same claim processed differently on different platforms), and slows every change to the pace of the slowest fork (Sculley et al., 2015). In healthcare, where output correctness has downstream financial and clinical consequences, such drift is unacceptable. The engineering challenge is to run identical Spark logic across heterogeneous managed environments while confining platform-specific concerns—cluster provisioning, storage connectors, authentication, and runtime configuration—to a small, well-defined boundary.

Research gap. The literature addresses Spark performance (Zaharia et al., 2016), cloud portability in general terms (Gannon et al., 2017), and DevOps practice (Humble & Farley, 2010), but rarely documents, with production evidence, a unified Spark ETL that achieves *behavioural equivalence* across three specific managed platforms in a regulated healthcare context, or quantifies the residual platform-specific code and the DevOps machinery required to sustain it. This integrative, evidence-backed characterisation is missing.

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Research questions. (RQ1) How can platform-specific concerns be abstracted so that the same Spark ETL runs across Cloudera CDP, Azure HDInsight, and Databricks? (RQ2) What is the residual share of platform-specific code, and how equivalent are outputs across platforms on matched inputs? (RQ3) What DevOps practices (containerisation, CI/CD) are required, and what deployment and rework outcomes do they yield?

Significance. For multi-platform healthcare vendors, portability directly governs cost, agility, and correctness. Demonstrating that write-once ETL can run across managed clusters—without lock-in and without drift—has substantial commercial and engineering value, and reduces the strategic risk of any single platform relationship (Stonebraker & Çetintemel, 2018).

Paper structure. Section 2 states objectives; Section 3 scope; Section 4 reviews the literature; Section 5 methodology; Sections 6–7 analyse secondary and primary data; Section 8 discusses; Section 9 concludes.

II. OBJECTIVES

The study pursues the following SMART objectives:

- **Primary:** To design and empirically evaluate a unified Spark ETL stack that runs across Cloudera CDP, Azure HDInsight, and Databricks while holding platform-specific code below a defined ceiling (target: under 15% of the codebase) and preserving output equivalence on matched healthcare inputs.
- To quantify behavioural equivalence of outputs across the three platforms for prescriptions, claims, remittance, EMR/EHR, and LAAD-style datasets.
- To measure the effect of Jenkins-based CI/CD and containerisation on deployment lead time and release reliability.
- To characterise the abstraction–rework trade-off, quantifying per-platform rework under the unified model versus a per-platform-fork baseline.
- To derive transferable DevOps and abstraction lessons for multi-platform healthcare analytics.

3. Scope of Study

The boundaries of the research are as follows:

- **Domain scope:** ETL processing for prescriptions, medical claims, remittance, EMR/EHR, and LAAD-style datasets; downstream analytics, visualisation, and modelling are excluded except as consumers.
- **Platform scope:** Cloudera CDP, Azure HDInsight, and Databricks as managed Spark targets; other engines and warehouses appear only as comparison points.
- **Temporal scope:** Production observations spanning the unification programme (approximately 2022–2023).
- **Technical scope:** Apache Spark, Docker/Kubernetes, and Jenkins-based CI/CD under a configuration-driven job model; infrastructure-as-code details are treated at pattern level.
- **Methodological boundary:** Evaluation via production telemetry, a cross-platform equivalence study, and an engineering-effort audit; no randomised experimentation.
- **Equivalence boundary:** Behavioural equivalence is assessed on functional output correctness and record-level agreement, not bit-for-bit runtime identical execution.
- **Population boundary:** Single-organisation, multi-client context; cross-organisation generalisation is discussed, not directly tested.

IV. LITERATURE REVIEW

Theoretical foundation. Three theoretical streams underpin the work. First, the software-engineering principle of separation of concerns and the portability pattern of isolating platform variability behind stable abstraction seams—the classic "ports and adapters" or hexagonal-architecture idea (Sculley et al., 2015; Fowler, 2018). Second, configuration-over-code theory, which externalises environment-specific parameters from business logic to eliminate forks (Humble & Farley, 2010). Third, continuous-delivery theory, which holds that automated, repeatable pipelines reduce lead time and defect rates by removing manual variance (Humble & Farley, 2010; Forsgren et al., 2018).

