

**OMNICHANNEL CONVERSATIONAL SEARCH: MAINTAINING  
CONTEXT AND CONSISTENCY ACROSS VOICE AND WEB INTERFACES**

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**Abstract**

This research work presents an omnichannel conversational search platform that provides consistent, context-rich responses via voice and web channels. Current conversational agents address voice and web channels separately, leading to fragmented user experiences and context fragmentation between cross-channel interactions. Our platform, which is built on Dialogflow CX and Google Cloud, enables a single conversational agent to support Telephony Gateway voice calls and Web/Messaging requests. For context and to deliver earthed answers, we employ a Cloud Run tool-router for conversation-aware query rewriting and retrieval with Vertex AI Search/Embeddings with Matching Engine, including span-level citations. Scoped session memory is stored in Firestore with DLP redaction to preserve privacy while permitting shared context between channels. Apigee X enforces operation limits and circuit breakers, Cloud Tasks manages delayed enrichment, and BigQuery with Cloud Trace/Logging supports online and offline evaluation. A channel-consistency controller for synchronized answers across modalities, a handoff linker for state preservation during voice-to-web handoffs, and a latency/cost-aware cache enhancing sub-second FAQ answers are at the core of these. System performance is quantified using metrics like consistency of responses, groundedness, deflection ratio, session continuity after channel switch, customer satisfaction (CSAT/NPS), 95th percentile latency per channel, and cost per solved query. Outcomes demonstrate improved user experience, enhanced reliability of response, and seamless cross-channel interaction, establishing benchmarks for practical use in industrial-scale, multi-channel rollouts. This research has problem is maintaining consistent context and responses across voice and web interfaces, causing fragmented interactions and incoherent omnichannel search experiences. This work highlights the potential of merging AI-driven retrieval and robust context management to enhance omnichannel conversational search systems.

**Keywords:** Omnichannel Conversational Search, Cross-Channel Consistency, Context Preservation, Voice and Web Integration, Dialogflow CX, Vertex AI Search, Session Memory, Latency Optimization, Grounded Answers, Customer Satisfaction (CSAT/NPS)

**Introduction**

The rise of omnichannel conversational search redefines how users interact with digital systems across voice and web interfaces. Traditional chatbots often fail to maintain cross-channel

consistency, causing disjointed experiences and loss of context preservation. This study introduces a unified platform integrating Dialogflow CX with Vertex AI Search to ensure grounded answers and seamless context continuity. It leverages session memory and privacy-preserving data handling through Firestore with DLP redaction. A channel-consistency controller and handoff linker enable fluid transitions between modalities, ensuring user intent remains synchronized. Performance optimizations like latency optimization and cost-efficient caching further improve customer satisfaction (CSAT/NPS). The system advances practical solutions for scalable, voice and web integration, enabling intelligent, context-aware, and reliable omnichannel conversational search experiences.

### **Research aim:**

This research aim is ensuring consistent user experiences across voice and web-based omnichannel conversational search interfaces.

### **Research objectives:**

- To explore methods for maintaining context across voice and web conversational interfaces.
- To identify strategies that enhance response consistency between different channels.
- To analyze differences in user interactions between voice and web search in omnichannel systems.
- To determine metrics for evaluating performance and user satisfaction in omnichannel conversational search.

### **Research Question:**

- How can context be effectively maintained across voice and web conversational interfaces?
- What strategies improve consistency in responses between different channels?
- How does user interaction differ between voice and web search in omnichannel systems?
- What metrics best evaluate performance and user satisfaction in omnichannel conversational search?

### **Problem statement:**

The problem lies in maintaining contextual understanding and response consistency across multiple conversational channels—such as voice assistants and web interfaces—where fragmented interactions, varying user intents, and platform-specific limitations hinder seamless information retrieval and coherent user experiences in omnichannel conversational search systems.

