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Experimental Performance And Statistical Validation Of The IoT-CKS Architecture For Infant Health Monitoring Under Resource-Constrained Network Conditions

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Abstract: Background: IoT architectures intended for community health monitoring must remain useful when communication and computing conditions deteriorate. This challenge is particularly relevant in resource-constrained environments where permanent access to remote Cloud services cannot be assumed. Methods: This study evaluates IoT-CKS, a distributed Edge-Fog-Cloud architecture for infant health monitoring. Four progressively constrained scenarios (S1-S4) were simulated. Each scenario was independently executed 30 times, yielding 120 observations. Mean transmission latency, message loss, and message duplication were analyzed using descriptive statistics and inferential procedures including Shapiro-Wilk, Levene, Welch ANOVA, Kruskal-Wallis, effect-size estimation, and supplementary pairwise comparisons. Results: Mean latency increased from 38.378 ms in S1 to 56.829 ms in S2, 112.602 ms in S3, and 223.683 ms in S4. Message loss increased from 0.320% to 6.360%, while duplication remained below 1%, reaching 0.905% in S4. Levene's test indicated variance heterogeneity ($F = 36.38$, $p < 0.001$). Welch ANOVA ($F(3, 55.71) = 419201.74$, $p < 0.001$) and Kruskal-Wallis ($H = 111.57$, $p < 0.001$) confirmed strong inter-scenario differences. Conclusion: The results provide preliminary numerical support for the resilience-oriented design of IoT-CKS. Performance degrades systematically as constraints increase, while local processing, temporary storage, and delayed synchronization provide an architectural basis for preserving essential local functions during temporary Cloud unavailability. These findings constitute simulation-based technical evidence, not clinical validation.

Keywords: Edge Computing; Fog Computing; Internet of Medical Things; IoT-CKS; infant health monitoring; performance evaluation; resilience; resource-constrained environments.

1. Introduction

The Internet of Things (IoT) and the Internet of Medical Things (IoMT) have expanded the capacity of health information systems to acquire, transmit, and process physiological data through interconnected sensing and computing resources [1]-[3]. In conventional deployments, remote Cloud services may provide persistent storage, visualization, supervision, and advanced analysis. However, the effectiveness of a monitoring architecture also depends on how communication and processing are organized when network availability becomes intermittent.

Cloud-centered designs can create a structural dependency on remote connectivity. Fog Computing and Edge Computing address this limitation by moving selected communication, storage, and processing functions closer to the data source [4]-[7]. In a

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health-monitoring context, this distribution can support local processing and temporary autonomy while retaining the benefits of remote supervision.

The problem is especially relevant in resource-constrained community settings, where connectivity, electrical infrastructure, and specialized technical resources may not be continuously available. For such environments, performance should not be evaluated only under nominal conditions. It is necessary to characterize how an architecture behaves as operating constraints increase and whether essential local functions can be preserved during temporary remote-service interruption.

IoT-CKS was developed as a distributed Edge-Fog-Cloud model for infant health monitoring. Its design allocates sensing and immediate processing to the Edge, coordination and buffering to the Fog, and persistent storage and broader supervision to the Cloud. Local processing, temporary storage, and delayed synchronization are incorporated to reduce dependence on permanent Cloud access.

The present article focuses on the experimental and statistical evaluation stage of the IoT-CKS research. It addresses the following question: How do progressively constrained network and operating conditions affect the communication performance of the IoT-CKS architecture, and to what extent do the experimental results support its reliability and resilience-oriented design?

The study has three objectives: (i) quantify the evolution of transmission latency, message loss, and message duplication across four experimental scenarios; (ii) determine whether the observed differences are statistically significant; and (iii) interpret the results in relation to the local-processing, buffering, and delayed-synchronization mechanisms of the architecture. The contribution is therefore experimental and analytical rather than a repetition of the architectural design itself.

The remainder of the paper is organized as follows. Section 2 reviews related work on distributed IoT processing and performance evaluation. Section 3 presents the methodology and experimental protocol. Section 4 reports the results, Section 5 provides the statistical analysis, Section 6 discusses the findings, and Sections 7 and 8 present limitations, future work, and conclusions.