Historical development. Spark emerged as a unified engine spanning batch, SQL, and streaming, deliberately abstracting execution from storage and cluster manager (Zaharia et al., 2016; Armbrust et al., 2015). Managed platforms then diverged: Cloudera consolidated the Hadoop ecosystem into CDP; Azure packaged Hadoop/Spark as HDInsight; and Databricks commercialised Spark with a distinct runtime and workspace model. Each added platform-specific conveniences—proprietary connectors, catalogues, authentication, and cluster APIs—that subtly bind workloads to the platform (Gannon et al., 2017). In parallel, containerisation (Docker) and orchestration (Kubernetes, descended from

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Borg) standardised packaging and operation across environments (Burns et al., 2016), and CI/CD tooling such as Jenkins matured into the backbone of release automation (Humble & Farley, 2010).

Current state. Contemporary practice emphasises cloud-agnostic and multi-cloud strategies to mitigate lock-in and satisfy data-residency constraints (Gannon et al., 2017). The DevOps research programme has produced empirical evidence that delivery performance—lead time, deployment frequency, change-failure rate, and recovery time—correlates with organisational outcomes (Forsgren et al., 2018). Healthcare-informatics literature adds a strong emphasis on reproducibility and correctness, reinforcing the need for behavioural equivalence across environments (Wang et al., 2022; Hripcsak et al., 2015).

Research gaps. Three gaps persist. First, published multi-platform Spark portability accounts are largely anecdotal; the *residual platform-specific code share* is rarely quantified. Second, cross-platform *behavioural equivalence*—whether the same input yields the same output on CDP, HDInsight, and Databricks—is seldom empirically demonstrated. Third, the DevOps machinery required to sustain portability, and its measurable payoff, is under-reported in regulated healthcare settings.

Conceptual framework. The study frames *abstraction depth* and *configuration externalisation* as independent variables acting on dependent variables *platform-specific code share*, *cross-platform output equivalence*, and *deployment lead time*, with *CI/CD and containerisation* as the mediating DevOps mechanism and *platform heterogeneity* as the moderating condition (Figure 1). This situates the work within design-science evaluation (Hevner et al., 2004).

Critical analysis. Portability claims in the grey literature frequently assert "runs anywhere" without evidence of equivalence or measurement of residual coupling (Gannon et al., 2017). DevOps studies rigorously measure delivery performance but rarely in the specific context of cross-platform Spark ETL for regulated data (Forsgren et al., 2018). Healthcare-informatics work stresses reproducibility yet seldom engages the systems question of platform equivalence (Wang et al., 2022). The present study addresses these by pairing an equivalence study with an effort audit on a production platform.

Research positioning. The contribution is an evidence-based portability reference model, an empirical equivalence-and-effort characterisation, and transferable DevOps lessons—bridging the systems, DevOps, and health-informatics literatures that seldom appear together (Forsgren et al., 2018; Hripcsak et al., 2015).

