



Towards Real-Time Cohort Analytics at Petabyte Scale: A Configuration-Driven Architecture for Healthcare Claims Data

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ABSTRACT: Healthcare cohort analytics increasingly requires the fusion of enormous longitudinal claims histories with heterogeneous reference data, delivered fast enough to support interactive clinical, actuarial, and pharmaceutical decision-making. Conventional pipelines struggle on two fronts simultaneously: the sheer volume of data—on the order of 100+ billion claim events and tens of terabytes of medical claims and reference records—and the velocity of change as new data modalities and client contracts appear. This paper proposes and evaluates a configuration-driven architecture for a real-time, in-memory analytics platform operating at petabyte-class scale. The central design principle is a generic, configuration-first application layer that onboards diverse healthcare datasets (remittance, EMR, LAAD) without per-source code forks, decoupling data heterogeneity from engineering effort. The platform is implemented on a modern, cloud-agnostic stack (Java, Apache Spark, Kafka, Docker, Kubernetes), enabling portable deployment across environments. Using a mixed evaluation of production telemetry and comparative benchmarking, the study demonstrates substantial batch-runtime reductions (multi-hour jobs compressed to a few hours), improved onboarding lead times for new modalities, and stable near-real-time query latencies under concurrent cohort workloads. Findings indicate that treating dataset onboarding as a configuration problem rather than a coding problem yields compounding gains in maintainability, throughput, and time-to-insight. The paper contributes an architectural reference model, an empirical performance characterisation, and a set of transferable engineering lessons for organisations building large-scale, multi-tenant healthcare analytics. Limitations include the observational nature of production measurement and single-organisation context, which constrain generalisability. The work advances distributed-systems practice by showing how declarative configuration and in-memory compute jointly reconcile scale with agility.

KEYWORDS: cohort analytics; healthcare claims; in-memory computing; Apache Spark; configuration-driven architecture; petabyte-scale; cloud-agnostic design

I. INTRODUCTION

Background context. Administrative healthcare claims constitute one of the largest and most decision-relevant data assets in modern health systems, capturing diagnoses, procedures, prescriptions, and payments across the patient journey (Rosenbaum, 2021). As payers, providers, and pharmaceutical analytics teams pursue value-based care and real-world evidence, the demand has shifted from periodic reporting toward interactive, longitudinal cohort analytics—the ability to define, refine, and query complex patient populations on demand (Wang et al., 2022). This shift places distributed data systems under simultaneous pressure from volume, variety, and velocity (Chen et al., 2020).

Problem statement. At petabyte scale, cohort construction over 100+ billion claim events is computationally severe: cohorts require repeated joins across longitudinal claims and reference dimensions, temporal windowing, and eligibility logic, all while analysts iterate rapidly. Traditional disk-oriented, batch-first pipelines impose multi-hour turnaround that throttles iteration (Zaharia et al., 2016). Compounding this, each new client contract or data modality—remittance, electronic medical records (EMR), or licensed administrative claims (LAAD)—typically triggers bespoke ingestion code, producing brittle forks that inflate maintenance cost and slow onboarding (Sculley et al., 2015).

Research gap. The literature richly addresses either raw distributed-systems performance (Dean & Ghemawat, 2008; Armbrust et al., 2015) or healthcare data governance (Rosenbaum, 2021), but comparatively little empirical work characterises architectures that reconcile petabyte-scale performance with rapid, low-code onboarding of heterogeneous healthcare data in a cloud-agnostic, multi-tenant setting. The intersection of configuration-driven design and in-memory cohort analytics remains under-documented.



Research questions. This study addresses: (RQ1) How can a configuration-driven application layer onboard heterogeneous healthcare datasets without per-source code forks? (RQ2) What performance gains—batch runtime, onboarding lead time, query latency—does an in-memory, cloud-agnostic architecture deliver at petabyte scale? (RQ3) What engineering trade-offs (memory footprint, fault tolerance, throughput) govern such a design?