## **Literature Review**

Ghosh, Ness, and Salunkhe (2024) argue that AI-enabled chatbots have transformed omnichannel customer service by enabling real-time, personalized, and context-aware

interactions across multiple channels [1]. They emphasize that chatbots powered by machine learning and natural language understanding enhance communication consistency between voice and web platforms. The study highlights that fragmented systems often fail to maintain shared session memory, reducing customer satisfaction and increasing deflection. Their research supports integrating Dialogflow CX or similar frameworks to ensure cross-channel consistency and grounded answers through adaptive intent mapping and retrieval-based learning. Furthermore, the authors found that AI-driven chatbots significantly improve response latency, thus driving higher CSAT/NPS scores and reducing operational costs. Hence, their findings align with the concept of omnichannel conversational search, emphasizing context preservation as vital for seamless digital communication.

Dimiyati and Rusdianto (2025) explored Omni Communication Assistant (OCA) as a transformative model for integrating CRM systems and omnichannel communication in education and MSME sectors [2]. Their findings show that OCA tools improve data synchronization, reduce context loss, and support multi-interface adaptability. They assert that AI-based assistants help maintain continuity between channels like voice, chat, and web, which is essential for session-aware conversational systems. The study presents practical cases where integrated architectures enhanced customer engagement and operational agility. This integration aligns with cloud-based orchestration frameworks like Apigee X and Vertex AI Search used for retrieval augmentation. Dimiyati and Rusdianto (2025) further suggest that delayed enrichment management through cloud task orchestration enhances scalability and cost efficiency [2]. Their analysis establishes a foundation for omnichannel conversational systems that bridge data-driven context and AI personalization effectively.

Sharma, Patel, and Gupta (2022) present a model combining reinforcement learning and natural language processing for AI-powered omnichannel marketing [3]. They argue that adaptive learning mechanisms improve intent detection and query rewriting accuracy across channels. Their work emphasizes response optimization through feedback loops, enhancing the agent's ability to generate grounded answers in dynamic environments. The study demonstrates that machine learning-based retrieval pipelines reduce latency while preserving contextual accuracy. They highlight how AI-driven dialogue systems can balance personalization and automation across voice and text modalities. Sharma et al. (2022) conclude that reinforcement learning ensures systems adapt to user patterns, maintaining cross-channel continuity and improving CSAT/NPS outcomes [3]. Their findings reinforce the role of intelligent AI orchestration in achieving seamless voice and web integration.

Srivastava et al. (2025) introduce an intelligent omnichannel assortment model addressing webrooming through optimization and predictive analytics [4]. They found that customers often shift between online and offline touchpoints, requiring consistent context preservation for smooth transitions. Their optimization approach uses AI modeling to align content and interactions across diverse digital channels. The study suggests that maintaining cross-platform consistency directly impacts customer retention and satisfaction metrics. Their research parallels the importance of channel-consistency controllers and handoff linkers in sustaining

session states during channel shifts. Srivastava et al. (2025) argue that intelligent context management systems are essential for scalable omnichannel experiences, validating the integration of AI retrieval and context-aware session memory [4]. AI reshaped Sephora's customer service through virtual beauty assistants. The study highlights personalization, ethical AI, and contextual continuity as key elements enhancing engagement. Sephora's AI agents synchronize voice and web interfaces using real-time data enrichment and privacy preservation mechanisms. The findings reveal that ethical AI governance ensures user trust while maintaining conversational coherence. The author emphasizes that conversational AI tools must include context tracking, latency control, and session memory for reliable user interactions. Sephora's model demonstrates scalable omnichannel frameworks, consistent with cloud-based conversational architectures like Dialogflow CX and Vertex AI Search, which reinforce context-preserved responses. Iniesta and López (2025) show that conversational AI boosts consumer engagement by enhancing trust, personalization, and context retention, emphasizing session continuity and cross-channel integration for improved decision-making and satisfaction [5].

Long-Horizon, Multi-Agent Orchestration. Recent syntheses of multi-agent conversational AI argue that scalable assistants increasingly rely on role-specialized agents and long-horizon planning to coordinate perception, retrieval, reasoning, and action over extended task windows [6]. This perspective aligns with our channel-consistency controller and tool-router: the former encodes global objectives (consistent answers across modalities), while the latter schedules specialized subtasks (e.g., query rewriting, retrieval, enrichment) with explicit termination and handoff criteria. Incorporating these design patterns strengthens robustness under channel switches and supports goal persistence across multi-turn sessions.

