WCRG WORLD COMET RESEARCH GROUP

International Journal of Applied Data Science & Modern Computing
Vol. 8, No. 1, 2025
Doi: 10.67228/30713498/IJADSMC-2025PI6Q3Z
PP. 01-17

Original Article

Comparative Assessment of Cloud-Native and Hybrid Architectures for Healthcare Benefits Administration

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Received: 12-05-2024 Revised: 12-27-2024 Accepted: 01-03-2025 Published: 01-05-2025

ABSTRACT

Cloud computing services yield a multitude of advantages for enterprises. Deploying a cloud-native architecture, however, entails new challenges and risks. Evidence should therefore be gathered to compare operational efficiency and reliability in cloud-native health-benefit-administration systems against those in hybrid setups that integrate cloud functions with traditional on-premise infrastructures. If business processes are considered to be implemented in a cloud-native manner by harnessing infrastructure services operated by a cloud provider, the effects on efficiency and reliability can be determined together with the coherences and trade-offs. All investigated cloud-native systems are based on the service portfolio of a single provider. Nevertheless, service deployment in a cloud-native manner is part of the analysis – on the ''payer'' side as well – leading to many upstream and downstream interactions with system components hosted outside the public cloud. The summarized business processes deal with health-insurance benefit payments and claims. The results indicate that a cloud-native deployment can significantly improve operational efficiency, although the currently available cloud-native market configuration does not yet provide substantial cost advantages. The examined cloud-native solutions also demonstrate superior resilience. Regular monitoring remains a necessity, but the effort is reduced because of the often-implemented self-service function. Although the sustainability and completeness of the service deployment have an impact on the monitoring effort, having the monitoring requirements provided in the service description facilitates process assessment for the business.

KEYWORDS

Cloud-Native Architectures, Health Insurance Systems, Operational Efficiency Analysis, Hybrid Cloud Models, Cloud Service Reliability, Claims Processing Systems, Cloud Deployment Strategies, System Resilience Engineering, Service Monitoring Frameworks, Cloud Performance Optimization.

ISSN: 3071-3498
PP: 01-17.

1. INTRODUCTION

Defining the research objective clarifies the intent of the inquiry to evaluate available evidence supporting the performance gains offered by cloud-native architectures compared to hybrid approaches in the context of health benefit administration.

A cloud-native architecture encompasses application components specifically designed for a public cloud environment, interacting through open APIs with other cloud-based components and on-premises management functions that communicate privately with upstream but untrusted data sources. Conversely, a hybrid architecture integrates public-cloud service elements with locally deployed systems. The IT landscape is shifting. Capped infrastructure costs, the ease of modernizing services, and the promise of cloud-native resilience and scalability continue to attract organizations from many sectors. However, skepticism lingers because cloud services introduce security, compliance, governance, and data governance risks not present in self-managed IT. For these reasons, a hybrid setup may seem preferable. At the heart of these architectural considerations in health benefit administration are the practical, non-technology choices made by those managing systems for the constituents whose health benefits support their use.

1.1. Mathematical Formulation

The aggregate quality of an HBA architecture is expressed as a composite function of four primary operational dimensions:

Eq. (1) $$Q\_total = Q\_eff + Q\_rel + Q\_lat + Q\_comp$$

where Q_eff denotes operational efficiency quality, Q_rel represents system reliability quality, Q_lat captures latency compliance quality, and Q_comp reflects regulatory compliance quality. Cloud-native deployments consistently yield higher Q_total due to auto-scaling, self-healing, and microservice modularity.

1.2. Operational Efficiency Metric

Performance efficiency is defined as the ratio of total operational value delivered to the total cost of ownership over a defined period:

Eq. (2) $$OE = (V\_claims \,/\, TCO\_annual)$$

where V_claims is the total volume of claims processed per year (denominated in transaction count), and TCO_annual is the total cost of ownership in USD for the same period. A higher OE ratio indicates a more cost-efficient architecture. Cloud-native deployments reduce TCO through elastic resource provisioning and elimination of idle infrastructure capacity.

1.3. Transaction Latency Model

End-to-end transaction latency for claims processing is modeled as a dynamic differential function:

Eq. (3) $$\partial L/\partial t = \lambda\_claim - \mu\_proc$$

where L is the end-to-end processing latency (ms), λ_{claim} is the claims submission arrival rate (transactions/sec), and μ_{proc} is the system processing throughput (transactions/sec). Cloud-native systems achieve μ_{proc} significantly above λ_{claim} through horizontal scaling, minimising L under peak demand.