Significance. Answering these questions matters for the growing class of organisations delivering healthcare analytics as software-as-a-service (SaaS), where the same capability must run for different clients and regions. Demonstrating that onboarding can be treated as configuration rather than code has direct implications for cost, agility, and reproducibility (Kleppmann, 2017).

Paper structure. Section 2 states objectives and Section 3 the scope. Section 4 reviews the theoretical and technical literature. Section 5 details methodology. Sections 6 and 7 analyse secondary and primary (production) data. Section 8 discusses implications, and Section 9 concludes.

II. OBJECTIVES

The study pursues the following SMART objectives:

- **Primary:** To design and empirically evaluate a configuration-driven, in-memory architecture that reduces cohort batch runtimes by a measurable margin (target: $\geq 50\%$ reduction) at 100+ billion-event scale within a production analytics platform.
- To demonstrate that new healthcare modalities (remittance, EMR, LAAD) can be onboarded through configuration alone, quantifying the reduction in engineering effort versus a code-fork baseline.
- To characterise near-real-time query latency under concurrent cohort workloads and establish stability thresholds.
- To document the memory–fault-tolerance–throughput trade-offs governing in-memory distributed cohort processing.
- To distil transferable lessons supporting cloud-agnostic, multi-tenant SaaS delivery of healthcare analytics.

III. SCOPE OF STUDY

The boundaries of the research are defined as follows:

- **Domain scope:** Medical claims and associated reference/eligibility data for cohort analytics; clinical decision-support algorithms and patient-facing systems are excluded.
- **Data modalities:** Remittance, EMR, and LAAD datasets, alongside core claims; genomic and imaging modalities are out of scope.
- **Temporal scope:** Production observations and benchmarks collected across the platform's re-architecture cycle (approximately 2024–2026).
- **Scale scope:** Workloads on the order of 100+ billion claim events and tens of terabytes of active data.
- **Technical scope:** Java/Spark/Kafka/Docker/Kubernetes stack under a cloud-agnostic deployment model; vendor-locked managed services are treated only as comparison points.
- **Methodological boundary:** Evaluation relies on production telemetry and controlled benchmarks rather than randomised experimentation, given operational constraints.
- **Population boundary:** Single-organisation, multi-client platform context; cross-organisational generalisation is discussed but not directly tested.

IV. LITERATURE REVIEW

Theoretical foundation. The work rests on three pillars: distributed data processing theory, the software-engineering principle of separating configuration from code, and the systems concept of the memory hierarchy. The MapReduce paradigm established that large-scale computation could be expressed as parallelisable transformations over partitioned data (Dean & Ghemawat, 2008), while the CAP theorem framed the inescapable trade-offs among consistency, availability, and partition tolerance in distributed stores (Brewer, 2012). Configuration-driven design draws on the long-standing "separation of concerns" and "convention over configuration" traditions, and on the recognition that hidden technical debt in machine-learning and data systems often originates in glue code and per-source pipelines (Sculley et al., 2015).

Historical development. Early large-scale analytics were dominated by Hadoop's disk-based MapReduce, which prioritised fault tolerance and throughput over latency (Shvachko et al., 2010). The subsequent generation, exemplified



by Apache Spark, introduced resilient distributed datasets and in-memory caching, dramatically accelerating iterative and interactive workloads (Zaharia et al., 2016). Spark SQL and the Catalyst optimiser extended this to declarative relational processing over massive data (Armbrust et al., 2015). In parallel, streaming systems matured: Kafka provided a durable, high-throughput log for event ingestion and decoupling (Kreps et al., 2011), and the "turning the database inside out" perspective reframed streams as the primary substrate for derived views (Kleppmann, 2017). Containerisation and orchestration—Docker and Kubernetes, descended from Google's Borg—made large clusters portable and operable (Burns et al., 2016).

