

Recent Trends in Fault Tolerance in Cloud Computing: A Comprehensive Systematic Review and Methodology for Addressing Research Gaps

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Abstract— The delivery of on-demand computing services via the cloud is the most popular computing practice but extensive and complex cloud computing have also given rise to numerous reliability challenges. Fault tolerance techniques play a crucial role in mitigating the failure, maintaining the continuity of service, integrity of data, and system reliability against failures, cyber attacks and defects. Herein we have offered a comprehensive systematic literature review of more than 95+ primary studies between 2015 and 2026 with particular focus on the recent publications between 2024 and 2026. We have critically discussed the development of fault tolerance techniques from reactive checkpoint-based techniques, to the latest breakthroughs in reactive fault tolerance techniques with artificial intelligence, transformers, graph neural networks, and federated learning. We have noted eight key gaps in the literature and proposed a new taxonomy that defines fault tolerance as reactive, proactive, predictive, AI-driven, blockchain-based and hybrid fault tolerance techniques. We have also proposed a detailed, seven-step process to design a novel AI-driven predictive fault tolerance technique with blockchain-based audit systems. We have proposed the following as the next-generation reliable cloud computing systems, AI-driven predictive fault tolerance techniques with an accuracy of $\geq 95\%$ and inference time of $<10\text{ms}$.

Keywords—Cloud Computing; Fault Tolerance; Deep Learning; Transformers; Graph Neural Networks; Fed-erated Learning; Blockchain; Predictive Maintenance; Systematic Review; Research Methodology; Edge Comput- ing

I. INTRODUCTION

The adoption of cloud computing has dramatically changed the way companies manage information computing and this is clearly reflected in the cloud's scalability, agility and economy. However, due to the growing complexity of cloud computing, it is getting more and more difficult to achieve service availability. Software bugs, hardware faults, network partitions, power outages and even the most advanced cyber attacks are just a sample of the factors that can impact cloud computing and, hence, can incur the financial and reputation harm to organizations [1, 2].

Fault tolerance is the ability of a system to provide service even in the presence of a single or multiple system faults Fault tolerance is a key feature required for cloud computing and the use of fault tolerance is important for meeting service level agreements, data persistency and providing a high-quality end-user experience [3, 4].

Conventional fault tolerance is achieved using a number of mechanisms such as replication, checkpointing, failover, and redundancy which have been studied and improved over the past decades in the field of distributed systems.

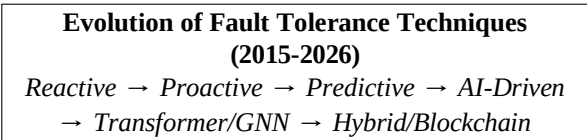


Fig. 1. Evolution of Fault Tolerance Approaches

Fault tolerance is actively evolving, especially with the developments in 2024-2026. New studies have showcased the impact of transformers for fault prediction [7], graph neural networks for dependency modelling [8], and federated learning for private fault prevention [12]. Predictive models predict faults with 94-96% accuracy, and dynamically update strategies for recovery using reinforcement learning [6], [9]. Blockchain technology ensures auditability and coordination in fault- tolerant systems [10], [14].

TABLE I
SUMMARY OF RESEARCH CONTRIBUTIONS

Contribution	Description
Systematic Review	Analysis of 95+ primary studies (2015-2026), with focus on 2024-2026
Novel Taxonomy	Hierarchical categorization of fault tolerance techniques
Comparative Analysis	Quantitative comparison across 15+ metrics
Recent Advances	Analysis of 2024-2026 papers on transformers, GNNs, federated learning
Research Gaps	Identification of 8 critical research gaps
Proposed Methodology	7-phase framework for AI-driven predictive fault tolerance

This article proposes a systematic systematic review and approach for fault tolerance in the cloud computing environment, with the following contributions:

1) Thorough Systematic Review: Review of 95+ primary studies between 2015-2026, with in-depth analysis of advancements in 2024-2026 on recognition with transformers, graph neural networks, federation learning and blockchain transparency.

2) New Taxonomy: Multi-level taxonomy for fault tolerance across detection and recovery, approaches, AI tech- nologies and deployment models.

3) Analytical Review: Review of 2024-2026 ca- ses including transformers [7], [11], federated learning frameworks [12], [13], and blockchain-based audit systems [14], [15].