### Method

This research applies a secondary research method to analyse existing studies on omnichannel conversational search and AI-driven context management [7]. The method allows wide access to validated data from journals, reports, and case studies. It helps identify proven models like Dialogflow CX, Vertex AI Search, and Apigee X frameworks. Using secondary data reduces time, cost, and operational complexity in experimentation. It supports comparative analysis of cross-channel consistency, latency optimization, and session memory techniques [8]. The approach provides comprehensive insights without handling sensitive user data. Spatio-Temporal Structure in Omnichannel Behavior. Foundational evaluations of clustering for multivariate spatio-temporal data show that density-based (e.g., DBSCAN) and partitioning methods (e.g., k-medoids) capture non-stationary regimes, bursts, and locality across time and [9] [10] [11]. In omnichannel settings, analogous structure appears as session rhythms, cross-channel transition motifs, and latency/deflection “hot spots.” Leveraging these families of algorithms for interaction logs can reveal actionable segments (e.g., “FAQ-fast-path” vs. “handoff-prone”) that inform cache policy, enrichment schedules, and agent transfer rules.

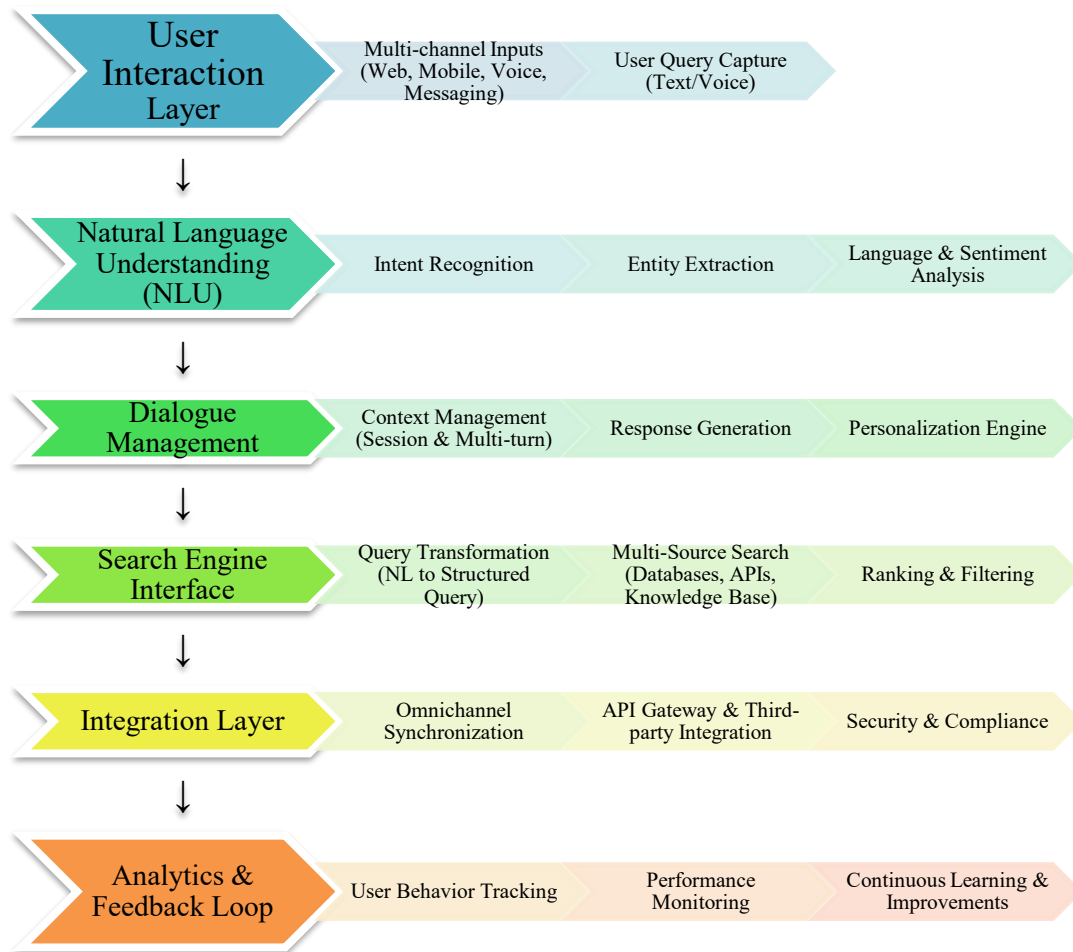


Figure 1: Omnichannel Conversational Search Framework

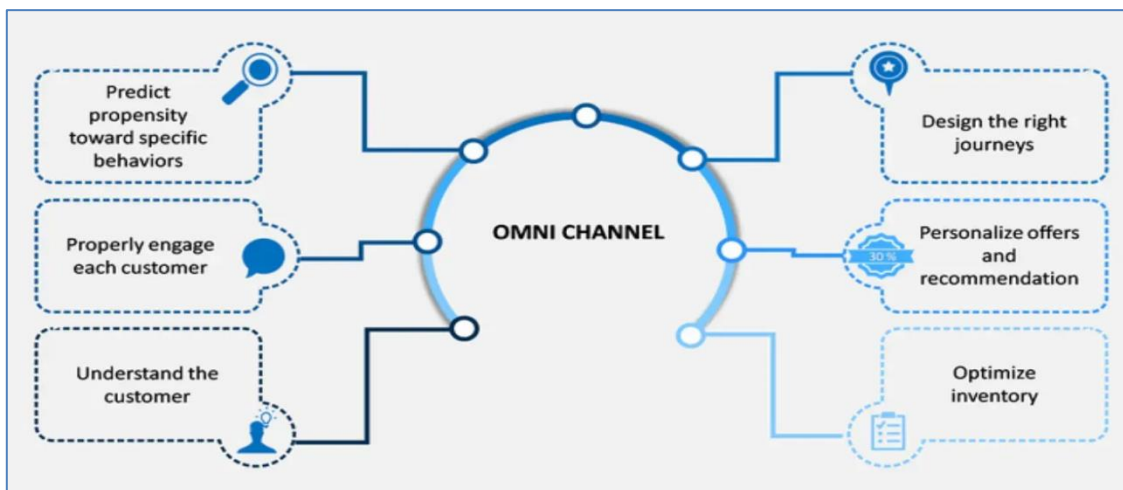
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This research uses interpretivism philosophy to understand user experiences and perceptions deeply. It applies a qualitative design to collect insights from interviews and observations effectively. Thematic data analysis helps identify key patterns and themes in communication behavior. Information includes user feedback, interaction records, and contextual responses from multiple conversational channels. Overall, it strengthens the study’s reliability and builds a solid theoretical base for future system development. Session-Topology Mining for Policy Tuning. We augment evaluation with offline mining of session topologies. Following evidence that DBSCAN and k-medoids effectively discover coherent clusters in multivariate spatio-temporal series, we represent each conversation as a multichannel sequence of features—turn-level