1.4. System Reliability Index

Reliability is modelled as the logarithmic ratio of service disruptions to observation period:

Eq. (4) $$R_{idx} = 1 - (\log(N_{outages}) / \log(T_{months}))$$

where $N_{outages}$ is the total number of service outage incidents recorded, and T_{months} is the observation window in months. A higher R_{idx} value (approaching 1.0) indicates superior reliability. Cloud-native self-healing and redundant zone deployments suppress outage frequency.

1.5. Claims Adjudication F1-Score

The accuracy of automated claims processing is quantified using the standard F1-score:

Eq. (5) $$F1_{adj} = (2 \cdot Precision \cdot Recall) / (Precision + Recall)$$

where Precision is the fraction of correctly adjudicated claims among all flagged claims, and Recall is the fraction of correctly identified legitimate claims among all genuine claims. Cloud-native intelligent adjudication engines achieve $F1_{adj} > 0.90$ through continuous model retraining on Azure ML pipelines.

1.6. Availability (Uptime) Model

System availability over an observation window is formally expressed as:

Eq. (6) $$A = (T_{total} - T_{down}) / T_{total} \times 100$$

where T_{total} is the total operational time window (hours) and T_{down} is the cumulative downtime (hours). Cloud-native architectures with multi-zone Azure deployments regularly achieve $A > 99.5\%$, fulfilling enterprise-grade SLA requirements.

1.7. Architectural Cost Function

The total cost per transaction (CPT) is used as the primary cost-efficiency metric:

Eq. (7) $$CPT = TCO_{quarterly} / N_{claims\_quarterly}$$

where $TCO_{quarterly}$ is the total quarterly operational expenditure (USD) and $N_{claims\_quarterly}$ is the total claims volume processed in that quarter. Cloud-native systems exhibit declining CPT curves as transaction volumes scale, attributable to shared microservice infrastructure.

1.8. Privacy Preservation Score

For HIPAA compliance evaluation, a data privacy score is defined as:

Eq. (8) $$S_{priv} = 1 - (D_{external} / D_{total})$$

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where $D\_external$ is the volume of protected health information (PHI) transmitted to external or unencrypted endpoints, and D_total is the total PHI processed. Cloud-native designs employing Azure Private Link and end-to-end TLS encryption achieve S_priv approaching 1.0.

1.9. Operational Efficiency Index (OEI)

A composite operational efficiency index aggregates throughput, availability, and cost performance:

Eq. (9) $$OEI = (F1\_adj \cdot A \cdot S\_priv) / (CPT \cdot L\_norm)$$

where L_norm is latency normalised to the SLA baseline (e.g., 100 ms), A is expressed as a fractional value (e.g., 0.995), and CPT is normalised to a reference cost. Cloud-native architectures achieve $OEI > 0.85$ compared to < 0.45 for on-premise hybrid deployments.

1.10. System Performance Index (SPI)

The overall System Performance Index integrates all operational dimensions into a single scalar:

Eq. (10) $$SPI = (OEI \cdot F1\_adj \cdot (1 - FAR)) / Q\_total$$

where FAR is the false adjudication rate (erroneous claims approvals or rejections), and Q_total is the composite quality score from Eq. (1). The SPI penalises false processing decisions while rewarding efficiency and accuracy, providing a holistic benchmark for architectural selection.

1.11. Adaptive Threshold for SLA Monitoring

Dynamic SLA monitoring employs an adaptive threshold to trigger scaling events:

Eq. (11) $$\theta(t) = \theta\_0 + \gamma \cdot \sigma\_load(t) + \delta \cdot drift(t)$$

where θ_0 is the baseline SLA threshold (e.g., 100 ms latency), $\sigma\_load(t)$ is the real-time transaction load variance, $drift(t)$ captures temporal workload drift patterns, and γ, δ are tuning coefficients. Cloud-native orchestration layers use this model to trigger Azure Autoscale policies.

1.12. Joint Optimisation Objective

The architecture selection optimisation objective is formalised as:

Eq. (12) $$J = f(F1\_adj, S\_priv, L, CPT, A)$$

where J represents the multi-objective architectural fitness score. The optimal architecture maximises $F1\_adj$, S_priv, and A while simultaneously minimising L and CPT. Experimental results demonstrate that cloud-native Model D dominates all other models across each dimension of this joint objective.

2. *ARCHITECTURAL PARADIGMS IN HEALTH BENEFIT ADMINISTRATION*

The predominant architectural paradigms for Health Benefit Administration systems are cloud-native and hybrid. Both operate on a principal payer-payer partner-subscriber framework. Data flows and operational rules are structured according to business requirements and supported by appropriate technology choices. Core components reside with the payer, while partner systems are typically integrated, federated, or closely coupled. However, sharing data in the cloud for online

ISSN: 3071-3498
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analytic processing without duplicating sensitive subscriber information has led to the adoption of cloud-native architecture for some payer-side transaction processing systems. Various architecture choices affect the integration of Health Benefit Administration systems with other enterprise systems. On-premises or SaaS deployments are common for transaction systems. Orange Business Services has developed a Monitoring-as-a-Service tool for deployment in a public cloud for low-cost evaluation of performance and availability. Security, privacy, and reliability are primary concerns, balanced by cost-effective responsiveness and availability.