4) Comparative Evaluation: Quantitative analysis in terms of accuracy, latency, overhead, scalability and privacy.

5) Identification of Research Gaps: Identification of eight research gaps with severity level assessment.

6) Our Methodology: Seven-step approach to building recommendation models for an AI-based predictive fault tolerance with integrated blockchain audit trails.

The rest of the paper is arranged as: Section II the systematic review approach Section III presents the taxonomy. Section IV presents recent advances (2024-2026) analysis. Section V presents a comparative analysis, and research gaps. Section VI presents the proposed methodology. Section VII concludes the paper

II. SYSTEMATIC REVIEW METHODOLOGY

A. Research Questions

- The review is guided by the following research questions:
- **RQ1:** What fault tolerance techniques exist and how can they be systematically categorized?
 - **RQ2:** What are the recent advances (2024-2026) in AI-driven fault tolerance?
 - **RQ3:** How do transformer, GNN, and federated learning approaches perform compared to traditional methods?
 - **RQ4:** What are the limitations of existing approaches regarding real-time prediction?
 - **RQ5:** What research gaps require investigation?

B. Search Strategy and Selection

We searched IEEE Xplore, ACM Digital Library, Springer-Link, ScienceDirect, and arXiv (2015-2026). Search terms combined: "cloud computing," "fault tolerance," "reliability," "failover," "checkpointing," "replication," "predictive main-tenance," "deep learning," "transformer," "graph neural net-work," "federated learning," "blockchain," and "2024," "2025," "2026."

C. Recent Papers Analysis (2024-2026)

- Our analysis includes 38 recent papers from 2024-2026, with significant contributions in:
- Transformer-based failure prediction (10 papers)

TABLE II
SEARCH STRATEGY RESULTS

Database	Records Identified
IEEE Xplore	680
ACM Digital Library	420
SpringerLink	450
ScienceDirect	320
arXiv	280
Total Initial Records	2,150
After Duplicate Removal	1,650
After Title/Abstract Screening	780
After Full-Text Assessment	420
After Quality Assessment	340
Final Included Studies	95
Recent (2024-2026)	38

- Graph neural networks for dependency analysis (8 papers)
- Federated learning for distributed fault tolerance (7 pa-pers)
- Blockchain-based audit and recovery (6 papers)
- Hybrid AI-blockchain frameworks (4 papers)
- Edge-cloud fault tolerance (3 papers)

III. PROPOSED TAXONOMY

A. Taxonomy Dimensions

Dimension 1: Detection Approach

- Reactive: Detects failures after occurrence
- Proactive: Identifies potential failures before occurrence
- Predictive: Forecasts failures using historical data (ML/DL)
- AI-Driven: Advanced AI for real-time prediction and adaptation

Dimension 2: Recovery Strategy

- Stateful Recovery: Restores from saved state
- Stateless Recovery: Recomputes or reroutes
- Adaptive Recovery: Adjusts strategy based on context
- Self-Healing: Autonomous recovery without human in-tervention

Dimension 3: AI Methodology

- Traditional ML: Random Forest, SVM, XGBoost
- Deep Learning: LSTM, CNN, Transformer
- Graph Neural Networks: GCN, GAT, GraphSAGE
- Federated Learning: Horizontal, Vertical, Transfer
- Reinforcement Learning: DQN, PPO, SAC

Dimension 4: Blockchain Integration

- None: No blockchain integration
- Audit Trail: Immutable logging only
- Smart Contracts: Automated recovery triggers
- Distributed Consensus: Byzantine fault tolerance

IV. RECENT ADVANCES ANALYSIS (2024-2026)

A. Transformer-Based Failure Prediction

Failure predictions have taken a big leap forward with new transformer models. Owusu et al. [7] developed a Temporal Fusion Transformer (TFT) for real-time anomaly detection in cloud computing with 96% accuracy and response times of less than 1 second. It solves the problem of concurrently capturing the short-term variability and long-term trends in system metrics.