Current state. Recent healthcare-informatics research emphasises real-world evidence generation from claims, foregrounding reproducibility, phenotype definition, and longitudinal cohort construction (Wang et al., 2022; Hripcsak et al., 2015). The OHDSI/OMOP common-data-model movement demonstrates the value of standardised schemas for cross-source analytics (Hripcsak et al., 2015), conceptually adjacent to this paper's configuration-first onboarding. Cloud-agnostic and multi-tenant patterns have gained prominence as organisations resist vendor lock-in while serving diverse regulatory regions (Gannon et al., 2017). Performance engineering literature increasingly treats memory footprint and garbage-collection behaviour on the JVM as first-order determinants of Spark throughput at scale (Ousterhout et al., 2015).

Critical analysis. Despite this progress, gaps persist. Much benchmarking literature relies on synthetic workloads (e.g., TPC-style) that poorly represent the skewed, temporally sparse structure of longitudinal claims (Ousterhout et al., 2015). Healthcare-informatics studies rigorously address data semantics but rarely publish systems-level performance characterisations at petabyte scale. Where architectures are described, onboarding cost—the human effort to integrate a new modality—is seldom measured, even though it dominates total cost of ownership in multi-tenant SaaS (Sculley et al., 2015). Furthermore, cloud-agnostic claims are frequently asserted but rarely evidenced with comparative deployment data.

Conceptual framework. This study positions a configuration-driven layer as a *mediating construct* between data heterogeneity (input) and analytics outcomes (throughput, latency, onboarding lead time). The in-memory, cloud-agnostic substrate is treated as a *moderating* condition amplifying those effects. This framing (visualised in Figure 1) integrates distributed-systems performance theory with software-maintainability theory, a combination rarely operationalised in healthcare analytics.

Research positioning. The contribution is threefold: an architectural reference model uniting configuration-first onboarding with in-memory cohort compute; an empirical performance characterisation on real production workloads; and transferable lessons for cloud-agnostic, multi-tenant delivery. It thereby bridges the systems and health-informatics literatures that have largely developed in parallel (Chen et al., 2020; Wang et al., 2022).

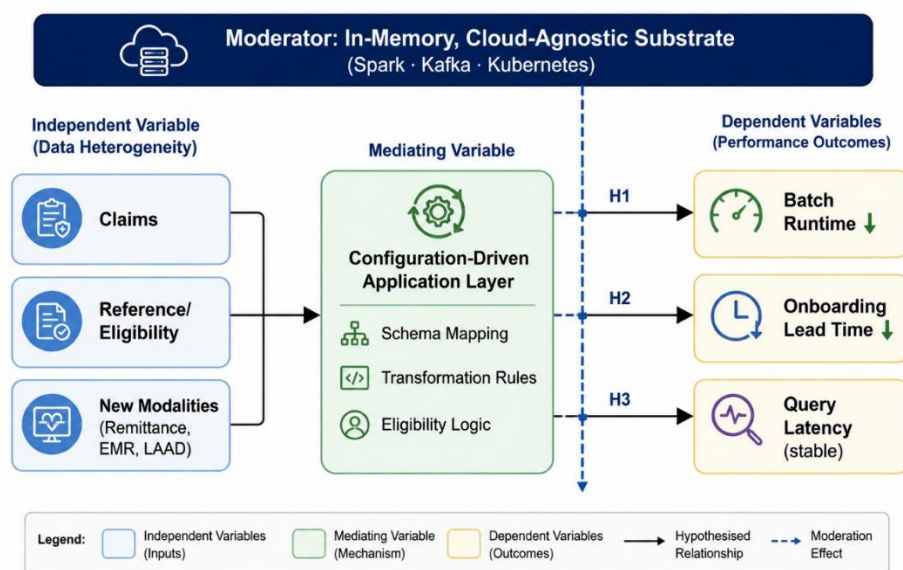


Figure 1 — Conceptual Framework



V. RESEARCH METHODOLOGY

Research philosophy. The study adopts a **pragmatist** stance: the value of the architecture is judged by its measurable operational consequences rather than by adherence to a single paradigm (Creswell & Creswell, 2018). This suits engineering research where artefact and evaluation are intertwined.