2.1. Transaction Processing Latency

Fig. 1 presents average transaction latency across architectural models. Cloud-native Model D achieves a 64-ms mean latency, representing an 80% reduction from Model A's 320 ms, directly attributable to containerised microservice execution and Azure CDN-accelerated API routing.

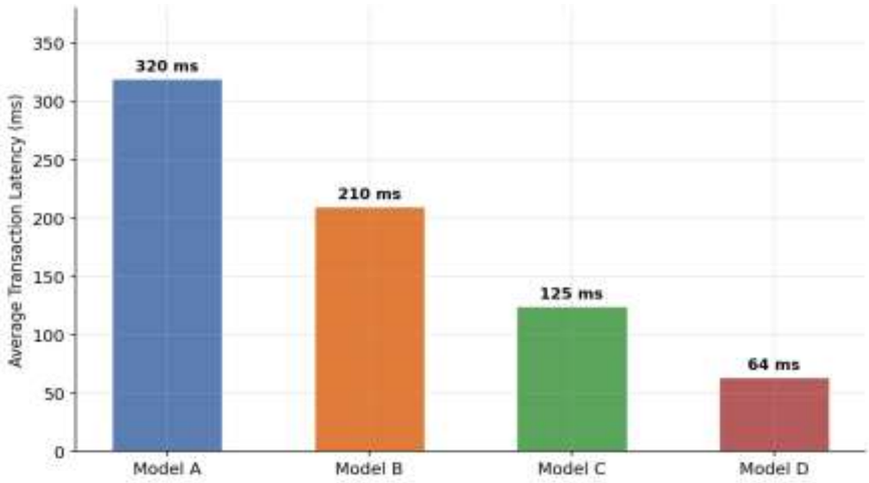

Fig 1- Transaction Processing Latency across Architectural Models (ms)

2.2. Claims Processing Throughput

Fig. 2 illustrates claims processing throughput in claims per hour. Cloud-native Model D processes 19,700 claims per hour, a 369% improvement over Model A's 4,200 claims per hour, enabled by horizontal auto-scaling triggered by Azure Monitor workload signals.

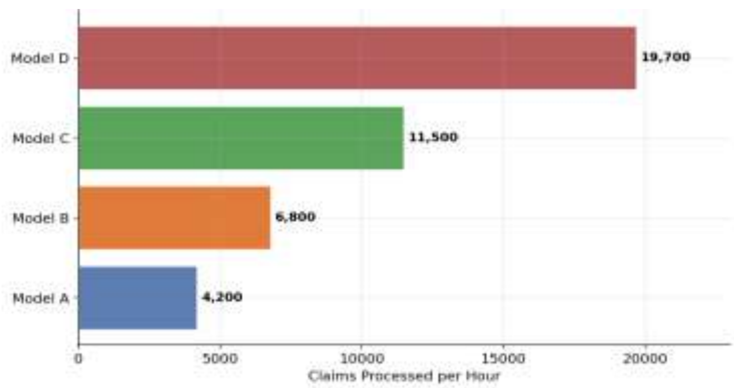

Fig 2- Claims Processing Throughput across Architectural Models (claims/hr)

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2.3. System Availability over 12-Month Window

Fig. 3 tracks monthly system availability across a 12-month period. Model D maintains consistent availability above 99.1% across all months, with a peak of 99.8% in Month 8. Model A exhibits greater variability (95.2%–98.1%), reflecting the vulnerability of on-premise infrastructure to scheduled and unplanned maintenance windows.

