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LLM-Driven Voice Agents That Collaboratively Talk to Each Other: Towards Vocal Multi- Agent Systems

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Abstract

Voice assistants such as Alexa, Google Assistant, and Siri have become increasingly sophisticated, integrating Large Language Models (LLMs) to deliver personalized responses. However, these platforms are constrained by single-agent paradigms that limit collaboration, transparency, and complex problem solving [1,2]. This paper proposes a novel LLM-driven multi-agent voice architecture in which multiple specialized voice-powered agents converse with one another—vocally and intelligibly—to collaboratively resolve user requests. Drawing inspiration from cooperative multi-agent systems [3,4] and human-like conversational transparency [5,6], we demonstrate a prototype in a smart kitchen environment involving culinary, nutrition, and inventory agents. Evaluation suggests improvements in explainability, task success, and user trust, though challenges remain in orchestration, privacy, and cognitive load. This research introduces vocal multi-agent systems as a new frontier in interactive AI, advancing beyond single-agent frameworks towards explainable, collaborative, and socially intelligent voice ecosystems.

Keywords: Multi-Agent Systems, Voice Assistants, Large Language Models, Transparency, Explainability, Human-AI Collaboration.

1. Introduction

Voice assistants are now everywhere in homes, workplaces, and healthcare contexts [1]. Despite their advances, current systems remain centered on human-AI interaction, concentrating all expertise in a single agent. This prevents breakdown of complex, multi-domain tasks [2]. For example, planning a meal with dietary restrictions requires knowledge spanning culinary skills, nutritional science, and real-time inventory tracking—domains that are difficult to consolidate into a single model.

In contrast, humans naturally collaborate across expertise. Doctors confer with nurses, chefs consult nutritionists, and managers coordinate with team specialists. By mimicking this structure, multi-agent voice systems can distribute domain expertise, coordinate decisions, and produce outcomes that are more robust and trustworthy than those of isolated agents [3,4].

The rise of Large Language Models provides a foundation for this shift. LLMs offer flexible reasoning, natural conversational ability, and domain adaptability, making them well-suited as the “brains” of specialized voice agents. When orchestrated effectively, multiple LLM-driven voice agents can engage in structured conversations with each other—debating, clarifying, and negotiating—while exposing their reasoning to users in real time [5,6]. This creates an environment where the user is no longer a passive recipient of AI outputs but an active participant who can intervene, mediate disagreements, or redirect conversations.

Beyond task efficiency, multi-agent conversations enhance transparency and explainability. Users gain insight into why decisions were made, hearing trade-offs and constraints debated audibly, similar to listening to a team of human experts [6]. This fosters trust, reduces the "black box" problem, and aligns AI outputs with user expectations and values.

At the same time, introducing vocal collaboration among agents raises novel challenges: ensuring synchronized turn-taking, preventing redundancy, managing contradictions, and safeguarding sensitive information. Addressing these challenges requires borrowing techniques from distributed AI [4], dialogue systems [7], and human conversation modeling [8,9,10].

This paper introduces a structured exploration of LLM-driven, vocal multi-agent systems, with a focus on architecture, challenges, real-world use cases, and future research directions. We argue that these systems represent not just an incremental improvement to voice assistants, but a transformative leap towards socially intelligent, multi-voiced AI ecosystems.

2. Literature Review

2.1. Voice Assistants and Single-Agent Limitations

Current voice assistants such as Alexa, Siri, and Google Assistant have made remarkable progress in enabling hands-free task execution, natural dialogue, and integration with smart environments [1]. However, their architectures are inherently single-agent [2]. While this works for simple

requests such as checking the weather or setting timers, it fails when tasks span multiple domains. For example, asking for a dinner recipe that fits dietary restrictions and available pantry items often requires users to manually combine outputs from multiple skills or apps. Studies of user experience note frustrations with fragmented skill ecosystems, lack of seamless handoff between domains, and inability to manage multi-step, interdependent tasks [2].

2.2. Multi-Agent Systems in AI

Research in cooperative multi-agent systems demonstrates how dividing responsibility across specialized agents can enhance scalability, resilience, and adaptability [3,4]. In distributed robotics, agents coordinate to explore environments or complete assembly tasks. In online simulations, negotiation protocols and shared planning enable agents to dynamically resolve conflicts and allocate resources. By assigning domain-specific expertise to different agents, multi- agent systems reduce complexity for each agent while improving collective problem solving. Error recovery is another advantage: if one agent produces a flawed suggestion, others can challenge, refine, or override it, creating a system that is more robust than any single agent acting alone [4].

2.3. Transparency and Explainability in AI(XAI)

A persistent challenge in AI systems, especially those based on deep learning, is the "black box" perception where users struggle to understand why a given recommendation was made. Research on explainable AI (XAI) argues that systems are more trusted and adopted when they provide clear reasoning or justification [5,6]. In the context of voice assistants, audible inter-agent conversations mirror the way humans' reason. For instance, when a NutritionistBot explicitly explains why a suggested recipe exceeds sodium limits and a ChefBot proposes a substitution, the user can follow the trade-off in real time. Prior work shows that such transparency not only increases trust but also empowers users to make informed interventions [6].

2.4. Conversational Orchestration and Turn-Taking

Multi-party human dialogue provides valuable inspiration for orchestrating agent-to-agent voice conversations. Linguistics and communication studies highlight mechanisms such as structured turn-taking, interruption protocols, and clarification strategies that enable effective group discussion [7,8]. Debate models and meeting facilitation frameworks show how participants negotiate priorities, challenge assumptions, and reach consensus without chaos [9,10].