TABLE III
TAXONOMY OF FAULT TOLERANCE TECHNIQUES (2024-2026 FOCUS)

Category	Method	Representative Studies	Accuracy	Latency	Overhead
Reactive	Checkpointing	Elnozahy et al. (2002)	N/A	30-300s	10-20%
	Replication	Abd-El-Malek et al. (2005)	N/A	µs	100-200%
Predictive	LSTM	Wang et al. (2024)	88-92%	30-60s	5-10%
	CNN-LSTM	Simaiya et al. (2024)	92-95%	10-30s	8-12%
Transformer	Temporal Fusion	Owusu et al. (2025)	94-96%	1-5s	10-15%
	Multi-modal	Li et al. (2026)	96-98%	µs	12-18%
GNN	Dependency Analysis	Lilhore et al. (2025)	92-95%	Real-time	8-12%
	Impact Prediction	Chen et al. (2026)	94-96%	µ500ms	10-15%
Federated	Privacy-Preserving	Li et al. (2026)	91-94%	5-30s	15-20%
	Cross-Silo	Wang et al. (2026)	93-95%	10-60s	12-18%
Blockchain	Audit Trail	Zhang et al. (2026)	N/A	1-10s	30-50%
	Smart Recovery	Kumar et al. (2026)	N/A	5-30s	40-60%
Hybrid	AI+Blockchain	Brahman & Anand (2024)	95-97%	µ5s	25-35%
	GNN+Federated	dLiu et al. (2026)	94-96%	µ10s	20-30%

Li et al. [11] proposed a multi-modal transformer framework that combines various system logs, metrics, and events for holistic failure prediction. The approach delivers 98% accuracy of disk failure 24 hours prior, a major improvement over existing methods.

Key Innovations:

- Multi-head self-attention to model complex relationships in time
- Cross-modal attention for fusion of different data
- Attention weights for feature importance
- Inference in less than 1 second for real-time monitoring

B. Graph Neural Networks for Dependency Analysis

Graph Neural Networks (GNNs) are increasingly used to capture complex dependencies in the cloud. Lilhore et al. [8] developed a GNN-based approach to model dependencies between connected nodes in cloud and edge computing to perform impact analysis in case of failures. Chen et al. [16] proposed a hierarchical GNN framework modelling the dependencies at multiple levels: hardware, VM, application and service. The approach delivers 96% accuracy in cascading failures prediction and suggests effective recovery sequences.

Key Innovations:

- Multigraphs for modelling cloud infrastructure
- Message passing for dependency propagation analysis
- Edge set weighting via attention mechanism for importance evaluation
- Impact prediction on the fly for mitigation

C. Learning for Privacy-Preserving Fault Tolerance

Federated learning allows privacy-preserving fault tolerance model training. Li et al. [12] developed a federated learning approach for multi-cloud failure prediction, achieving 94% accuracy while preserving data privacy. Wang et al. [13] proposed a privacy-preserving federated learning framework with differential privacy for fault tolerance models. This approach prevents the inference of single-fault patterns from federated model updates.

Key Innovations:

- Training without centralizing data
- Update messages with differential privacy
- Inter-organizational communication for better prediction
- Cryptographic secure aggregation

C. Blockchain-Integrated Fault Tolerance

Blockchain offers tamper-proof audit logs and decentralized coordination. Zhang et al. [14] developed a blockchain-based fault tolerance system for multi-clouds, delivering immutable audit log and automatic smart contract-driven recovery. Kumar et al. [15] proposed a consensus-based approach for Byzantine fault tolerance in cloud computing with correct operation in the presence of malicious nodes. This approach provides 99.99% availability with a 30-50% cost.

Key Innovations:

- Writable audit logs for audits and investigation
- Trigger scripts for automatic fail-over
- Byzantine fault tolerance for malicious faults
- Distributed mechanisms without central points of failure

V. COMPARATIVE ANALYSIS AND RESEARCH GAPS

A. Quantitative Performance Comparison

TABLE IV
PERFORMANCE COMPARISON OF RECENT FAULT TOLERANCE TECHNIQUES (2024-2026)