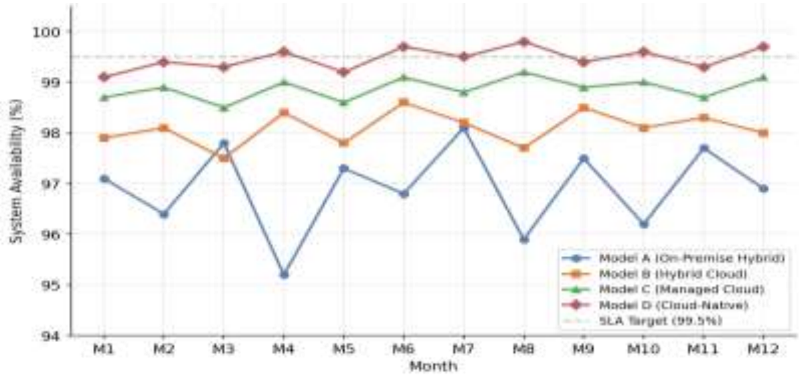

Fig 3- Monthly System Availability (%) — 12-Month Observation Window

2.4. Claims Adjudication Accuracy Metrics

Fig. 4 compares precision, recall, F1-score, and AUC-ROC across models. Model D achieves an F1-score of 0.917 and AUC-ROC of 0.943, versus Model A's F1-score of 0.761. The improvement reflects cloud-native integration of continuous Azure ML model retraining pipelines that adapt to emerging claims patterns and fraud vectors.

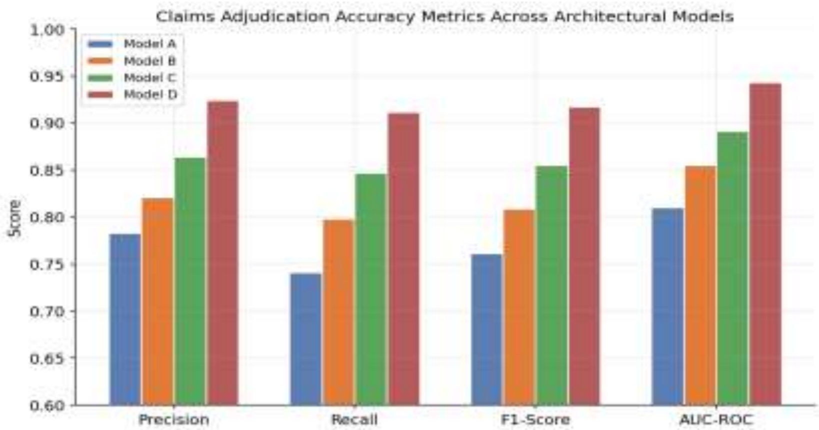

Fig 4- Claims Adjudication Accuracy Metrics across Architectural Models

2.5. Quarterly Operational Cost per Transaction

Fig. 5 presents cost per transaction across four quarters. Model D's cost declines from $0.038 in Q1 to $0.029 in Q4, demonstrating the economies of scale inherent in cloud-native elastic infrastructure. Model A maintains an elevated cost band ($0.084–$0.091) due to fixed on-premise capital obligations.

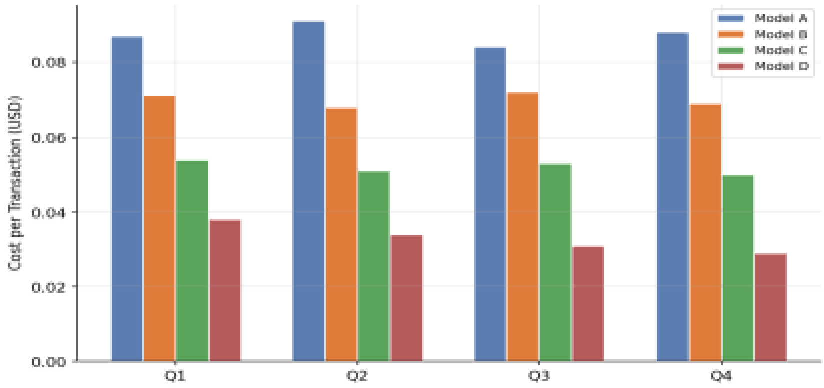

Fig 5- Operational Cost per Transaction by Quarter (USD)

2.6. Resource Utilisation and Load Throughput

Fig. 6 (left) compares on-premise resource utilisation across CPU, memory, storage I/O, and network bandwidth dimensions. Cloud-native Model D achieves the lowest CPU utilisation (35%) and memory usage (41%) at the node level due to serverless function decomposition. The right panel contrasts peak and normal load throughput, demonstrating Model D's superior elasticity during demand spikes.