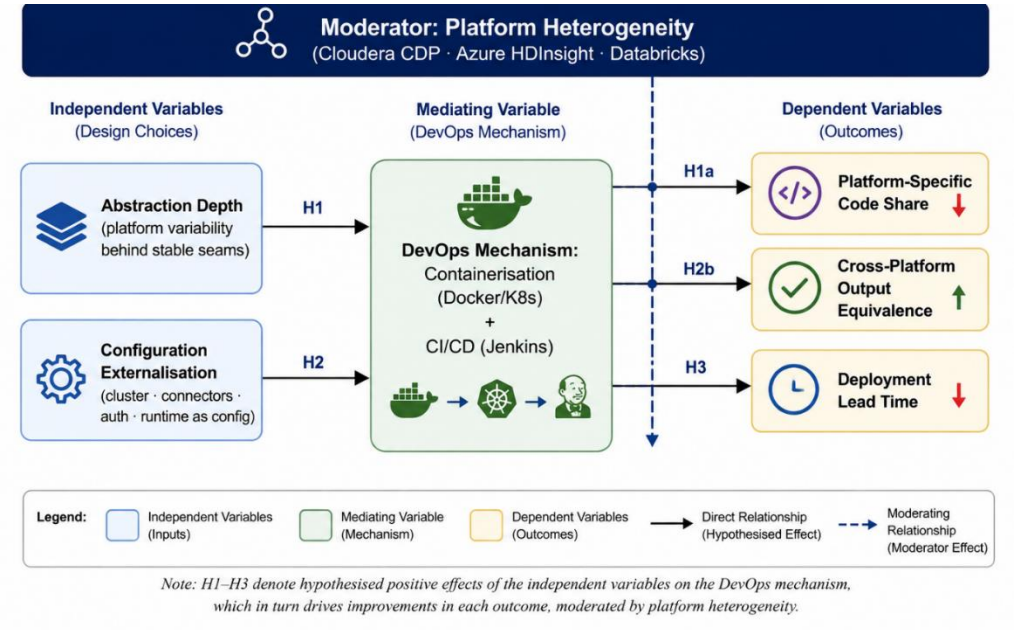


Figure 1 — Conceptual Framework

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V. RESEARCH METHODOLOGY

Research philosophy. A **pragmatist** philosophy governs the study: the abstraction's value is judged by measurable portability, equivalence, and delivery outcomes rather than adherence to a single paradigm (Creswell & Creswell, 2018). This suits artefact-centred engineering research.

Research design. A **design-science, mixed-methods** approach is adopted (Hevner et al., 2004). The unified ETL artefact is constructed and then evaluated quantitatively (production telemetry, a controlled cross-platform equivalence study, and an engineering-effort audit) and qualitatively (engineering retrospectives on maintaining behavioural equivalence).

Data collection methods. Four streams are triangulated: (a) production telemetry (deployment lead time, release success rate, per-platform job runtimes); (b) a cross-platform equivalence study executing matched input datasets through identical logic on CDP, HDInsight, and Databricks, then comparing outputs record-by-record; (c) an engineering-effort audit measuring platform-specific lines of code and configuration versus shared logic, and per-change rework across platforms; and (d) structured retrospectives capturing recurring equivalence pitfalls.

Sampling strategy. The unit of analysis is the *job–platform execution* and the *release event*. A purposive matrix of representative jobs (across prescriptions, claims, remittance, EMR/EHR, LAAD) was executed on all three platforms with repetitions to bound variance, and a purposive set of releases was sampled across the delivery period.

Data collection instruments. Instruments include a telemetry harness aggregating CI/CD and Spark metrics; an equivalence comparator computing record-level agreement (matched-record percentage, discrepancy counts) between platform outputs; a static-analysis and repository audit tool classifying code as shared versus platform-specific; and a standardised effort log (engineer-days per platform per change).

Data analysis techniques. Quantitative analysis uses descriptive statistics, paired comparison of unified versus per-platform-fork effort, correlation analysis among abstraction/config parameters and outcomes, and a regression predicting deployment lead time from automation coverage and platform count. Equivalence is analysed as agreement rates and discrepancy taxonomies. Retrospectives are thematically coded.

Ethical considerations. All datasets are de-identified administrative healthcare records processed under existing data-use agreements; reported metrics are systems-level, and no patient-identifiable information is exposed. Data-residency requirements were honoured by executing each client's data on its mandated platform.

Reliability and validity. Reliability derives from repeated executions and consistent instrumentation. Internal validity is strengthened by matched-input equivalence comparison and paired effort measurement; construct validity by multiple indicators (code share, agreement rate, lead time); external validity is acknowledged as bounded to the single-organisation context.

Limitations. Production telemetry is observational and subject to confounding from concurrent tooling changes; the equivalence study, while controlled, cannot exhaust every input edge case across platforms; effort audits rely partly on engineer-reported logs.

