

Scaling Conversational AI: SRE Challenges and Solutions for High-Availability CCAI Systems

Contact Center AI (CCAI) systems now power billions of daily customer interactions worldwide, creating unique reliability challenges at scale. This presentation explores the critical SRE principles required to maintain 99.99% uptime for enterprise-grade conversational platforms while handling unpredictable traffic spikes and complex integration dependencies.

Drawing on real-world implementation data, we'll examine monitoring approaches, observability frameworks, and automated remediation techniques that have proven successful across multiple production environments. Join us as we share battle-tested strategies for building robust CCAI platforms that balance innovation with enterprise-grade stability.

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The CCAI Reliability Challenge

99.99%

Uptime Target Required for enterprise-grade CCAI systems

300ms

Response Latency
Maximum acceptable response time

73%

MTTR Reduction

Achieved with automated remediation

CCAI systems face unique reliability challenges that traditional SRE approaches often fail to address. These systems must handle unpredictable traffic patterns while maintaining consistent response times across complex integration dependencies.

The high-stakes nature of customer interactions means failures are immediately visible and costly. Additionally, the AI components introduce variability that can be difficult to predict and monitor using conventional methods.





Traditional Monitoring Limitations

Black Box AI Models

Traditional monitoring tools cannot effectively inspect the internal state of transformerbased NLP models, creating significant observability gaps.

Unpredictable Load Patterns

Conventional threshold-based alerting often fails to account for the unique query patterns and resource consumption models of CCAI workloads.

Complex Dependencies

CCAI systems integrate with multiple backends, channels, and data sources, creating intricate dependency chains that traditional monitoring cannot fully map.

When applied to AI systems, traditional monitoring approaches consistently fall short, leading to both false positives and missed critical incidents. The distributed nature of CCAI architectures further complicates effective observability, requiring specialized approaches tailored to these unique environments.

CCAI Observability Framework



Our specialized CCAI observability framework addresses these challenges by providing multi-dimensional visibility across four key layers. This approach enables teams to quickly correlate system issues with business impacts and pinpoint root causes.

The framework integrates model-specific metrics with traditional SRE observability practices, creating a comprehensive view that bridges technical and business perspectives.

Automated Remediation Strategies

Anomaly Detection

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ML-based pattern recognition identifies deviations from normal operation across conversation flows and system metrics

Triage & Classification

Automated issue categorization based on symptom patterns and affected components

Remediation Action

Self-healing procedures tailored to specific failure modes (scaling, failover, throttling)

Continuous Learning

Feedback loop improves detection accuracy and remediation effectiveness over time

Automated remediation techniques have reduced Mean Time To Recovery (MTTR) by 73% across production environments. The system is particularly effective during unexpected query pattern shifts, which frequently occur as customer behavior evolves.



Scaling Strategies for Peak Loads



Maintaining consistent response latency under 300ms during peak loads requires specialized scaling approaches for transformerbased NLP systems. Our multi-tiered strategy implements gradual resource allocation that closely tracks demand curves.

By combining predictive scaling with sophisticated throttling mechanisms, systems can efficiently handle 10x traffic spikes while preserving quality of service for all customers.



Common CCAI Failure Patterns

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Intent Classification Degradation

Gradual decline in model accuracy leading to increased escalations and customer frustration

Latency Amplification Cascades

Small delays in backend systems compound through AI processing pipelines, creating exponential slowdowns

Resource Starvation Events

Specific conversation patterns trigger excessive resource consumption, impacting all concurrent sessions

Dependency Chain Failures

Integration points between AI systems and external services create complex failure modes that propagate unpredictably

Our reliability data reveals recurring failure patterns specific to CCAI architectures. Understanding these patterns enables teams to implement targeted chaos engineering approaches and build more resilient systems.

CCAI Chaos Engineering

Hypothesis Formation

Define expected system behavior under specific failure conditions

Analysis & Improvement

Document findings and implement system hardening measures



Experiment Design

Create targeted fault injections that simulate real-world scenarios

Controlled Execution

Run experiments in production-like environments with safety guardrails

Specialized chaos engineering approaches have proven highly effective in building resilient CCAI systems. Our methodology focuses on AI-specific failure modes, including conversation state corruption, intent misclassification cascades, and model resource exhaustion.

Through carefully designed experiments, teams can proactively discover system vulnerabilities before they impact customers and implement targeted mitigations.

Progressive Deployment Models

Shadow Testing

Run new models in parallel with production, comparing outputs without affecting customers

Canary Deployment

Route a small percentage of traffic to new models, closely monitoring performance metrics

Progressive Expansion

Gradually increase traffic allocation based on confidence thresholds and business hours

Automated Rollback

Implement instant fallback mechanisms triggered by deviation from expected performance

Full Deployment

Complete transition to new models after confirming stability across all metrics

Implementing progressive deployment models for CCAI is essential for safely introducing new language models and capabilities without disrupting ongoing customer interactions. Our staged approach minimizes risk while providing early validation of model improvements.

SLIs and SLOs for Cost Optimization



Proper implementation of Service Level Indicators (SLIs) and Service Level Objectives (SLOs) has helped organizations achieve 30-40% cost optimization while improving overall system reliability. By setting appropriate thresholds for each metric, teams can identify opportunities for resource optimization without compromising performance.

The most significant cost reductions came from better resource utilization patterns, where properly sized infrastructure and effective auto-scaling policies eliminated waste while maintaining headroom for traffic spikes.

Building Reliable CCAI: Key Takeaways

Specialized Observability

Implement multi-dimensional monitoring that spans from infrastructure to business impact metrics, with particular focus on model performance indicators.



Balanced SLOs

Define practical service level objectives that balance cost efficiency with resilience, using data-driven approaches to set meaningful thresholds.

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Automated Remediation

Develop self-healing capabilities specific to AI failure modes, reducing MTTR through pattern recognition and targeted recovery procedures.



Progressive Deployment

Adopt staged rollout practices that protect customer experience while enabling continuous innovation in Al capabilities.

This presentation has delivered actionable SRE frameworks specifically designed for AI-driven systems. By implementing these specialized approaches, teams can build robust CCAI platforms that balance innovation with the enterprise-grade stability required for mission-critical customer interactions.

Thank you