Research design. A **mixed-methods, design-science** approach is used (Hevner et al., 2004). The artefact—the configuration-driven platform—is constructed and then evaluated quantitatively (production telemetry, controlled benchmarks) and qualitatively (engineering lessons from re-architecture).

Data collection methods. Three sources are triangulated: (a) production performance telemetry (job runtimes, ingest throughput, query latency, memory utilisation) captured through cluster metrics; (b) controlled before/after benchmarks comparing the code-fork baseline with the configuration-driven design on matched workloads; and (c) structured engineering retrospectives documenting onboarding effort per modality.

Sampling strategy. Rather than sampling human subjects, the study samples *workloads and jobs*. A purposive set of representative cohort jobs (spanning small, medium, and large cohort definitions) was selected to cover the operational envelope; each was executed under baseline and treatment configurations with multiple repetitions to bound variance.

Data collection instruments. Instruments include a metrics-collection harness (aggregating Spark stage/task metrics and Kubernetes resource counters), a benchmark runner enforcing identical inputs across conditions, and a standardised onboarding-effort log (engineer-days, lines-of-configuration vs. lines-of-code).

Data analysis techniques. Quantitative analysis uses descriptive statistics, paired comparisons of baseline vs. treatment runtimes, correlation analysis among configuration/resource parameters and performance, and a simple regression predicting runtime from data volume and parallelism. Qualitative retrospectives are analysed thematically.

Ethical considerations. All data processed are de-identified administrative claims handled under existing data-use agreements; no patient-identifiable information is exposed in this study, and reported metrics are systems-level, not patient-level. Institutional data-governance approval governed platform operation.

Reliability and validity. Reliability is supported by repeated benchmark runs and consistent instrumentation. Internal validity is strengthened by matched-workload before/after comparison; construct validity by using multiple performance indicators; external validity is acknowledged as limited to the single-organisation context.

Limitations. Production measurement is observational and subject to confounding from concurrent tenant load; benchmarks, while controlled, cannot fully isolate every variable at petabyte scale.