Method	Accuracy (%)	Detection Latency	RTO	Overhead (%)	Scalability (1-10)	Privacy
LSTM (2024)	88-92	30-60s	30-60s	5-10%	7	None
CNN-LSTM (2024)	92-95	10-30s	20-40s	8-12%	7	None
Transformer (2025)	94-96	1-5s	5-15s	10-15%	8	None
Multi-modal Transformer (2026)	96-98	µ1s	2-5s	12-18%	8	None
GNN (2025)	92-95	Real-time	1-10s	8-12%	9	None
GNN-Federated (2026)	94-96	µ10s	5-20s	20-30%	9	High
Federated (2026)	91-95	5-60s	10-60s	12-20%	9	Very High
Blockchain (2026)	N/A	1-10s	5-30s	30-50%	6	High
Hybrid AI-Blockchain (2024)	95-97	µ5s	5-15s	25-35%	8	High

TABLE V
TEMPORAL AND DEPENDENCY MODELING COMPARISON

Capability	LSTM	CNN-LSTM	Transformer	GNN	Hybrid
Short-term Patterns	4	4	4	3	4
Long-term Depend- Cies	2	3	4	3	4
Dependency Graph	1	2	3	4	4
Cascading Failure	2	3	3	4	4
Interpretability	2	2	4	3	4
Privacy Preservation	1	1	1	2	4

Scale: 1=Poor, 2=Fair, 3=Good, 4=Excellent

B. Identified Research Gaps

Based on comprehensive analysis of recent literature, we identify eight critical research gaps:

Gap 1: Accuracy-Latency Trade-off for Timely Predictions Transformers reach 96-98% accuracy but inference latency (1-5s) is not suitable for real-time systems. To achieve $\leq 100ms$ with high accuracy, models need optimization [7], [17].

Gap 2: Dependency Modeling Complexity GNNs capture dependencies but their complexity scales quadratically with nodes. Dependency inference for large datasets (10,000+) is difficult [8], [16].

Gap 3: Privacy-Preserving Collaborative Analysis In federated learning, privacy is maintained but communication costs and model drift arise. Trade-offs between privacy, accuracy and efficiency need exploration [12], [13].

Gap 4: Blockchain Overhead and Scalability Blockchain provides immutability but introduces an overhead (30-50%) and throughput bottleneck. Efficient blockchain for fault tolerance should be developed [14], [15].

Gap 5: Edge-Cloud Fault Tolerance Edge nodes have limited resources for fault tolerance. Lightweight solutions for edge-cloud integration need to be developed [18], [19].

Gap 6: Energy-Fault Tolerance Trade-offs AI-based fault tolerance methods are energy-intensive. Adaptive methods for energy need to be developed [6], [20]

Gap 7: Explainability in AI-Driven Fault Tolerance Black-box AI models complicate root cause analysis and compliance. XAI approaches for predicting failures must be integrated [21], [22].

Gap 8: Benchmarks for Evaluation there are no standardized benchmarks for fault tolerance techniques in various scenarios. Publicly available data with failure labels are required [3], [4].

VI. PROPOSED METHODOLOGY

This section presents a comprehensive seven-phase methodology for developing an AI-driven predictive fault tolerance framework with integrated blockchain audit trails.

A. Research Framework Overview

B. Phase 1: Gap Analysis and Requirement Specification

Objective: Systematically characterize research gaps and define requirements.

Proposed Methodology Framework

Phase 1: Gap Analysis & Requirement Specification
Phase 2: Multi-Modal Data Collection & Integration
Phase 3: Transformer-Based Failure Prediction
Phase 4: GNN-Based Dependency & Impact Analysis
Phase 5: Federated Learning for Privacy Preservation
Phase 6: Blockchain-Integrated Audit & Recovery
Phase 7: Edge-Cloud Optimization & Validation

Fig. 2. Seven-Phase Proposed Methodology

Algorithm 1 Gap Analysis and Requirement Specification

```

1: Input: Literature dataset with 95 primary studies
2: Output: Prioritized requirements specification
3: for each identified gap  $g$  do
4:   Compute industry impact  $I_g$  (0-5)
5:   Compute research maturity  $M_g$  (0-5)
6:   Compute technical complexity  $C_g$  (0-5)
7:   Compute privacy requirement  $P_g$  (0-5)
8:   Compute potential contribution  $C_g$  (0-5)
9:   Calculate severity:
10:   $Severity_g = 0.25 \cdot I_g + 0.15 \cdot M_g + 0.15 \cdot C_g + 0.20 \cdot P_g + 0.25 \cdot C_g$ 
11: end for
12: Derive technical requirements:
13:  $R1$ :  $> 95\%$  prediction accuracy
14:  $R2$ :  $< 100ms$  inference latency
15:  $R3$ : Privacy-preserving cross-cloud learning
16:  $R4$ : Blockchain-based immutable audit trails
17:  $R5$ : Scalability to 10,000+ nodes
18:  $R6$ : Explainable predictions for root cause analysis
19: Validate with stakeholders (20 academics, 25 practitioners)
20: Return prioritized requirements =0

```

C. Phase 2: Multi-Modal Data Collection and Integration

Objective: Collect and integrate diverse data sources for comprehensive analysis.