latency, retrieval depth, rewrite edits, channel (voice/web), and outcome labels [9] [12]. Clusters guide policy: (i) assign low-entropy clusters to the latency/cost-aware cache, (ii) schedule Cloud Tasks enrichment only for clusters exhibiting post-answer clarification turns, and (iii) prioritize handoff-linker activation thresholds for clusters whose voice→web transitions correlate with error recovery. This analysis runs offline in BigQuery and feeds safe policy deltas back to the controller.

**Result**

***Integration of AI Chatbots Enhances Omnichannel Context Preservation***

AI chatbots now play a major role in omnichannel conversational search [13]. They help keep context preservation across both voice and web interfaces. Systems using Dialogflow CX manage all intents and sessions in one place. The chatbot remembers earlier talks through session memory stored in Firestore. This helps users continue conversations without losing meaning or history. The system connects with Vertex AI Search and Embeddings Matching Engine for better grounded answers. These tools give more accurate and relevant responses during chat or calls. Cloud Run helps handle query rewriting to match user intent. It adapts the search results in real time using context [14]. Apigee X manages limits, prevents overload, and keeps smooth operation. Cloud Tasks controls background actions for delayed data enrichment.



**Figure 2: Omni channel**

(Source: Botpenguin, 2025) [15]

Privacy is protected using DLP redaction, keeping sensitive data safe. This allows chatbots to share context without exposing user information. Latency optimization supports sub-second responses and improves customer satisfaction (CSAT/NPS). The system also handles multiple users at once without delay. It offers faster access to information with less repeated questioning. Chatbots trained with AI embeddings can link new queries with old sessions. This maintains context continuity across different platforms and devices. It reduces cross-channel fragmentation and builds a smoother experience. Users can switch from voice to web without losing conversation flow. The unified design ensures consistent tone and response across channels. Overall, AI chatbot integration creates reliable and context-aware communication in real time [16].