2. Related Work

2.1 IoT and IoMT Performance Requirements

IoMT systems combine biomedical sensing, embedded devices, communication networks, and computing services to support health-related data acquisition and exchange [3]. Their evaluation should consider more than sensor availability: the communication path must be characterized in terms of responsiveness, successful delivery, and data consistency. In the present study, these dimensions are represented by transmission latency, message loss, and message duplication.

2.2 From Cloud-Centered Processing to Edge-Fog-Cloud Computing

Fog Computing extends processing, storage, and networking capabilities between end devices and remote Cloud resources [4]. Edge Computing further emphasizes computation close to the point of data generation [5]-[7]. These paradigms can reduce communication dependence on remote infrastructure and support time-sensitive or connectivity-sensitive services. Their value in IoT-CKS lies not in the novelty of the paradigms themselves, but in the allocation of functions according to the constraints of the target environment.

2.3 Resilience under Connectivity Degradation

For this study, resilience is not defined as the absence of failures or invariant performance. It is treated as the capacity to preserve essential local functions during temporary disruption and to recover deferred communication after connectivity returns. This interpretation is compatible with distributed processing, buffering, and local autonomy principles described in the Edge/Fog literature [4]-[6].

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2.4 Need for Progressive Experimental Evaluation

A single nominal operating condition provides limited information about system sensitivity. Experimental design principles recommend controlled modification of relevant factors, repeated observations, and statistical analysis of resulting differences [10], [11]. The IoT-CKS evaluation therefore uses four scenarios with progressively constrained external availability, Fog processing load, event activity, and a prolonged Cloud interruption in the offline/recovery scenario.

2.5 Research Gap

The gap addressed in this article is the quantitative characterization of a context-oriented Edge-Fog-Cloud healthcare architecture under progressively constrained operating conditions. The purpose is not to claim universal superiority over existing IoMT systems. Instead, the study connects a reproducible simulation protocol, three communication indicators, inferential statistics, and an explicit resilience-oriented operational model.

3. Materials and Methods

3.1 Research Design

The broader IoT-CKS research follows Design Science Research (DSR), in which an artefact is constructed and evaluated in response to an identified problem [8], [9]. The present article concentrates on the evaluation phase. The artefact is the modeled IoT-CKS architecture; the study does not constitute clinical experimentation or certification of a medical device.

3.2 Architecture under Evaluation

IoT-CKS is organized in three layers. The Edge layer acquires physiological data, performs preliminary processing, supports predefined local abnormal-condition detection, generates immediate local alerts, and provides temporary storage. The Fog layer supports aggregation, message management, buffering, coordination, and synchronization. The Cloud layer provides persistent storage, remote visualization, supervision, and broader analytical services. This distribution permits essential local operations to continue conceptually when the remote Cloud is temporarily unavailable.

3.3 Simulation Environment and Reproducibility

The experimental campaign used a network-simulation workflow based on ns-3, with scripted scenario execution and distinct pseudo-random seeds for independent runs. The simulation configuration described in the research includes 187 Edge nodes, a 72 h simulation horizon, and a 30 s acquisition period. Each scenario was executed 30 times, resulting in 120 simulation-run observations; these observations are independent simulation executions, not patients or clinical cases. Repeated runs reduce dependence on a single pseudo-random realization and support descriptive and inferential statistical analysis [10], [11].

3.4 Experimental Scenarios

Table 1. Experimental scenario parameters

Parameter	S1	S2	S3	S4
External availability (%)	100	85	65	40
Fog load (%)	20	55	70	85
Critical events	0	30	60	90
Cloud interruption	0 h	0 h	12 h	0 h
Runs	30	30	30	30

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S1 represents nominal operation. S2 introduces moderate degradation. S3 is the offline/recovery scenario and combines reduced availability, increased event activity, and a 12 h Cloud interruption. S4 represents the most severe tested condition, with the lowest external availability and the highest Fog load and event activity.

3.5 Performance Indicators

Three indicators were used. Transmission latency is the elapsed time between message transmission and reception and is expressed in milliseconds. Message loss is the proportion of sent messages that are not received. Message duplication is the proportion of received traffic corresponding to repeated delivery. Lower values indicate better communication performance for all three indicators.