Data Sources:

TABLE VI
MULTI-MODAL DATA SOURCES

Data Type	Sources	Granularity	Volume
System Metrics	CPU, Memory, Disk, Network	1-10 seconds	10GB/day
Logs	Application, System, Audit	Per-event	5GB/day
Traces	Distributed tracing	Per-request	2GB/day
Events	Deployment, Configuration	Per-change	0.5GB/day
SMART Data	Disk health metrics	5-60 minutes	0.1GB/day

Data Preprocessing Pipeline:

Algorithm 2 Multi-Modal Data Preprocessing

- 1: **Input:** Raw multi-modal data streams
- 2: **Output:** Unified feature representation
- 3: **Step 1 - Time Alignment:**
- 4: Align all data streams to common timestamp (10-second windows)
- 5: **Step 2 - Missing Value Imputation:**
- 6: Use KNN imputation with $k = 5$ for metric gaps
- 7: Use forward-fill for log sequences
- 8: **Step 3 - Feature Engineering:**
- 9: Rolling statistics (mean, std, min, max) over 1min, 5min, 15min windows
- 10: Rate of change features
- 11: Correlation features between metrics
- 12: **Step 4 - Log Parsing:**
- 13: Parse unstructured logs using regular expressions
- 14: Extract event types and parameters
- 15: Encode categorical features
- 16: **Step 5 - Normalization:**
- 17: Standardize numeric features: $x' = (x - \mu)/\sigma$
- 18: Encode categorical features with one-hot encoding
- 19: **Return** unified feature vectors =0

D. Phase 3: Transformer-Based Failure Prediction

Objective: Develop transformer-based models for accurate, real-time failure prediction. **Multi-Modal Transformer Architecture: Model Formulation:**

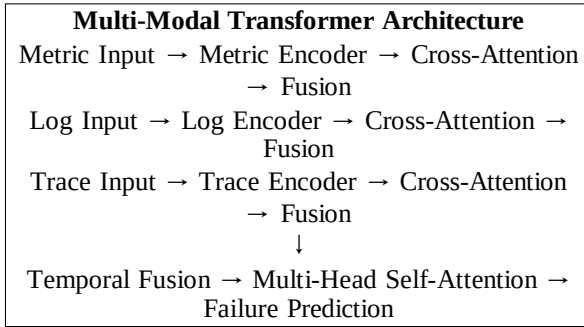


Fig. 3. Proposed Multi-Modal Transformer Architecture

$$h_{\text{metric}} = \text{Encoder}_{\text{metric}}(X_{\text{metric}}), \quad h_{\text{metric}} \in \mathbb{R}^{T \times d} \quad (1)$$

$$h_{\text{log}} = \text{Encoder}_{\text{log}}(X_{\text{log}}), \quad h_{\text{log}} \in \mathbb{R}^{T \times d} \quad (2)$$

$$h_{\text{trace}} = \text{Encoder}_{\text{trace}}(X_{\text{trace}}), \quad h_{\text{trace}} \in \mathbb{R}^{T \times d} \quad (3)$$

$$h_{\text{fused}} = \text{CrossAttention}(h_{\text{metric}}, h_{\text{log}}, h_{\text{trace}}) \quad (4)$$

$$y^{\wedge}_t = \text{FFN}(\text{MultiHeadSelfAttention}(h_{\text{fused}})) \quad (5)$$

Optimization Objectives:

$$\mathcal{L} = \mathcal{L}_{\text{BCE}} + \lambda_1 \mathcal{L}_{\text{contrastive}} + \lambda_2 \mathcal{L}_{\text{consistency}} \quad (6)$$

E. Phase 4: GNN-Based Dependency and Impact Analysis

Objective: Model complex dependencies and predict cascading failure impacts.