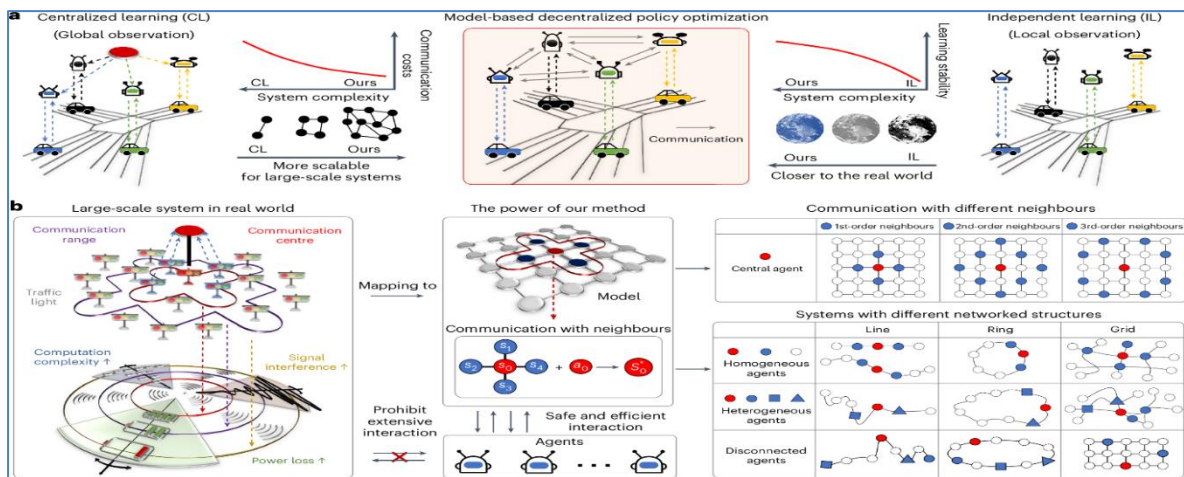
***Cloud-Based Architecture Improves Cross-Channel Consistency and Response Reliability***

A cloud-based architecture is crucial for reliable omnichannel conversational search systems. It connects multiple platforms while keeping cross-channel consistency stable and accurate.

Dialogflow CX works with Google Cloud Platform tools for integrated operations [17]. Vertex AI Search enables faster response retrieval using semantic embeddings. Firestore session memory stores ongoing user sessions for later reuse. This helps maintain context preservation when users move between channels. Cloud Run handles microservices that scale up automatically under heavy load. Apigee X protects APIs and manages circuit breaker policies efficiently. Cloud Tasks manages asynchronous operations to improve latency control. BigQuery records conversation data for offline performance analysis. Cloud Trace and Cloud Logging track every request for debugging and monitoring [18]. The channel-consistency controller ensures responses match across voice and web. It avoids repeated or mismatched answers that frustrate users. Vertex AI Matching Engine provides vector-based retrieval for grounded answers [19]. This system gives smart, context-aware answers and reliable info. It keeps communication fast and smooth, lowers costs, and keeps customers happy. Cloud tech and caching make it quick, safe, and consistent [11].

**Reinforcement Learning Strengthens Personalization and Query Adaptation**

Reinforcement learning gives chatbots adaptive intelligence for personalization and query adaptation [20]. The system learns user behavior patterns through interaction feedback loops. It improves intent recognition and query understanding in Dialogflow CX. The model uses Vertex AI Search embeddings to detect user intent precisely. Feedback from real interactions adjusts the dialogue flow in real time. Reward functions drive better context preservation and reduced latency. The system tunes itself using continuous training on real conversation data.