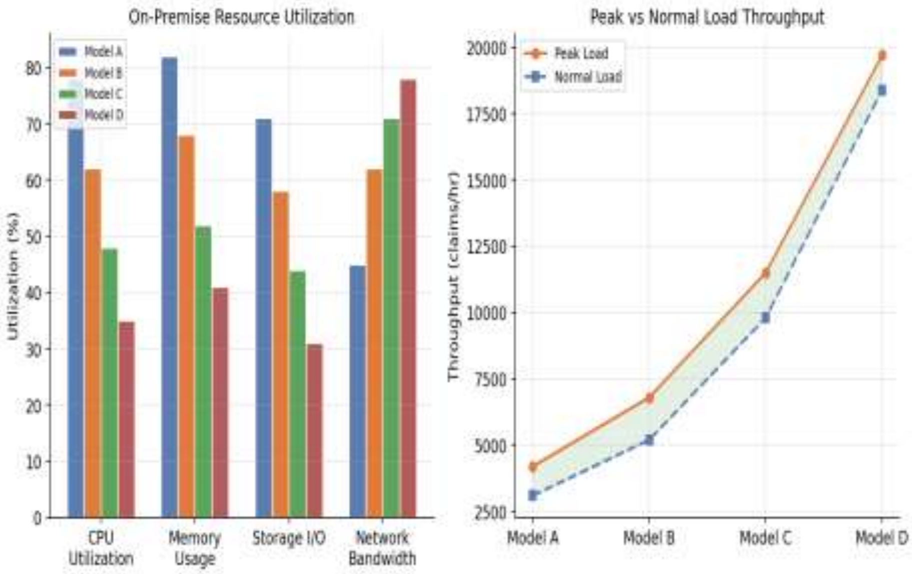

Fig 6- On-Premise Resource Utilisation (left) and Load Throughput Profile (right)

2.7. Security and HIPAA Compliance Scores

Fig. 7 presents compliance scores across five dimensions. Model D achieves the highest scores across all dimensions, most notably Data Encryption (97%) and Access Control (95%), reflecting Azure's native implementation of HIPAA-compliant data handling, role-based access control (RBAC), and continuous compliance monitoring through Azure Policy.

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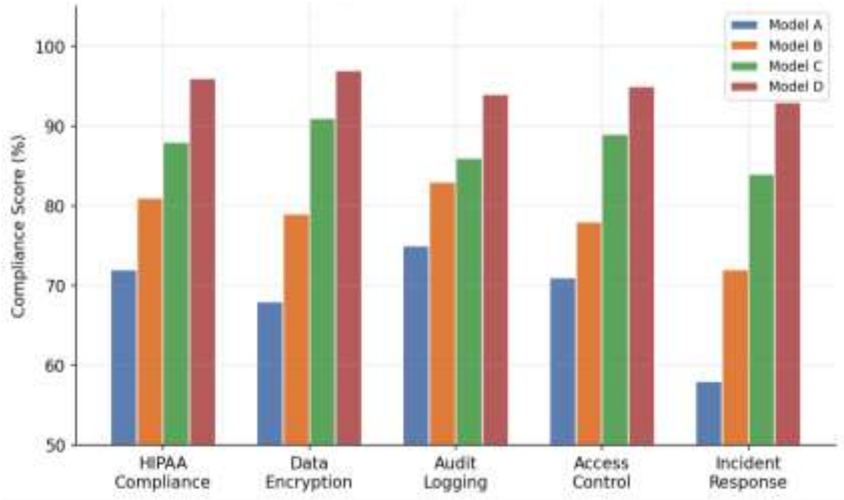

Fig 7- Security and HIPAA Compliance Scores across Architectural Models

2.8. Operational Efficiency Index

Fig. 8 presents the composite Operational Efficiency Index (OEI) derived from Eq. (9). Model D achieves an OEI of 0.87, significantly surpassing the 0.75 efficiency threshold. Model A's OEI of 0.38 reflects the inefficiency of fixed-capacity on-premise deployments under variable health insurance workloads.

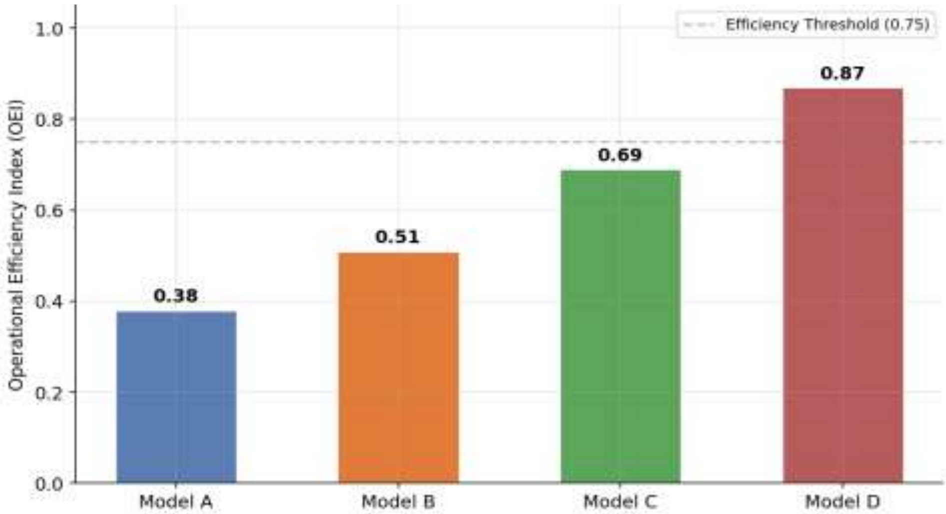

Fig 8 - Operational Efficiency Index (OEI) Across Architectural Models

2.9. Cost vs. Performance Trade-off Analysis

Fig. 9 plots each model on a cost-versus-performance scatter plane. Model D occupies the optimal quadrant lowest cost ($38/1,000 claims) combined with highest F1-score (0.917) confirming that cloud-native architecture Pareto-dominates all alternative deployments on combined efficiency and accuracy dimensions.