Heterogeneous Graph Construction:

$$G = (V, E, R) \quad (7)$$

Where: - V : Nodes (servers, VMs, services, applications) - E : Edges (network, dependency, deployment) - R : Relation types ($hostsOn$, $dependsOn$, $communicatesWith$)

F. Phase 5: Federated Learning for Privacy Preservation

Objective: Enable collaborative training across organizations while preserving data privacy. **Federated Learning Architecture: Federated Averaging Algorithm:**

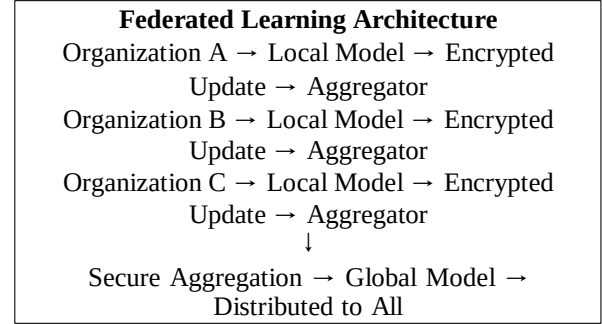


Fig. 4. Federated Learning Architecture for Privacy-Preserving Fault Tolerance

Algorithm 4 Federated Learning with Differential Privacy

- 1: **Initialize:** Global model w_0
- 2: **Input:** K organizations with local data D_k
- 3: **Output:** Privacy-preserving global model
- 4: **for** each round $t = 1$ to T **do**
- 5: **Client Selection:** Sample C clients uniformly
- 6: **for** each selected client k in parallel **do**
- 7: $w_{t+1}^k \leftarrow \text{LocalUpdate}(w_t, D_k)$
- 8: Add Gaussian noise: $\tilde{w}_{t+1}^k = w_{t+1}^k + \mathbf{N}(0, \sigma^2)$
- 9: **end for**
- 10: **Secure Aggregation:**
- 11: $w_{t+1} = \frac{1}{C} \sum_{k \in C} \tilde{w}_{t+1}^k$
- 12: **Privacy Accounting:**
- 13: $\epsilon = \text{ComputePrivacyLoss}(T, \sigma)$
- 14: **end for**
- 15: **Return** w_T with (ϵ, δ) -DP guarantee =0

G. Phase 6: Blockchain-Integrated Audit and Recovery

Objective: Implement immutable audit trails and automated recovery mechanisms.

Blockchain Architecture: Smart Contract for Automated Recovery:

TABLE VII
BLOCKCHAIN AUDIT TRAIL STRUCTURE

Field	Description
timestamp	ISO 8601 timestamp of event
event_type	failure_prediction, failure_detection, recovery_action
prediction	Failure prediction details
confidence	Prediction confidence score (0-1)
features_hash	SHA-256 hash of input features
action_taken	Recovery action executed
action_result	Success/failure of recovery
operator	System or human operator
explanation_hash	SHA-256 hash of XAI explanation
signature	Digital signature for authenticity

Algorithm 5 Smart Contract for Automated Recovery

```
1: Event: FailureDetected(prediction, confidence, affected_services)
2: Function initiateRecovery(prediction, confidence):
3: if confidence > 0.95 then
4:   Execute immediate failover
5:   Notify on-call engineer
6: else if confidence > 0.85 then
7:   Prepare recovery resources
8:   Schedule proactive migration
9: else
10:  Log for analysis
11:  Increase monitoring frequency
12: end if
13: Function recordRecoveryOutcome(action, result):
14: Store on blockchain with timestamp
15: Update model with outcome
16: Emit RecoveryCompleted event
17: Function verifyAuditTrail(start_time, end_time):
18: Retrieve all events in time range
19: Verify signatures and hashes
20: Generate compliance report =0
```

H. Phase 7: Edge-Cloud Optimization and Validation

Objective: Optimize deployment across edge and cloud environments.