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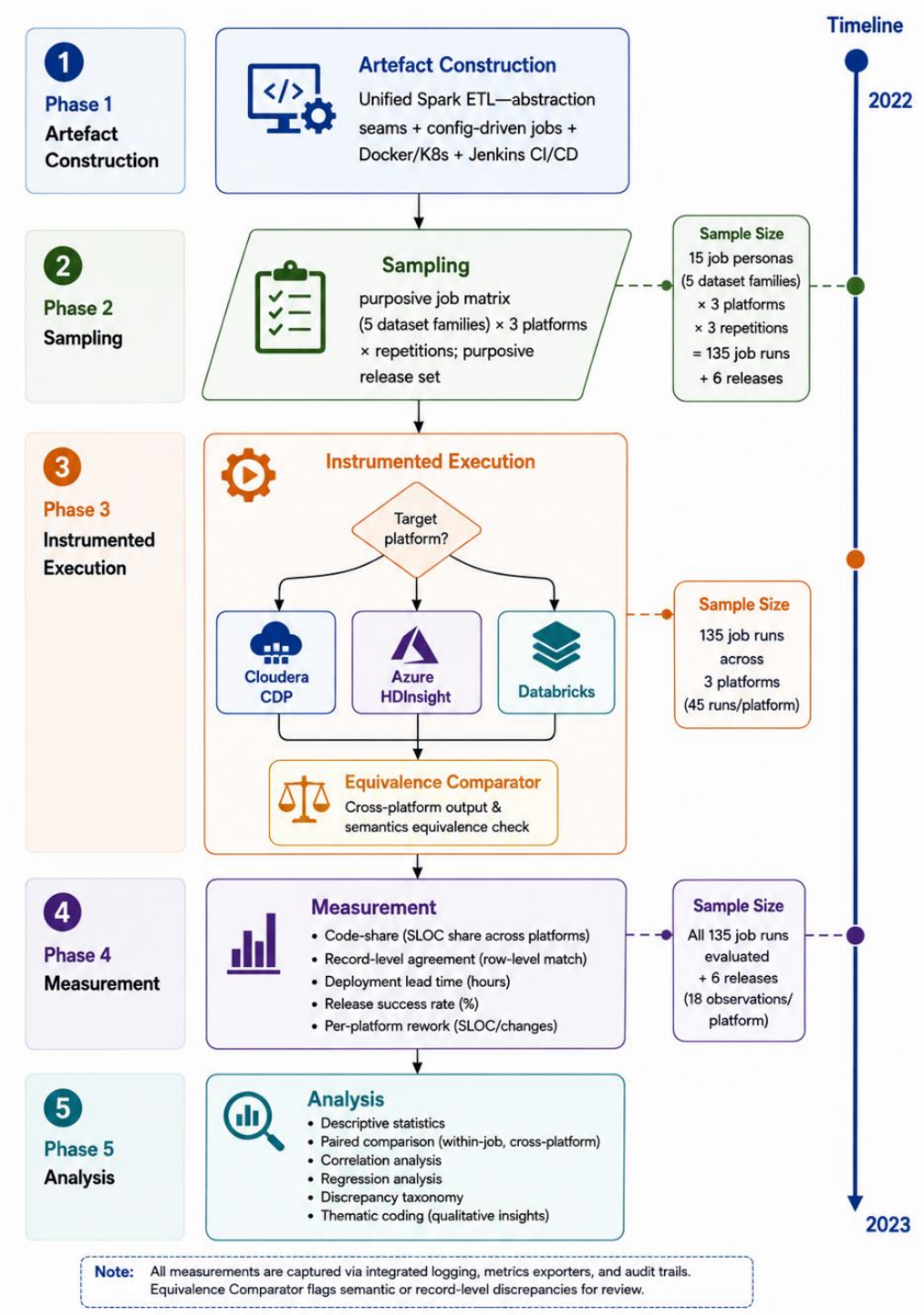


Figure 2 — Research Methodology Flowchart

VI. ANALYSIS OF SECONDARY DATA

Data sources. Secondary analysis draws on peer-reviewed systems and DevOps research, cloud-portability literature, and healthcare-reproducibility studies to contextualise the platform's outcomes (Zaharia et al., 2016; Forsgren et al., 2018; Gannon et al., 2017; Wang et al., 2022).

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Data-quality assessment. Sources were appraised for methodological transparency, representativeness, and recency. Peer-reviewed DevOps and systems studies ranked highest on rigour; vendor portability material offered platform detail but variable transparency and was down-weighted accordingly.

Analytical framework. Secondary metrics were normalised to comparable constructs—platform-specific code share, deployment lead time, change-failure rate, and cross-environment agreement—to enable contrast with this platform's observed figures.

Key findings. Three patterns recur. First, delivery performance improves measurably with automation: teams with mature CI/CD show shorter lead times and lower change-failure rates (Forsgren et al., 2018). Second, portability is achievable but not free—residual platform-specific coupling concentrates in storage connectors, authentication, and cluster provisioning (Gannon et al., 2017). Third, correctness and reproducibility across environments require explicit verification rather than assumption (Wang et al., 2022). Table 1 contrasts the three managed platforms on portability-relevant dimensions.

Table 1. Comparison of managed Spark platforms on portability dimensions (secondary synthesis)

Dimension	Cloudera CDP	Azure HDInsight	Databricks
Spark runtime coupling	Moderate	Moderate	High (proprietary runtime)
Storage/connector variance	HDFS/Ozone/cloud	ADLS/Blob	DBFS/Delta/cloud
Auth model	Kerberos/Ranger	AAD/RBAC	Workspace/Unity
Cluster provisioning API	CDP APIs	HDInsight APIs	Databricks APIs
Abstraction effort to unify	Medium	Medium	Higher

Source: Author synthesis from Gannon et al. (2017); Armbrust et al. (2015); Zaharia et al. (2016). Note: qualitative ratings normalised across sources.