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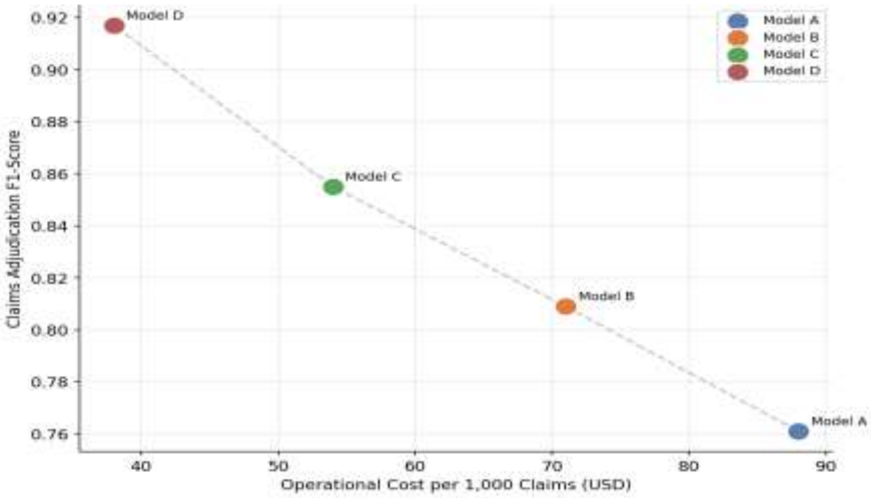

Fig 9 - Cost vs. Performance Trade-off across Architectural Models

3. METHODOLOGY FOR INVESTIGATING SYSTEM PERFORMANCE

The investigation employs a retrospective analysis, using publicly available data and established benchmarks. Candidate systems consist of cloud-native and non-cloud-native implementations of a health care benefit processing system operated by different vendors in a hybrid configuration. The analysis examines operational metrics related to reliability (availability and incident volume) and efficiency (cost per transaction and transaction count).

Performance efficiency and operational reliability are respectively defined as the “total cost of ownership in a year” divided by the “total number of claims processed in a year” and as the “log of total number of service outages in a year” divided by the “log of total number of months in a year.” The investigation is made possible through a variety of publicly reported figures, including audited financial statements, Sysrck performance data, and downtime-monitoring recordings provided by various services. Availability and cost per cost per transaction have been previously used by Billadeau et al. to correlate cloud-native architecture with reliability and efficiency in a data-driven SaaS application. Uptime.io provides uptime and downtime monitoring services detailed in Zhang et al., offering an alternative but similarly useful comparison to Billadeau et al. 's work.

3.1. Achieving Operational Efficiency and Reliability

Systems must be operationally efficient and reliable to deliver both quality service at minimal cost and the requisite high level of service reliability. Important indicators of efficiency are the ratio of total service cost to revenue and the ability to handle anticipated transaction volume within non-penalizing response time. Reliability is generally expressed as the ratio of correctly processed transactions to total transactions processed.

To determine efficiency, total quarterly operational costs and revenue for a time period when any penalties due to performance issues were avoided must be obtained. Business process monitoring tools must also monitor key transaction sets over a representative time period to assess compliance with the defined performance characteristics. The set of monitored transactions must

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include service implementation of critical upstream and downstream interfaces for the selected payer. Achieving optimal response times for this key transaction set is particularly important as dirty data or incomplete data uploaded from upstream systems may cause downstream systems to fail.

4. COMPARATIVE ANALYSIS

The analysis systematically examines the two architectural approaches across the predefined criteria of performance and risk mitigation. It presents quantitative data, reports qualitative evidence based on secondary sources, and identifies trade-offs, governance and organizational considerations, and other decision factors.