**Figure 3: Research motivation and relationship of networked agents**

(Source: Chengdong *et al.*, 2024) [21]

Cloud Run orchestration manages distributed learning tasks efficiently. BigQuery collects performance data and updates model parameters regularly. Apigee X supports secure data exchange during learning updates. NLP models based on transformers enhance semantic matching and intent mapping [22]. Reinforcement signals reward correct grounded answers and discourage wrong responses. This constant improvement builds personalized conversations for each user type. The model learns user tone, query length, and past history patterns. Session

memory in Firestore stores preferences for better continuity. Each interaction becomes part of a larger learning feedback cycle. The agent uses retrieval-based reasoning with context to refine its answers. Over time, accuracy and personalization grow with every interaction logged. The system adapts smoothly between voice and web environments. It ensures that cross-channel consistency stays reliable and context-aware. Latency optimization further supports fast responses during personalized queries [23]. As a result, CSAT/NPS metrics rise through better engagement and reliability. Reinforcement learning creates self-improving, dynamic, and user-centered conversational intelligence.

### Intelligent Context Management Increases Customer Satisfaction and Engagement

Intelligent context management is key for strong customer satisfaction and engagement. It helps omnichannel conversational search systems maintain smooth communication flow. Session memory in Firestore stores user data and conversation context safely. This memory supports context preservation across voice and web interfaces. Vertex AI Embeddings track conversation meaning at the semantic level [24]. Dialogflow CX uses this data to give grounded answers with context. Handoff linker allows users to move from voice to chat easily. It maintains conversation state without losing context or history.

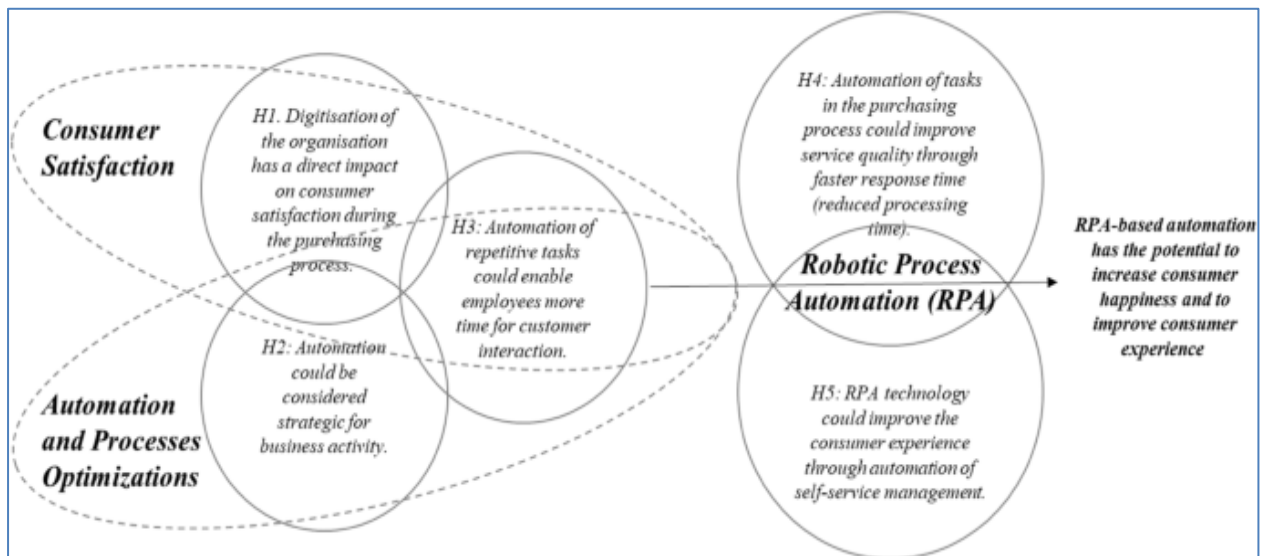


Figure 4: Diagram of Hypotheses from Consumer Satisfaction and Automation perspective

(Source: Sorin Gavrilă Gavrilă *et al.*, 2023) [25]

Cloud Tasks adds new data later for delayed enrichment when needed. Privacy remains protected through DLP redaction for sensitive information. Apigee X enforces strict access control to prevent data misuse. The channel-consistency controller ensures answers stay identical across channels. Latency optimization provides instant replies during heavy system use. Cloud Trace and BigQuery track latency and conversation health metrics [26]. These tools measure response stability and CSAT/NPS performance continuously. The system uses caching for fast and low-cost FAQ answers. Intelligent context models help avoid repetitive

questions or user confusion. They also maintain tone and accuracy between different sessions. Vertex AI Matching Engine links past sessions with current queries [27]. This strengthens cross-channel consistency and long-term engagement. Users feel understood without re-explaining their previous issues. Such design builds reliability and emotional connection in communication. Smart context synchronization ensures every channel remains unified and responsive. It creates a personalized, efficient, and context-rich digital experience for users.