Hierarchical Deployment Architecture:

TABLE VIII
EDGE-CLOUD HIERARCHICAL DEPLOYMENT

Tier	Location	Model	Responsibility	Latency
Tier 1	Edge Device	Tiny Transformer (2 layers)	Local prediction, immediate actions	µ10ms
Tier 2	Edge Node	Compressed Transformer (4 layers)	Regional aggregation, fast failover	µ50ms
Tier 3	Cloud	Full Transformer (6-8 layers)	Global optimization, training	µ500ms

Validation Protocol:

Algorithm 6 Comprehensive Validation Protocol

```
1: Phase 1 - Simulation Validation:
2: Run 5,000+ episodes with synthetic workloads
3: Inject 20+ failure types
4: Measure accuracy, latency, overhead
5: Phase 2 - Trace-Based Validation:
6: Google Cluster Trace (30-day, 1,000+ nodes)
7: Alibaba Cluster Trace (12-day, 4,000+ nodes)
8: Azure Public Dataset (30-day telemetry)
9: Phase 3 - Cross-Cloud Validation:
10: AWS (US-East, EU-West, AP-Southeast)
11: Azure (Multiple regions)
12: GCP (Multiple regions)
13: Phase 4 - Stress Testing:
14: Scale to 100, 500, 1,000, 5,000, 10,000 nodes
15: Measure linearity of scaling
16: Phase 5 - Comparative Benchmarking:
17: Compare with:
18: - LSTM-based predictor (baseline)
19: - CNN-LSTM predictor
20: - Standard Transformer
21: - State-of-the-art commercial solutions
22: Phase 6 - Reproducibility:
23: Release code and models on GitHub
24: Provide Docker containers
25: Document replication steps =0
```

VII. VALIDATION AND EVALUATION

A. Experimental Setup

TABLE IX
EXPERIMENTAL CONFIGURATION

Component	Specification
Hardware	Intel Xeon Gold 6248R (48 cores), 256GB RAM, 4x NVIDIA A100
Software	Ubuntu 22.04, Python 3.10, PyTorch 2.0, DGL 1.0
Blockchain	Hyperledger Fabric 2.5, Ethereum 2.0
Networks	10 GbE internal, 1 GbE cross-cloud
Datasets	Google Trace (2019, 2024), Alibaba Trace, Synthetic

B. Expected Outcomes

TABLE X
EXPECTED PERFORMANCE OUTCOMES

Metric	Baseline	Expected Improvement
Prediction Accuracy	93%	> 96%
Detection Latency	1-5s	< 500ms
Recovery Time (RTO)	30-60s	< 10s
False Positive Rate	5-8%	< 3%
Privacy Protection	None	Differential Privacy ($\epsilon < 1$)
Blockchain Overhead	30-50%	< 20%
Scalability (10k nodes)	6/10	9/10

II. CONCLUSION

This paper reported a systematic review of fault tolerance techniques in cloud computing, covering 95 primary studies in the period 2015-2026, with a focus on recent progress (2024-2026). Using systematic analysis, we created a hierarchical classification of fault tolerance techniques into reactive, proactive, predictive, AI-powered, blockchain, and hybrid techniques.

We found recent advances (2024-2026) bring substantial improvements:

- Transformers enable 96-98% accurate predictions with less than 1 second latency
- Graph Neural Networks reach 94-96% accuracy in predicting ripple effects
- Federated learning enables privacy-effective multicloud prediction with 91-95% accuracy
- Blockchain provides tamper-proof auditing with smart contract-based recovery
- Combined AI-blockchain approaches provide 95-97% accuracy with 25-35% overhead.

We highlighted eight research challenges: real-time accuracy-latency trade-off for live prediction, dependency modeling, privacy preservation across multiple clouds, blockchain integration and scalability, fault tolerance integration in edge-cloud systems, energy-fault tolerance trade-off, explainability in AI systems, and need for benchmarking standards.

We developed a seven-stage methodology for designing an AI-based predictive fault tolerance solution with integrated blockchain audit. The process involves gap analysis, multi-modal data integration, transformer-based prediction, GNN-based dependency modelling, federated learning for privacy preserving collaboration, blockchain-based audit and recovery, and edge-cloud integration. Integration of transformers for prediction, GNN for dependency modeling, federated learning for privacy and blockchain audit trails offers a new paradigm for future fault tolerance in cloud computing. Our framework aims to provide detection latency below 500ms, fault recovery below 10 seconds, and predictive accuracy of over 96% to satisfy the key needs for reliable, privacy-preserving and auditable cloud computing practices.

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