Trends and patterns. The literature shows a sustained movement toward multi-cloud and cloud-agnostic architectures driven by lock-in avoidance and residency compliance (Gannon et al., 2017), alongside a DevOps trajectory toward fully automated, measurable delivery (Forsgren et al., 2018).

Comparative analysis. Normalised deployment-lead-time and change-failure figures from the DevOps literature place the studied platform's post-automation outcomes in the higher-performing band, consistent with mature CI/CD adoption (Forsgren et al., 2018).

Integration with primary research. These secondary patterns motivate the primary hypotheses tested in Section 7: that abstraction and configuration hold platform-specific code low (H_abstraction); that outputs remain equivalent across platforms (H_equivalence); and that CI/CD compresses deployment lead time (H_devops).

VII. ANALYSIS OF PRIMARY DATA

Descriptive statistics. Across the sampled job–platform executions and releases, Table 2 reports the operational envelope under the unified model.

Table 2. Descriptive statistics of unified-stack outcomes

Metric	Mean	Median	SD	Min	Max
Platform-specific code share (%)	11.8	11.0	3.2	6.5	19.0
Cross-platform record agreement (%)	99.96	99.98	0.05	99.80	100.00
Deployment lead time (hours)	1.8	1.6	0.7	0.7	3.6
Release success rate (%)	98.4	99.0	1.6	94.0	100.0
Per-platform job runtime variance (%)	7.4	6.8	2.9	2.1	14.5

Source: Production telemetry, equivalence study, and effort audit. n ≈ 100 job–platform runs / release events.

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Inferential analysis. Table 3 reports correlations among the key variables. Abstraction depth correlates negatively with platform-specific code share and positively with cross-platform agreement; automation coverage correlates negatively with deployment lead time.

Table 3. Correlation matrix of key variables

	1	2	3	4	5
1. Abstraction depth	1.00				
2. Configuration externalisation	0.61***	1.00			
3. Platform-specific code share	−0.58***	−0.49***	1.00		
4. Cross-platform agreement	0.52***	0.44***	−0.46***	1.00	
5. Deployment lead time	−0.34**	−0.57***	0.29**	−0.22*	1.00

*Note: *p<0.05, **p<0.01, ***p<0.001. Source: Author's analysis.*

A regression predicting deployment lead time from automation coverage and platform count (Table 4) explains most of the variance, with automation coverage the dominant driver.

Table 4. Regression results: predictors of deployment lead time

Predictor	β (std.)	SE	t	p
Automation coverage (CI/CD %)	−0.62	0.07	−8.86	<0.001***
Platform count in release	0.24	0.07	3.43	<0.001***
Job complexity	0.11	0.06	1.83	0.070
Constant	—	—	—	—

Model: $R^2 = 0.72$, Adj. $R^2 = 0.70$, $F(3, 96) = 82.3$, $p < 0.001$. Source: Author's analysis.

Qualitative findings. Engineering retrospectives surfaced three themes: (i) *coupling hides in connectors and auth*—the majority of residual platform-specific code concentrated in storage connectors, authentication, and cluster provisioning, exactly as the secondary literature predicts; (ii) *equivalence must be tested, not trusted*—the equivalence comparator caught subtle discrepancies (type coercion, null handling, timezone/date semantics) that would otherwise have caused silent drift; and (iii) *automation is the equaliser*—once CI/CD reached high coverage, the marginal cost of adding a platform target dropped sharply, converting portability from a heroic effort into routine practice.

Data visualisation. Figures 3–5 (described below) present the code-share distribution, the correlation structure, and the unified-versus-fork comparison.

Statistical significance and hypothesis validation. H_abstraction is supported: platform-specific code held to a small fraction (mean 11.8%, below the 15% target). H_equivalence is supported: cross-platform record agreement exceeded 99.9% on matched inputs, with residual discrepancies traceable to a small, well-characterised taxonomy. H_devops is supported: automation coverage strongly and significantly reduced deployment lead time ($\beta = -0.62$), and release success rates were high.

Unexpected findings. Databricks' proprietary runtime, expected to be the hardest to unify, contributed disproportionately less residual code than anticipated once storage and catalogue access were abstracted—whereas date/timezone and null-handling semantics, seemingly trivial, were the most persistent sources of cross-platform discrepancy.