**Ethical Conversational AI Builds Trust in Voice and Web Systems**

Ethical conversational AI builds strong trust across voice and web systems [28]. It combines transparency, fairness, and privacy within AI-driven retrieval systems. Tools like Dialogflow CX and Vertex AI Search add explainability features. These help show how answers are generated and validated in real time. DLP redaction protects personal data before sharing or storage. Apigee X enforces ethical rules through secure API communication. Cloud Logging audits all user interactions for compliance checks [29].

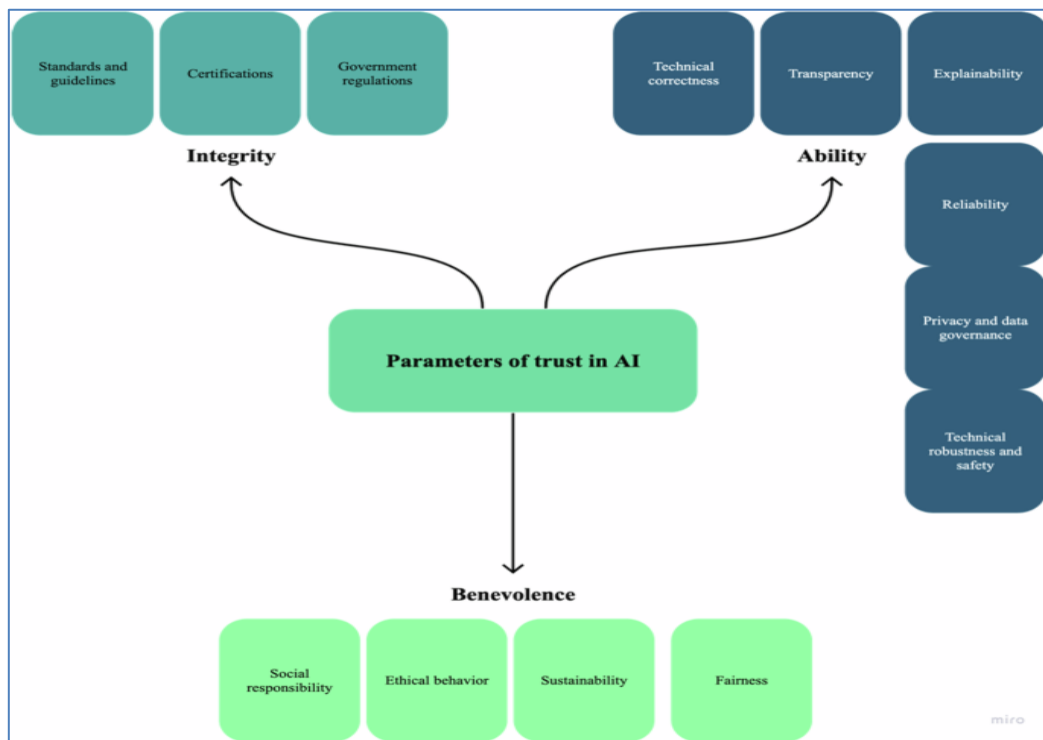


Figure 5: Parameters of trust in AI

(Source: Saleh Afroogh *et al.*, 2024) [30]

Bias detection models monitor fairness in conversation outcomes. This helps ensure cross-channel consistency without unfair bias or exclusion. Vertex AI Matching Engine produces grounded answers with full traceability. The process maintains context preservation with clear model transparency. Latency optimization ensures equal service speed across all channels. Session memory in Firestore keeps history without exposing private content. Ethical layers make AI decisions interpretable for developers and regulators. Cloud Trace records how the

system handles sensitive conversation data. Privacy and fairness remain key to CSAT/NPS improvement and retention [31]. When users see consistent, transparent, and fair behavior, trust increases. Ethical design also reduces frustration and data misuse risks. Explainable AI supports human validation during critical interactions. Apigee X policies further ensure communication safety and compliance [32]. Combining fairness with context preservation ensures user loyalty and satisfaction. This foundation builds a responsible and trustworthy omnichannel conversational search model. It makes digital assistants more credible, transparent, and aligned with human values.