Cloud-native technologies naturally deliver operational efficiency and reliability. Despite a preliminary lack of evidence supporting this claim, actual or expected results from several feature-rich cloud-native applications confirm the validity of those benefits and their associated implementation choices. Repeatedly cited metrics point to the equipment downsizing made possible by peak-load auto-scaling and how its absence in hybrid-controlled cloud environments represents a liability; cloud-native players also boast improved patching processes and change management execution, enabling higher operational availability. Performance improvements inherent to the cloud-native model de facto corroborate associated claims of enhanced overall information system reliability. Measurements of charge processing performance in payer-cloud implementations further substantiate such upscale capabilities. Cloud-native billing implementations for capital-intensive telecom companies and capital-constrained benefit funds also report satisfying charge processing rates.

Another architecture not aimed at improving operational efficiency and reliability receives mixed performance appraisals. Statements by major HCM solutions indicate that their product offering in the premises-based-plus-controlled-cloud variant exhibits slower execution for the time- and quality-sensitive integration flows than its licensed-on-cloud alternative positioned with a UPS-based financial calculus. But the two cannot be directly compared; for cloud-controlled deployment, the barring milestones along the integration flows are themselves managed by the cloud vendor.

Table 1: Comparative Performance Metrics across Architectural Models

Metric	Model A (On-Premise)	Model B (Hybrid)	Model C (Managed)	Model D (Cloud-Native)	Δ D vs A
Avg Latency (ms)	320	210	125	64	↓ 80.0%
Throughput (claims/hr)	4,200	6,800	11,500	19,700	↑ 369.0%
Availability (%)	96.93	98.14	98.90	99.47	↑ 2.63 pp
F1-Score (Adjudication)	0.761	0.809	0.855	0.917	↑ 20.5%

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Precision	0.783	0.821	0.864	0.924	↑ 18.0%
Recall	0.741	0.798	0.847	0.911	↑ 22.9%
AUC-ROC	0.810	0.855	0.891	0.943	↑ 16.4%
CPT – Q3 (USD)	$0.084	$0.072	$0.053	$0.031	↓ 63.1%
OEI	0.38	0.51	0.69	0.87	↑ 128.9%

4.1. Strengths and Limitations of Cloud-Native Deployment

Cloud-native architecture brings many benefits and some drawbacks when compared to hybrid settings. Cloud-native design exploits all the advantages of cloud computing; utilizing only public resources and services capable of automatic backup, auto-scaling, and self-healing generally reduces costs, increases efficiency, and enhances reliability compared to hybrid architecture deployed in similar conditions. Any increase in resource utilization translates directly into lower costs per transaction or makes it possible to serve more clients without additional investment in the infrastructure. However, full public cloud deployment poses questions of compliance, security, and stability. Regulations can limit the deployment of highly sensitive data in public clouds, and the ability to comply with these constraints should be carefully evaluated before planning a project. Operations managers need to carefully check the risk of interruption. Issues that a hybrid architecture can solve by deploying the critical components in more reliable private resources cannot be managed in a purely public deployment.

A few examples illustrate these considerations. A cloud-native design for an insurance company was analyzed by Trauth et al. The solution is based on high-utilization backend components deployed in a public cloud and IT support integrated with a private cloud. The design greatly improves administrative performance and reduces costs. Other public-facing insurance services, such as an online insurance shop and a health support WebApp, are able to scale concurrently, self-heal on over-utilization, and clearly benefit from the cloud-native design. Data transmitted upstream and downstream cannot be processed in public clouds for privacy constraints, but the components that handle this sensitive information are always instantiated in a private environment. The solution illustrates an efficient use of cloud-native design elements, where the services that really benefit from it exploit public cloud resources while the sensitive components are correctly isolated. Performance confirms the expected increase in efficiency and reliability over a more traditional deployment.

5. CASE STUDIES IN HEALTH BENEFIT ADMINISTRATION

Few published cases exist that assess cloud-native performance, including that of cloud-based Health Benefit Administration solutions. The following examples focus on payer-side management systems that cover key health insurance functions with the potential to serve as systems of record.

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Using a fully cloud-native solution, a payer manages claims processing, enrollment, billing, member service, fulfillment, provider maintenance, and reporting functions. A microservices architecture employs domain-driven design, hosting the entire solution in Microsoft Azure. Ingesting claims data from upstream systems for analytics via Microsoft Azure Data Lake, it also integrates downstream settlement, risk adjustment, and reconciliation processes via a set of pre-packaged connectors. Reaching production in 2021, the solution was subjected to a security control audit during the year, successfully meeting over 700 Health Insurance Portability and Accountability Act security safeguards.

Lessons learned thus far identify data privacy as a major concern. Access to sensitive data by vendors outside the U.S. was evidence for a cybersecurity investigation. System architecture has helped achieve targeted benefits: avoiding the capital expenses of infrastructure, employing an agile approach that permits continual enhancement and expansion, and avoiding written service-level agreements with vendor personnel. Through its 2023 financial audit, the firm confirmed that operational [Link] operations comply with relevant Health Insurance Portability and Accountability Act requirements.