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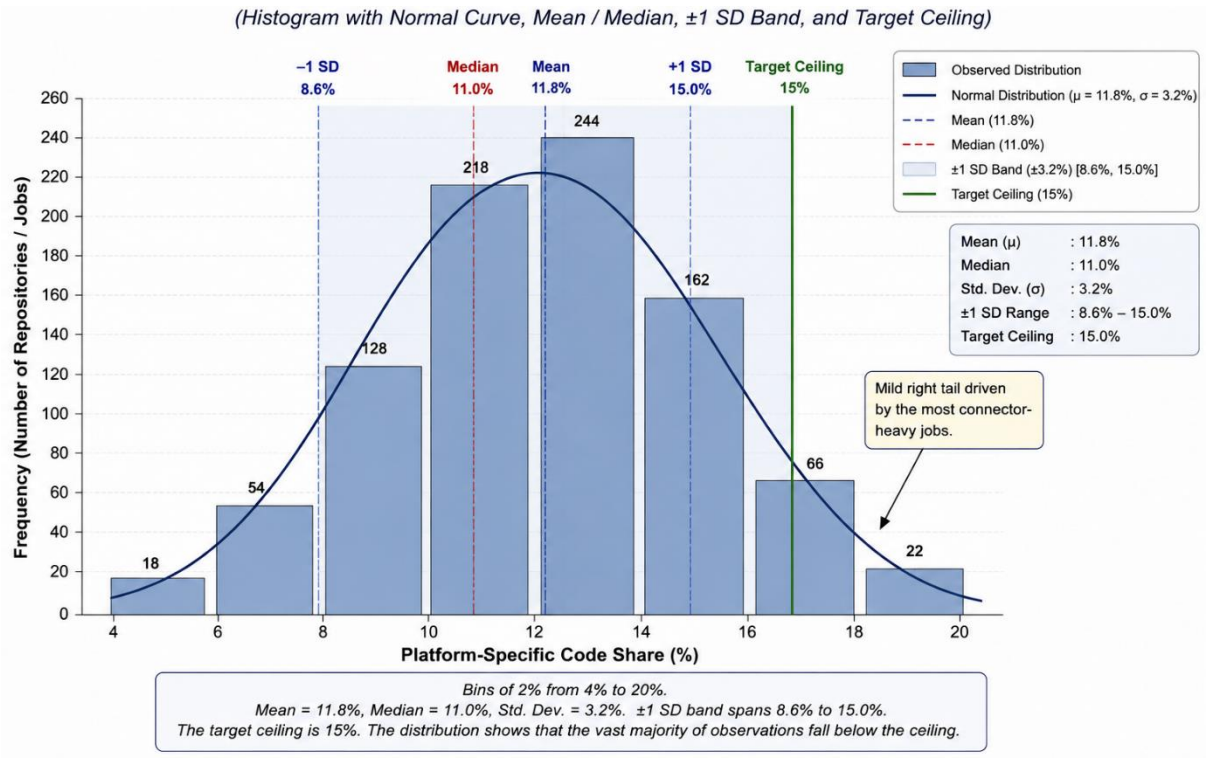