Latency: $L_i = t_{r,i} - t_{s,i}$ | *Loss (%) = (Nsent - Nreceived) / Nsent × 100* | *Duplication (%) = Nduplicate / Nreceived × 100*

3.6 Statistical Analysis

Normality of latency observations was assessed using the Shapiro-Wilk test [12]. Homogeneity of variances was examined with Levene's test [13]. Because variance heterogeneity was detected, the principal parametric comparison relied on Welch ANOVA [14], with Kruskal-Wallis used as a non-parametric corroborative test [15]. This choice is consistent with recommendations to avoid relying on equal-variance methods when group variances differ [16]. Effect magnitude was reported using eta-squared, with interpretation informed by established effect-size conventions [17]. The significance threshold was $\alpha = 0.05$. The research also reports Tukey HSD pairwise comparisons; because variance heterogeneity was present, these are treated here as supplementary rather than the primary inferential basis.

4. Results

4.1 Overall Communication Performance

Table 2. Overall communication performance

Scenario	Mean latency (ms)	Message loss (%)	Duplication (%)
S1	38.378	0.320	0.113
S2	56.829	1.427	0.289
S3	112.602	2.567	0.402
S4	223.683	6.360	0.905

All three indicators deteriorated monotonically from S1 to S4. Latency showed the largest relative increase, while duplication remained below 1% throughout the experimental campaign.

4.2 Transmission Latency

Table 3. Descriptive statistics for transmission latency

Scenario	n	Mean (ms)	SD (ms)	95% CI
S1	30	38.378	0.115	0.041
S2	30	56.829	0.220	0.079
S3	30	112.602	0.481	0.172
S4	30	223.683	1.367	0.489

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Mean latency increased by 18.451 ms between S1 and S2, by 55.773 ms between S2 and S3, and by 185.305 ms between S1 and S4. The standard deviation also increased as conditions became more restrictive, from 0.115 ms in S1 to 1.367 ms in S4.

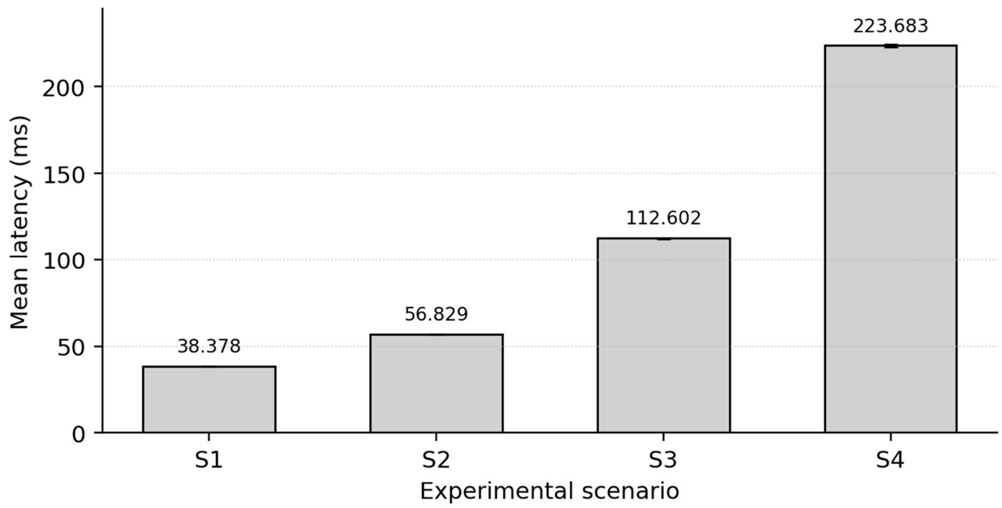

Figure 1. Mean transmission latency across scenarios S1-S4 with reported 95% confidence intervals.

4.3 Message Loss

Message loss increased from 0.320% in S1 to 1.427% in S2, 2.567% in S3, and 6.360% in S4. The S4 result corresponds mathematically to 93.640% of messages not being classified as lost according to this communication indicator; it should not be interpreted as a measure of clinical reliability.