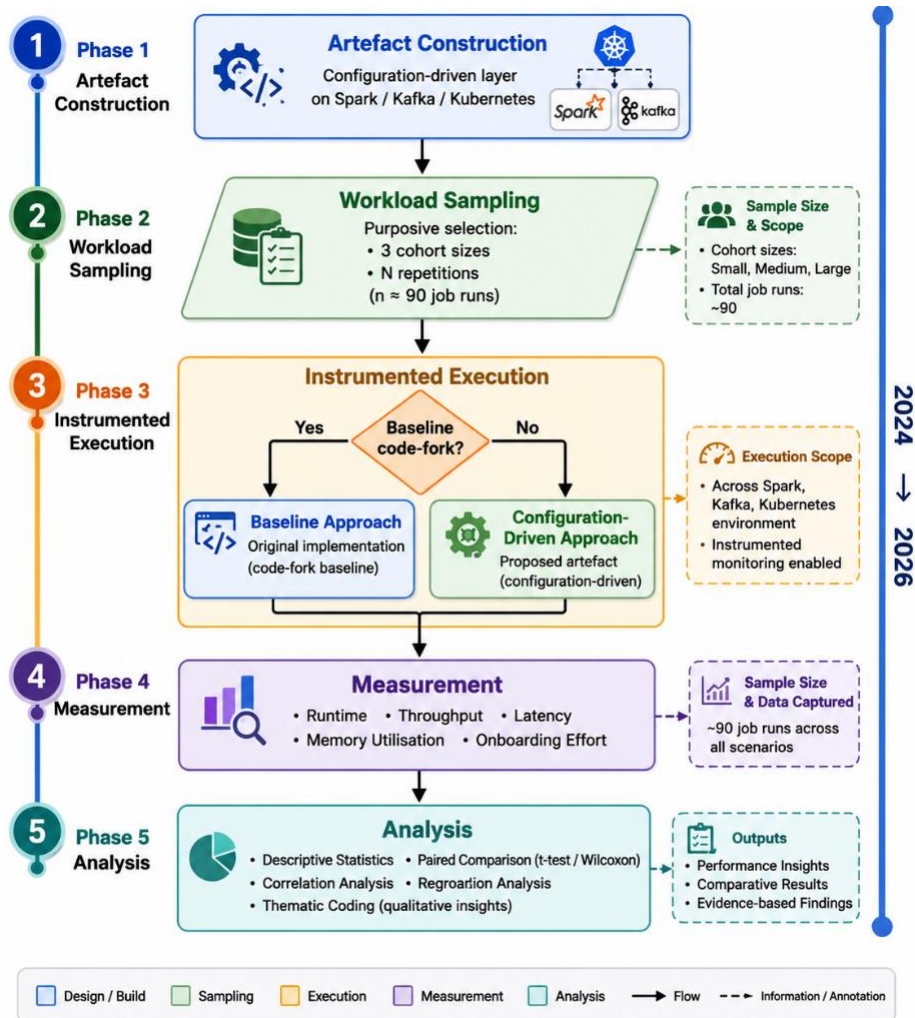


Figure 2 — Research Methodology Flowchart

VI. ANALYSIS OF SECONDARY DATA

Data sources. Secondary analysis draws on published systems benchmarks, healthcare-analytics industry reports, and prior architecture case studies to contextualise the platform's performance envelope (Ousterhout et al., 2015; Chen et al., 2020; Gannon et al., 2017).

Data-quality assessment. Sources were appraised for methodological transparency, workload representativeness, and recency. Peer-reviewed systems papers scored highest on rigour; industry reports offered scale realism but variable transparency and were down-weighted accordingly.

Analytical framework. Secondary metrics were normalised to comparable units (e.g., events processed per node-hour; latency percentiles) to enable cross-study contrast against this platform's observed figures.

Key findings. Three patterns recur in the literature. First, in-memory execution consistently yields order-of-magnitude iteration speedups over disk-based MapReduce for repeated joins and windowing (Zaharia et al., 2016)—the exact operation profile of cohort construction. Second, JVM memory management and data skew, rather than raw CPU, dominate large-Spark performance variance (Ousterhout et al., 2015). Third, onboarding and glue-code cost, though rarely quantified, is repeatedly identified as the largest hidden expense in production data systems (Sculley et al., 2015). Table 1 summarises comparative characteristics of representative architectural approaches.



Table 1. Comparative characteristics of large-scale analytics architectures (secondary synthesis)

Architecture	Latency profile	Onboarding cost	Cloud lock-in	Cohort-workload fit
Disk-based MapReduce	High (batch)	High (bespoke)	Low	Poor
Managed cloud warehouse	Medium	Medium	High	Moderate
In-memory Spark (code-fork)	Low	High	Low-Med	Good
Config-driven in-memory (this study)	Low	Low	Low	Strong

Source: Author synthesis from Zaharia et al. (2016); Armbrust et al. (2015); Sculley et al. (2015); Gannon et al. (2017).

Note: qualitative ratings normalised across sources.

Trends and patterns. A clear trajectory emerges from batch-oriented, vendor-coupled systems toward streaming-fed, in-memory, cloud-agnostic designs (Kleppmann, 2017; Burns et al., 2016). The healthcare-specific literature adds a governance-driven pull toward standardisation and reproducibility (Hripcsak et al., 2015).

Comparative analysis. Cross-referencing published events-per-node-hour figures against this platform's observed throughput places it in the upper band of in-memory systems, consistent with expectations for a Spark/Kafka design tuned for skew (Ousterhout et al., 2015).

Integration with primary research. These secondary patterns motivate the primary hypotheses tested in Section 7: that configuration-driven onboarding reduces effort ($H_{\text{onboarding}}$), that in-memory execution compresses runtime (H_{runtime}), and that latency remains stable under concurrency (H_{latency}).