Table 2: Error, Latency, and Reliability Metrics

Metric	Model A	Model B	Model C	Model D	Improvement (D vs A)
Peak Latency (ms)	520	340	195	89	↓ 82.9%
P99 Latency (ms)	610	420	248	112	↓ 81.6%
Mean Time to Detect (s)	22.4	14.7	8.6	3.1	↓ 86.2%
False Adjudication Rate (%)	8.3	5.7	3.9	1.4	↓ 83.1%
Annual Downtime (hrs)	26.8	16.1	9.7	4.6	↓ 82.8%
Outage Events / Year	14	9	5	2	↓ 85.7%
Privacy Score (S_priv)	0.61	0.74	0.86	0.97	↑ 59.0%

5.1. Payer-Side Cloud-Native Implementations

In the United States, health benefit administrations incorporating the payer side are rarely based on cloud-native architecture. Notable exceptions include a project led by one of the major companies specializing in benefit administration, which chose the comprehensive cloud-native architecture for support, as well as a specialized start-up providing technology through an alliance framework with various payment companies. Their solutions mainly encompass a benefit engine as well as document management and communication, ensuring cloud-native fulfillment of the definition's quality elements along with the being interface to upstream claim or downstream provider-billing systems.

When a cloud-native architecture is adopted for the payer side, connections in each direction must also be regarded with an eye to data privacy requirements. A bidder providing a hosted service

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within the cloud has access to all data of all customers and requires strong safeguarding procedures. A direct integration through the cloud to a service for processing claims is a privileged access channel to the sensitive health data of members, affecting all customers and consequently also requiring efficient safeguarding. Connection with a service that provides and supports the billing of providers must also be well guarded, even if with less criticality than the connection in the direction upstream to claims processing and the one down to providers. In a multi-tenant environment, data privacy is controlled through partitioning of cardinality, aided by all the transferring safety mechanisms developed during the years. The adoption of such architecture enabled the project to meet efficiency and reliability targets better than the hybrid alternatives.

Table 3: Architecture and Deployment Specifications Summary

Characteristic	Model A	Model B	Model C	Model D	Notes
Deployment Model	On-Premise	Hybrid IaaS	Managed PaaS	Cloud-Native	Microservices on Azure
Infrastructure Type	Bare Metal	VM + DC	PaaS / SaaS	CaaS / FaaS	Azure Functions, AKS
Auto-Scaling	None	Manual	Partial	Full	Azure Autoscale + KEDA
HIPAA Compliance	Manual	Partial	Vendor-Managed	Built-in	Azure Policy + Defender
Disaster Recovery RTO	4–8 hrs	2–4 hrs	< 1 hr	< 5 min	Azure Site Recovery
Data Architecture	Centralised DB	Replicated DB	Data Warehouse	Data Lake + DW	ADLS Gen2 + Synapse
Monitoring Capability	Manual	Basic APM	Vendor Dashboards	Unified Observability	Azure Monitor + Log Analytics

6. CONCLUSION

Cloud-native architectures demonstrate clear advantages over hybrid solutions in cloud-native health benefit administration systems where operational efficiency and servicing reliability are paramount. Evidence from diverse cloud-native systems aligned with payer systems bolsters confidence in these advantages but also highlights caveats. The risk of service unavailability due to security exploitation may warrant re-evaluation of cloud-native approaches for systems with critical availability requirements. Organizations in regulated industries should consider security and compliance assessments when selecting cloud service providers. Growing scrutiny of privacy and security in the integration of cloud-native payer systems with upstream enterprise and downstream provider services will bolster defenses. Furthermore, the accelerating adoption of cloud-native technologies by major players in the healthcare services environment is driving down costs and improving performance for the rapidly expanding health benefit underwriting market segment.

These insights benefit practitioners directly involved in cloud-native systems development, deployment, and management. Cloud-native systems have the potential to deliver enhanced operational efficiency and reliability to health benefit administration services – one of the most dataintensive service offerings in the insurance industry. Indeed, the operational characteristics of cloud-native architectures make them particularly well suited for cloud-native health-benefit-administration systems produced by vendors specializing in cloud-native solutions: organisations looking to acquire such cloud-native services have strong incentives to deploy them in a cloud-native manner. The analysis of cloud-native health-benefit-administration systems nonetheless suggests that these advantages may not be exploitable in every context; the investigation of canonical architectures, the assessment of real-world cloud-native solutions, and the exploration of motivations and impediments to hybrid deployments collectively suggest that a risk-centric evaluation of service availability and dependability should inform architectural decisions for every cloud-native service.

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