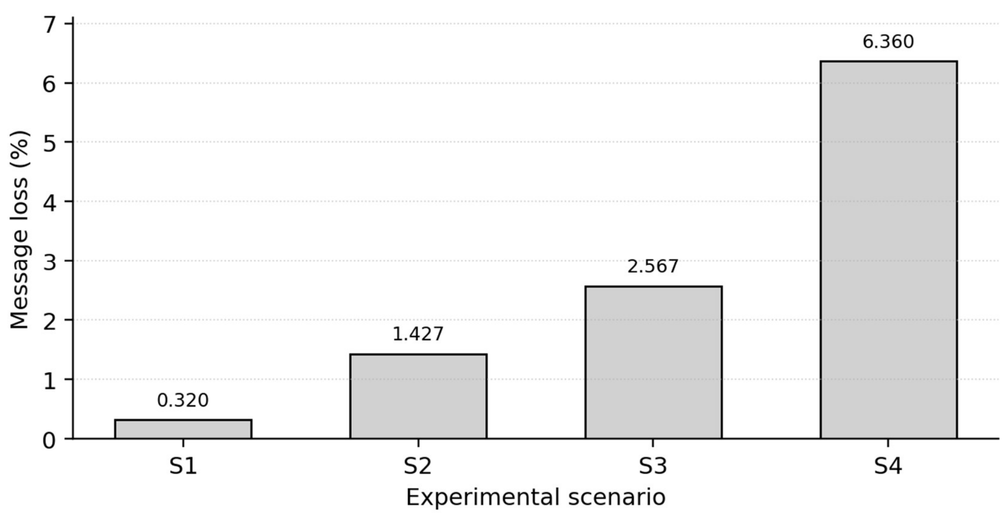

Figure 2. Message loss rate across scenarios S1-S4.

4.4 Message Duplication

Message duplication followed the same monotonic pattern, increasing from 0.113% in S1 to 0.289% in S2, 0.402% in S3, and 0.905% in S4. Despite progressive degradation, duplication remained below 1% in all four simulated conditions.

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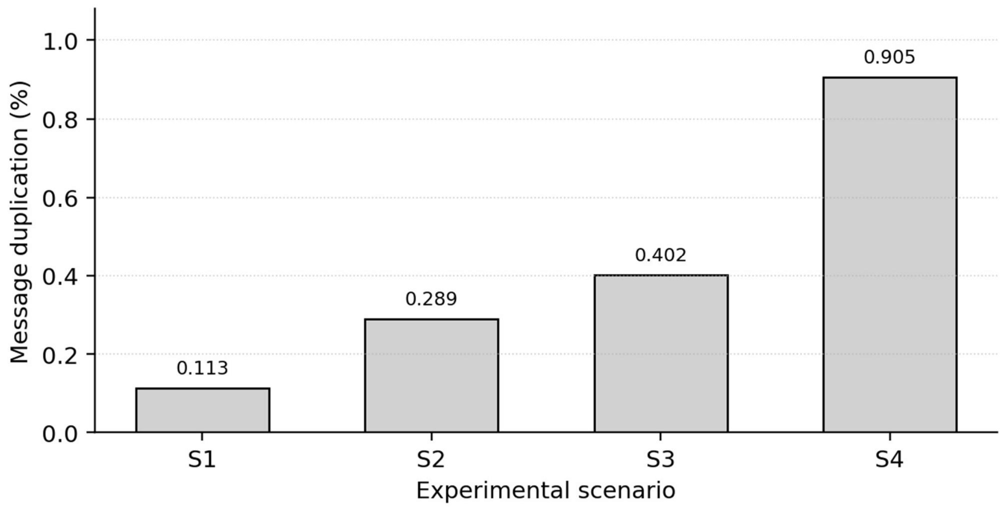

Figure 3. Message duplication rate across scenarios S1-S4.

4.5 Behavior of the Offline/Recovery Scenario

S3 is the central resilience-oriented scenario because it includes a 12 h Cloud interruption. During this condition, the modeled operational logic relies on local processing and temporary storage, followed by delayed synchronization after connectivity restoration. S3 produced intermediate values for all three indicators: 112.602 ms mean latency, 2.567% message loss, and 0.402% duplication.