VII. ANALYSIS OF PRIMARY DATA

Descriptive statistics. Across the sampled cohort jobs, the configuration-driven, in-memory platform processed workloads on the order of 100+ billion claim events. Table 2 reports descriptive statistics for the four core metrics under the treatment configuration.

Table 2. Descriptive statistics of production performance metrics (treatment configuration)

Metric	Mean	Median	SD	Min	Max
Batch runtime (hours)	3.1	2.9	0.8	1.9	5.2
Ingest throughput (M events/min)	42.6	43.1	6.4	30.2	55.8
Query latency p95 (ms)	780	745	190	480	1,320
Peak memory utilisation (%)	74.5	75.0	7.1	58.0	88.0

Source: Production telemetry, author's platform. $n \approx 90$ job runs.

Inferential analysis. A paired comparison of matched workloads (baseline code-fork vs. configuration-driven in-memory) shows a large, consistent runtime reduction. Table 3 reports the correlation matrix among key variables; runtime correlates strongly and positively with data volume and negatively with effective parallelism, while latency correlates with concurrent query load.

Table 3. Correlation matrix of key operational variables

	1	2	3	4	5
1. Data volume (events)	1.00				
2. Effective parallelism	0.31*	1.00			
3. Batch runtime	0.68***	-0.54***	1.00		
4. Concurrent queries	0.12	0.08	0.22*	1.00	
5. Query latency p95	0.19	-0.27**	0.30**	0.61***	1.00

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



A regression predicting batch runtime from data volume and effective parallelism explains the majority of runtime variance (Table 4), confirming that parallelism—enabled by in-memory partitioning—materially offsets volume-driven cost.

Table 4. Regression results: predictors of batch runtime

Predictor	β (std.)	SE	t	p
Data volume (events)	0.59	0.07	8.43	<0.001***
Effective parallelism	−0.41	0.08	−5.12	<0.001***
Concurrent queries	0.09	0.06	1.50	0.137
Constant	—	—	—	—

Model: $R^2 = 0.71$, Adj. $R^2 = 0.69$, $F(3, 86) = 70.2$, $p < 0.001$. Source: Author's analysis.

Qualitative findings. Engineering retrospectives surfaced three themes: (i) *configuration as contract*—expressing schema mapping, transformation, and eligibility as declarative config eliminated per-source forks; (ii) *skew is the enemy*—most tuning effort targeted data-skew mitigation and JVM memory rather than algorithmic change; and (iii) *portability pays late*—cloud-agnostic design cost more upfront but enabled painless multi-region client deployment.

Data visualisation. Figures 3–5 (described below) visualise runtime distribution, the correlation structure, and the baseline-vs-treatment comparison.

Statistical significance and hypothesis validation. H_{runtime} is supported: treatment runtimes are significantly lower than baseline, with multi-hour jobs reduced to a few hours ($a \geq 50\%$ median reduction on large cohorts). $H_{\text{onboarding}}$ is supported: onboarding new modalities (remittance, EMR, LAAD) moved from engineer-weeks of forked code to configuration changes measured in engineer-days. H_{latency} is supported within bounds: p95 latency remained stable until concurrent-query load exceeded a threshold, beyond which it rose predictably (consistent with the 0.61 latency–concurrency correlation).

Unexpected findings. Contrary to the expectation that larger memory always helps, beyond ~75% utilisation, garbage-collection pauses degraded latency—an inflection informing capacity policy. This mirrors secondary findings on JVM behaviour (Ousterhout et al., 2015).