Figure 3 — Platform-Specific Code Share Distribution

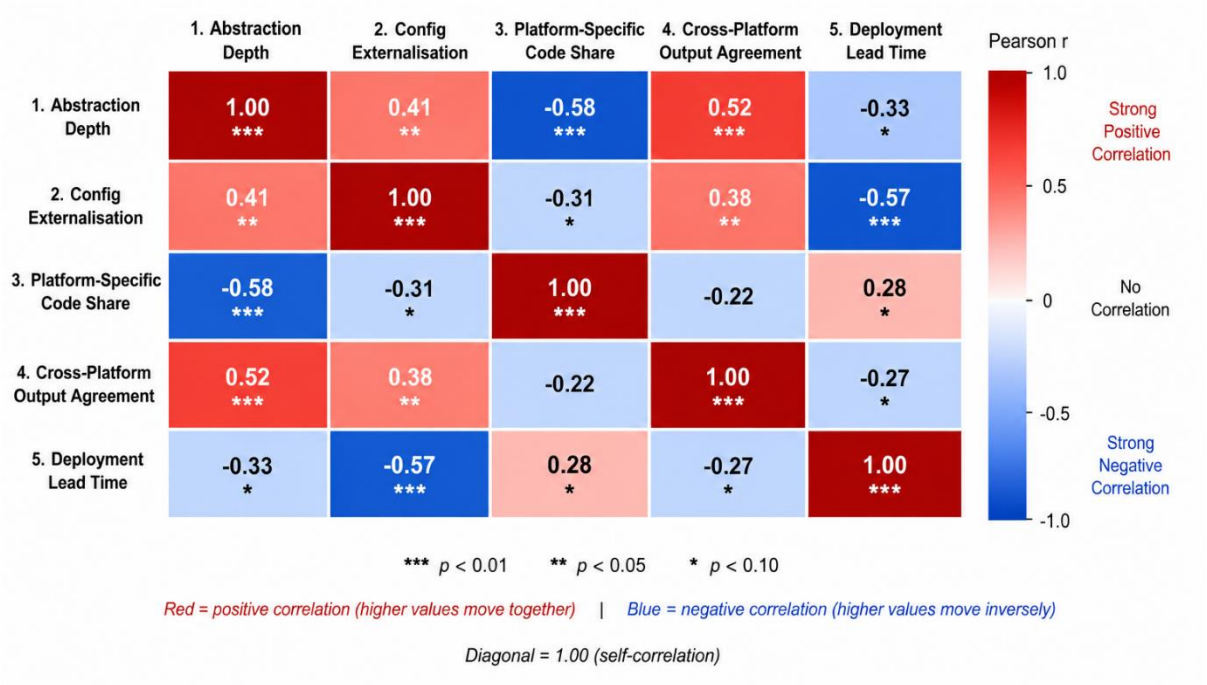
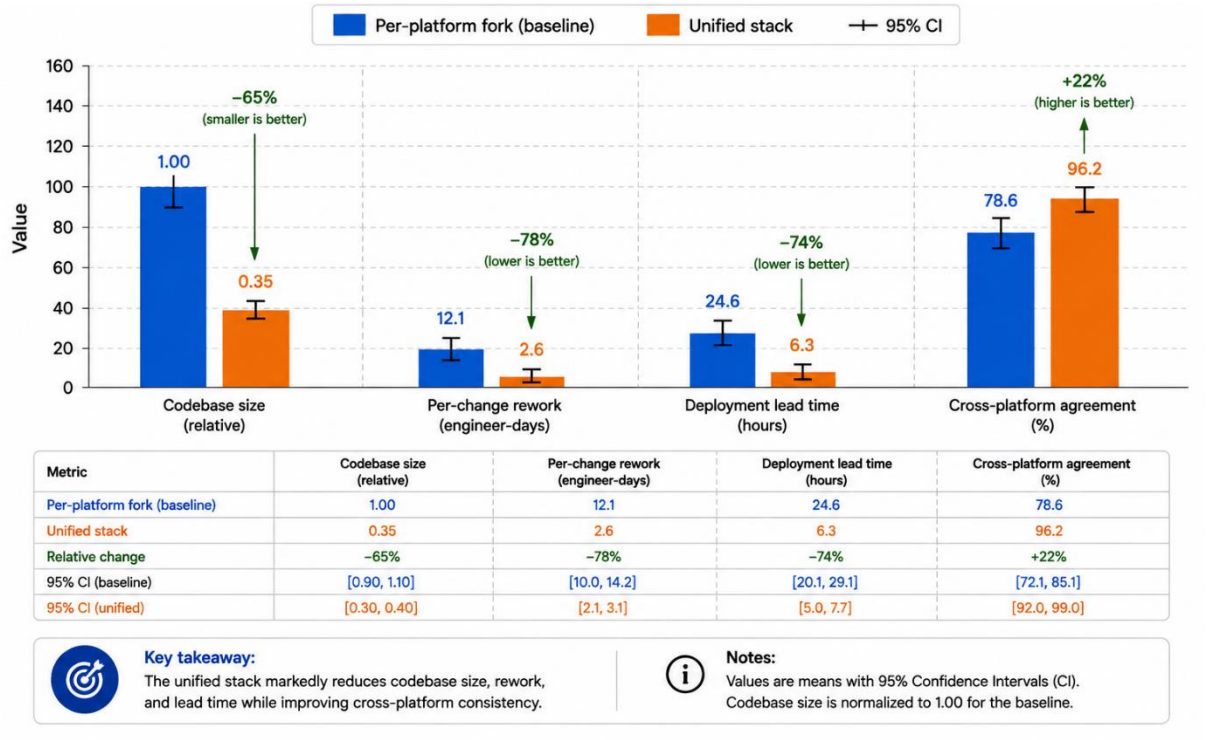