5. Statistical Analysis and Interpretation

5.1 Normality

Table 4. Shapiro-Wilk normality results for latency

Scenario	Shapiro-Wilk W	p-value	Decision ($\alpha = 0.05$)
S1	0.937	0.078	Normality not rejected
S2	0.962	0.340	Normality not rejected
S3	0.975	0.680	Normality not rejected
S4	0.979	0.790	Normality not rejected

All four p-values exceeded 0.05; therefore, the latency distributions did not provide sufficient evidence to reject normality. This result does not prove exact normality, but it supports the use of parametric procedures provided their other assumptions are considered.

5.2 Variance Heterogeneity and Welch ANOVA

Levene's test indicated significant variance heterogeneity ($F = 36.38$, $p < 0.001$). This result is consistent with the strong increase in standard deviation across scenarios and makes a conventional equal-variance one-way ANOVA inappropriate as the principal test. Welch ANOVA therefore served as the main parametric comparison and showed a highly significant scenario effect: $F(3, 55.71) = 419201.74$, $p < 0.001$.

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5.3 Non-Parametric Confirmation and Effect Size

The Kruskal-Wallis analysis independently confirmed strong differences among the four scenarios ($H = 111.57$, $p < 0.001$). The agreement between the robust parametric and non-parametric procedures strengthens the inference that the observed scenario differences are systematic. The original analysis reports an effect-size estimate of $\eta^2 = 0.9999$, indicating an extremely large scenario effect within the simulated dataset. Because this estimate is unusually close to 1, it is reported conservatively and should be interpreted only within the controlled simulation; the calculation should be independently reproduced from the raw run-level data before it is used for broader generalization.

5.4 Pairwise Comparisons

The original research protocol reports that all six Tukey HSD pairwise comparisons were significant at $p < 0.001$. The descriptive differences are consistent with that result: S1-S2 = 18.451 ms, S2-S3 = 55.773 ms, and S1-S4 = 185.305 ms. Because Levene's test demonstrated unequal variances, however, Tukey HSD is not used here as the principal basis for pairwise inference. The primary inferential conclusion rests on Welch ANOVA and the Kruskal-Wallis corroboration; a future raw-data reanalysis should use a heteroscedasticity-robust post-hoc procedure such as Games-Howell for pairwise contrasts.

5.5 Statistical versus Clinical Significance

The statistical results establish that the simulated scenarios produce clearly distinguishable communication performance. They do not establish clinical acceptability thresholds. In particular, the S4 latency of 223.683 ms is a technical performance value observed in simulation, not a validated pediatric clinical threshold. Likewise, 6.360% message loss cannot be converted into a claim of 93.640% clinical reliability.

6. Discussion

6.1 Progressive Degradation rather than Abrupt Collapse

The principal finding is the coherent, monotonic deterioration of latency, loss, and duplication as operational constraints increase. Mean latency rose by a factor of approximately 5.83 between S1 and S4. Message loss increased by 6.04 percentage points, while duplication remained quantitatively limited below 1%. These results show that IoT-CKS is sensitive to adverse operating conditions, as expected, but the modeled communication path retains measurable functionality across the tested scenarios.

6.2 Interpretation of S3 and Resilience

S3 provides the most direct evidence relevant to the resilience-oriented design. A 12 h Cloud interruption does not conceptually terminate all local monitoring functions because sensing, preliminary processing, predefined local alerting, and temporary storage are assigned below the Cloud layer. The recovery sequence is therefore: local acquisition and processing -> buffering during remote unavailability -> delayed synchronization after restoration. This supports the architectural proposition that loss of Cloud connectivity need not imply loss of all local monitoring functions.

The result should nevertheless be described as simulation-based architectural support rather than proof of real-world resilience. A deployed system would be exposed to additional factors such as hardware failures, radio propagation variability, storage saturation, energy depletion, and user interaction.