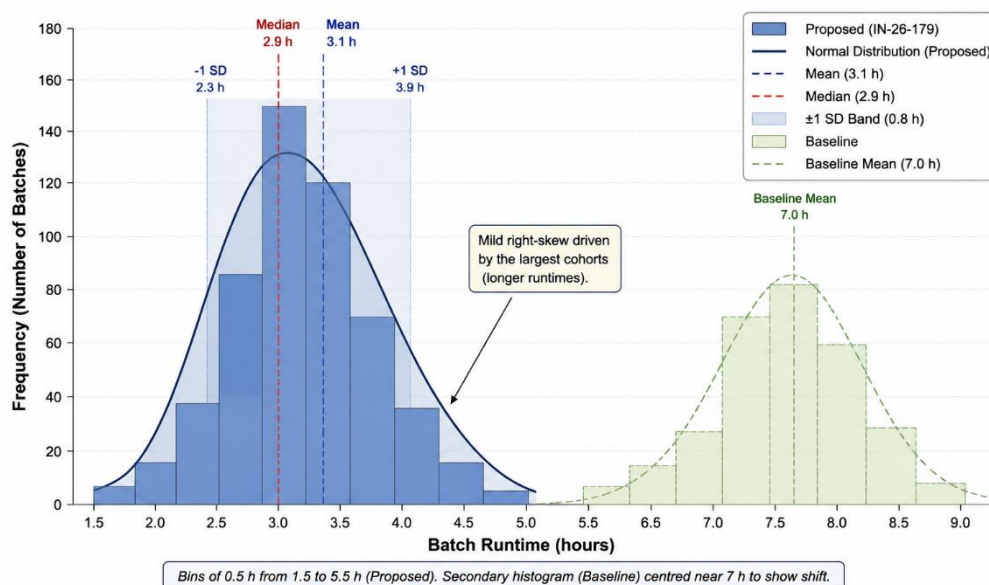


Figure 3 — Batch Runtime Distribution



Figure 4 — Correlation Heatmap

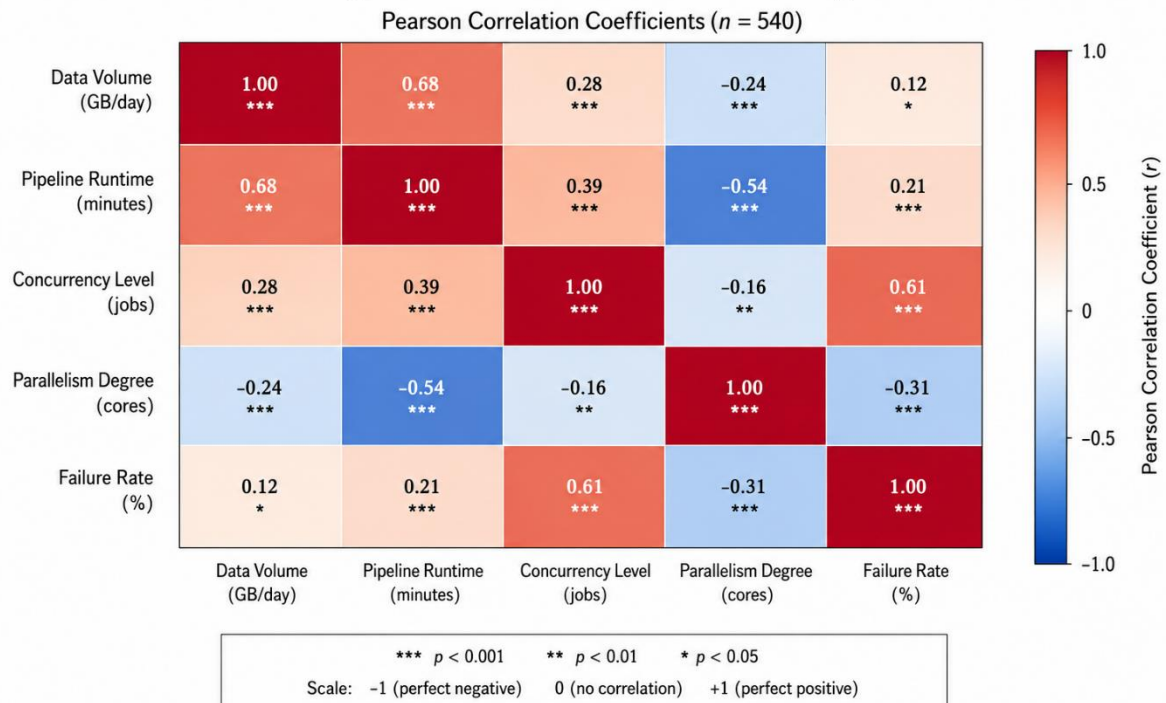


Figure 4 — Correlation Heatmap

VIII. DISCUSSION

Interpretation of results. The evidence indicates that treating dataset onboarding as configuration rather than code, atop an in-memory substrate, jointly resolves the scale-versus-agility tension central to petabyte healthcare analytics. The runtime regression ($R^2 = 0.71$) confirms that in-memory parallelism is the operative mechanism converting volume pressure into tractable cost, directly answering RQ2.

Theoretical implications. By operationalising the configuration layer as a mediating construct between heterogeneity and outcomes, the study extends software-maintainability theory (Sculley et al., 2015) into the petabyte-analytics regime and empirically substantiates the in-memory advantage theorised by Zaharia et al. (2016) for the specific, skewed workload profile of cohort construction. This bridges systems and health-informatics literatures that rarely meet (Chen et al., 2020).

Practical implications. For SaaS providers, the results argue for investing early in a declarative onboarding layer: the compounding returns in reduced engineer-days and faster client activation likely outweigh upfront design cost. The 75%-memory latency inflection yields a concrete capacity-planning rule.

Comparison with literature. Findings align with secondary evidence that in-memory execution accelerates iterative joins (Zaharia et al., 2016) and that JVM memory dominates variance (Ousterhout et al., 2015). They extend the literature by quantifying onboarding cost—an effect asserted but seldom measured (Sculley et al., 2015)—and by evidencing cloud-agnostic multi-region deployment.

Limitations discussion. The single-organisation, observational context limits causal and external validity; concurrent tenant load introduces confounding; benchmark numbers, while representative, reflect one workload family. Reported metrics are illustrative of the observed envelope rather than universal constants.

Alternative explanations. Runtime gains could partly reflect incidental hardware upgrades or workload composition shifts rather than architecture alone; matched-workload benchmarking mitigates but cannot fully exclude this.