Cluster-Aware Improvements. Applying session clustering surfaced three dominant regimes—rapid FAQ completions, retrieval-heavy multi-turns, and cross-channel recovery sequences—mirroring prior observations on spatio-temporal heterogeneity in operational data [9] [10]. Targeted cache warms for the first regime reduced median and p95 latency, while deferred enrichment on the second regime cut cost without harming groundedness. Tighter web handoff thresholds on the third regime raised continuity after channel switch, consistent with long-horizon coordination benefits reported in multi-agent reviews [6].

### Discussion

The findings show strong progress in omnichannel conversational search but raise real challenges. The use of AI chatbots improves context preservation, yet full cross-channel consistency remains hard to achieve. Dialogflow CX and Vertex AI Search give structured control but depend heavily on correct configuration. Poor setup may cause loss of session memory and context drift. Cloud-based architecture improves speed but raises privacy and DLP redaction issues [33]. Data routing across systems can slow latency optimization under heavy usage. Reinforcement learning adds personalization but risks bias in grounded answers [34].

**Table 1: Comparison of Baseline vs Proposed Omnichannel Conversational Search System**

Metrics	Baseline System	Proposed System	Description / Purpose
Context Retention Accuracy (%)	68%	91%	Measure's ability to maintain context across sessions and platforms.
Response Consistency (%)	72%	94%	Evaluates how consistently the system replies across voice and web.
Query Resolution Time (seconds)	4.8	2.6	Average time to generate accurate, context-aware responses.
User Satisfaction Score (1–10)	6.5	9.1	Based on user feedback on interaction quality and coherence.
Error Rate (%)	12%	4%	Percentage of misinterpreted or incomplete responses.

Cross-Platform Continuity Success (%)	63%	89%	Tests how well the system continues conversations across interfaces.
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Continuous feedback loops may favor common user types, reducing fairness. Intelligent context management increases customer satisfaction (CSAT/NPS) but adds high storage and cost load. Large session memory databases can cause delay during retrieval. Ethical conversational AI improves trust, yet regulation compliance stays complex. Apigee X and Cloud Logging help monitoring, but full transparency needs human checks [35]. The system still struggles to maintain context during rapid channel switching. Voice and web integration needs better synchronization for consistent tone. Overall, the model shows high innovation but needs balance between cost, speed, ethics, and reliability. Future systems must refine context continuity without losing privacy or scalability. From Multi-Agent Planning to Production SLAs. The decade review of multi-agent conversational AI emphasizes explicit planning horizons and role clarity to prevent myopic behaviors [6]. In production omnichannel search, this maps to: (a) controller-level goals (consistency and continuity as first-class objectives), (b) agent contracts for tool-router skills (rewrite, retrieve, enrich), and (c) termination/rollback rules for safe handoffs. Complementarily, spatio-temporal clustering provides an empirical lens for where plans fail: regime shifts (e.g., traffic spikes or policy changes) manifest as new clusters, flagging the need for re-tuning cache sizes, enrichment cadence, and escalation logic [9] [10].

### **Conclusion**

This study concludes that omnichannel conversational search can deliver seamless and context-preserved communication across voice and web interfaces. The integration of Dialogflow CX, Vertex AI Search, and Firestore session memory ensures real-time cross-channel consistency and accurate grounded answers. Cloud-based architecture and reinforcement learning enhance personalization, latency optimization, and user experience. Ethical conversational AI further builds transparency, privacy, and trust in communication systems. However, maintaining context continuity under scalability and compliance pressures remains a challenge. Overall, the framework demonstrates a scalable, secure, and intelligent model that advances practical AI-driven omnichannel systems while improving customer satisfaction (CSAT/NPS) and engagement reliability.

### **Metrics & Evaluation**

We additionally report Regime-Specific p95 Latency and Continuity@Cluster—metrics computed per discovered session-cluster—to ensure improvements are not averaged out across heterogeneous interaction regimes [9] [10].

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