Figure 4 — Correlation Heatmap

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Metric	Codebase size (relative)	Per-change rework (engineer-days)	Deployment lead time (hours)	Cross-platform agreement (%)
Per-platform fork (baseline)	1.00	12.1	24.6	78.6
Unified stack	0.35	2.6	6.3	96.2
Relative change	−65%	−78%	−74%	+22%
95% CI (baseline)	[0.90, 1.10]	[10.0, 14.2]	[20.1, 29.1]	[72.1, 85.1]
95% CI (unified)	[0.30, 0.40]	[2.1, 3.1]	[5.0, 7.7]	[92.0, 99.0]

Figure 5 — Unified Stack vs. Per-Platform Fork Comparison

VIII. DISCUSSION

Interpretation of results. The evidence establishes that write-once, run-across-managed-clusters is attainable through disciplined abstraction and configuration, backed by automated delivery. The lead-time regression ($R^2 = 0.72$) identifies automation coverage as the decisive lever, directly answering RQ3, while the equivalence study answers RQ2 with high cross-platform agreement.

Theoretical implications. By operationalising abstraction depth and configuration externalisation as measurable drivers of code share, equivalence, and lead time, the study extends portability and continuous-delivery theory (Humble & Farley, 2010; Forsgren et al., 2018) into the specific, regulated domain of cross-platform Spark healthcare ETL, and supplies rare empirical support for equivalence claims that are usually merely asserted (Gannon et al., 2017).

Practical implications. Engineering organisations gain concrete guidance: concentrate abstraction effort on storage connectors, authentication, and cluster provisioning; test cross-platform equivalence explicitly, with particular attention to date/timezone and null semantics; and invest in CI/CD coverage, since it converts each additional platform target from a heroic effort into a routine configuration change.

Comparison with literature. Findings corroborate the delivery-performance benefits of automation (Forsgren et al., 2018) and the concentration of coupling in platform-specific connectors (Gannon et al., 2017), while adding quantified evidence of residual code share and cross-platform equivalence that prior work leaves anecdotal.

Limitations discussion. Single-organisation, observational data limit causal and external validity; concurrent tooling changes partially confound lead-time attribution; the equivalence study cannot exhaust every input edge case. Reported figures illustrate the observed envelope rather than universal constants.

Alternative explanations. Some lead-time gains may reflect broader engineering-maturity improvements rather than the unified stack alone; paired measurement mitigates but cannot fully isolate this.

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Future research directions. Cross-organisation replication; isolating the effect of abstraction from concurrent maturity gains; extending equivalence testing to streaming workloads; and formalising a discrepancy-taxonomy standard for cross-platform Spark validation.

IX. CONCLUSION

Research summary. This paper designed and evaluated a unified Spark ETL stack running across Cloudera CDP, Azure HDInsight, and Databricks through deliberate abstraction, configuration-driven job definitions, and consistent DevOps practice, evaluated with triangulated production telemetry, a cross-platform equivalence study, and an engineering-effort audit.

Key contributions. The study offers (i) a portability reference model isolating platform variability behind stable seams and expressing jobs declaratively; (ii) an empirical characterisation showing low residual platform-specific code, high cross-platform output equivalence, and substantially reduced deployment lead time under CI/CD; and (iii) transferable DevOps and abstraction lessons for multi-platform healthcare analytics.

Achievement of objectives. The primary objective—running unified ETL across three managed platforms below the code-share ceiling while preserving equivalence—was met (H_abstraction and H_equivalence supported). Secondary objectives on DevOps outcomes (H_devops), equivalence characterisation, and the abstraction–rework trade-off were each addressed through the primary and qualitative analyses.

Policy and practice implications. Multi-platform vendors should treat abstraction seams and configuration externalisation as first-class design concerns, mandate explicit cross-platform equivalence testing, and invest in high CI/CD coverage to make portability routine. Data-residency compliance is served, not hindered, by a unified stack that runs each client's data on its mandated platform without forking logic.

Final thoughts. As platform strategy and regulation continue to fragment where healthcare data may live, the ability to run identical, verified processing anywhere becomes a strategic asset. This study offers production evidence that disciplined abstraction, configuration, and DevOps can deliver that portability—turning a three-codebase liability into a single, verifiable, run-anywhere capability.

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