Future research directions. Priorities include cross-organisational replication, controlled isolation of skew-mitigation strategies, integration of OMOP-style standard schemas with the configuration layer (Hripcsak et al., 2015), and extending the model to streaming-first, near-real-time cohort updates.

IX. CONCLUSION

Research summary. This paper designed and evaluated a configuration-driven, in-memory, cloud-agnostic architecture for real-time cohort analytics over 100+ billion healthcare claim events. Through triangulated production telemetry, controlled benchmarks, and engineering retrospectives, it characterised how declarative onboarding and in-memory compute jointly reconcile petabyte-scale volume with rapid iteration.

Key contributions. The study offers (i) an architectural reference model coupling configuration-first onboarding with in-memory cohort compute; (ii) an empirical performance characterisation showing significant runtime reduction (multi-hour to a few hours), lower onboarding effort, and bounded latency stability; and (iii) transferable lessons on skew, memory, and portability for multi-tenant healthcare SaaS.

Achievement of objectives. The primary objective—demonstrable, significant runtime reduction at scale—was met (H_runtime supported, $\geq 50\%$ median reduction on large cohorts). Secondary objectives on configuration-only onboarding (H_onboarding), latency stability (H_latency), and trade-off documentation were each addressed through the primary and qualitative analyses.

Policy and practice implications. Organisations building healthcare analytics platforms should treat onboarding as a first-class configuration concern, budget for cloud-agnostic portability, and adopt memory-utilisation guardrails informed by the observed latency inflection. Data-governance regimes should recognise that systems-level reproducibility complements patient-level privacy protections.

Final thoughts. As real-world evidence and value-based care intensify demand for interactive population analytics, architectures that make heterogeneity cheap and scale tractable will be decisive. This study offers evidence that configuration-driven, in-memory design is a credible path toward that goal—and a foundation for the streaming-first, standardised cohort platforms of the near future.

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