6.3 Role of Edge-Fog-Cloud Functional Distribution

The experimental behavior is consistent with the rationale for distributed processing described in the Edge and Fog literature [4]-[7]. Edge resources support immediacy and local autonomy, Fog resources support coordination, buffering, and communication management, and Cloud resources support persistence and remote services. The contribution of IoT-CKS is the context-oriented allocation of these functions and their evaluation under constraints relevant to the reference setting, rather than the invention of the underlying paradigms.

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6.4 Reliability Indicators

Message loss and duplication provide complementary views of communication reliability. Loss represents unsuccessful delivery, whereas duplication represents repeated delivery and potential overhead. Their common S1 < S2 < S3 < S4 ordering independently confirms the effect of scenario severity. The persistence of low duplication does not compensate for message loss, and neither indicator alone represents overall system safety or clinical effectiveness.

6.5 Interpretation of the Research Hypotheses

The results provide different levels of support for the research hypotheses. Requirements-to-specification coherence is supported conceptually and methodologically. The Edge-Fog-Cloud hypothesis receives architectural support from the modeled offline/recovery behavior, particularly S3. The evaluation hypothesis receives direct numerical support through 120 observations, explicit performance indicators, and convergent statistical analyses. The general hypothesis is therefore supported within the modeled and simulated scope, but not clinically validated.

6.6 Scientific Contribution

This experimental study contributes: (i) a progressive four-scenario evaluation rather than a nominal-only benchmark; (ii) joint analysis of latency, loss, and duplication; (iii) repeated execution with 30 runs per scenario and explicit pseudo-random variation; (iv) robust inferential analysis under variance heterogeneity; and (v) interpretation of performance degradation in relation to explicit local-processing, buffering, and recovery mechanisms.

7. Limitations and Future Work

7.1 Limitations

The evaluation is simulation-based and does not constitute large-scale operational deployment. Real hardware failures, radio interference, environmental variability, unexpected energy interruptions, and human behavior are therefore not fully represented. The study does not provide clinical validation, diagnostic accuracy, medical-device certification, or pediatric safety evidence. Sensor metrology was not clinically validated in this experimental campaign. The three communication indicators also do not cover energy consumption, throughput, storage occupancy, synchronization recovery time, scalability, cybersecurity, privacy, usability, or long-term maintainability.

The four scenarios were deliberately constructed to represent increasing constraint levels. They therefore provide internal comparability but cannot reproduce every possible combination of field conditions. Generalization beyond the reference context requires additional validation.

7.2 Future Work

Future work should proceed from simulation to a physical prototype, followed by controlled laboratory validation under real connectivity and power disturbances. Offline buffering capacity, synchronization recovery time, data consistency after reconnection, and energy autonomy should be quantified. Cybersecurity testing, multi-node scalability studies, usability and acceptability assessment, and field evaluation should follow. Only after adequate technical, metrological, ethical, security, and regulatory preparation should clinical evaluation be considered.

Simulation -> Prototype -> Laboratory validation -> Field validation -> Clinical evaluation

8. Conclusion

This study quantitatively evaluated the IoT-CKS Edge-Fog-Cloud architecture under four progressively constrained operating scenarios. Thirty independent repetitions per scenario produced 120 observations. Mean latency increased from 38.378 ms in S1 to 223.683 ms in S4; message loss increased from 0.320% to 6.360%; and duplication increased from 0.113% to 0.905%, remaining below 1% throughout the experiment.

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Statistical analysis confirmed strong scenario effects. Levene's test identified variance heterogeneity, Welch ANOVA and Kruskal-Wallis both yielded $p < 0.001$, and the reported effect size was $\eta^2 = 0.9999$. These results establish that the progressive performance changes are systematic within the simulated dataset.

S3, which included a 12 h Cloud interruption, is particularly important for resilience interpretation. The architecture is designed so that local sensing and processing can continue, unsent information can be buffered, and deferred communication can resume through delayed synchronization. Resilience is therefore better understood as graceful degradation plus recovery capability rather than invariant performance.

The findings provide preliminary numerical support for the resilience-oriented design of IoT-CKS, but they remain technical and simulation-based. Physical prototyping, energy and security evaluation, field testing, and ultimately appropriately authorized clinical validation remain necessary before stronger real-world claims can be made.

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