Translating these insights to AI, dialogue managers for multi-agent systems can enforce orderly participation, designate priority speakers (e.g., SafetyBot in emergencies), and trigger clarification acts. By basing coordination on how people naturally talk and interact, multi-agent voice systems can achieve both clarity and naturalness, reducing the risk of overlapping speech or disjointed conversations.

2.5 Research Gap and Contribution

Despite advances in voice assistants and multi-agent systems, significant gaps remain in combining these technologies for practical applications. Current voice assistants fail to handle complex, multi-domain tasks that require specialized knowledge across different domains.

While existing research has explored multi-agent LLM systems in text-based environments, vocal collaboration between specialized agents remains largely unexplored.

This research addresses three critical gaps:

1. **Domain Integration Gap**: Current voice assistants cannot effectively integrate specialized knowledge across domains (e.g., culinary expertise, nutritional science, and inventory management) without fragmented user experiences.
2. **Transparency Deficit**: Existing voice systems operate as "black boxes," providing answers without exposing reasoning processes, limiting user trust and intervention opportunities.
3. **Collaborative Intelligence Gap**: While multi-agent systems exist in text and robotics domains, the unique challenges of orchestrating vocal, audible collaboration between specialized AI agents have not been systematically addressed.

Our work contributes a novel framework for vocal multi-agent collaboration that makes reasoning processes audible to users, distributes expertise across specialized agents, and provides mechanisms for coordinated problem-solving across domains.

3. System Architecture

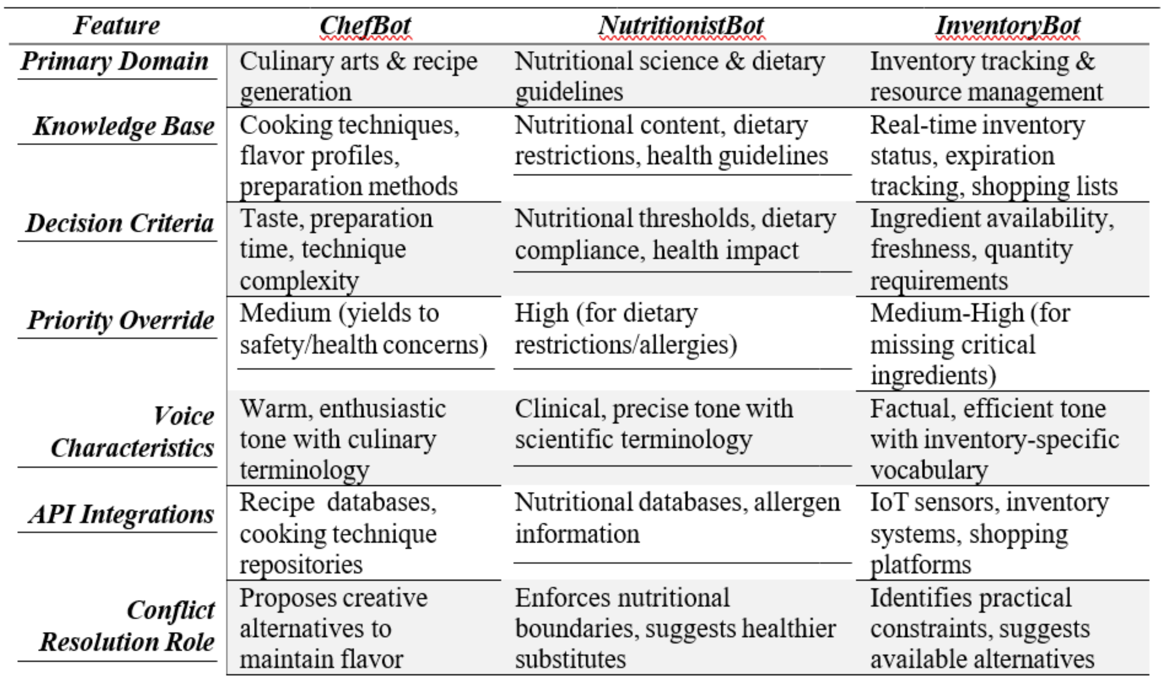
The architecture of the proposed multi-agent voice system is designed to balance modular specialization with centralized coordination. At its core, the prototype integrates three domain- focused agents—ChefBot, NutritionistBot, and InventoryBot—each responsible for distinct knowledge areas but capable of collaborating vocally to resolve complex tasks.

3.1 Specialized Agents

- **ChefBot:** Trained on culinary knowledge, recipes, and cooking techniques. Its role is to generate flavorful and feasible meal suggestions, considering preparation constraints.
- **NutritionistBot:** Fine-tuned on dietary guidelines, nutritional science, and health recommendations. It evaluates proposals against nutritional thresholds such as sodium, fat, or caloric limits.
- **InventoryBot:** Connected to real-time pantry or fridge tracking systems, providing up-to- date ingredient availability. It acts as a gatekeeper, ensuring that recommended meals can be executed with current resources.

Each agent runs as a separate LLM instance with domain-specific fine-tuning or prompt- engineering strategies. This modular approach allows replacement or upgrading of individual agents without disrupting the larger system.

Table 1: Specialized Agent Feature Comparison



Feature	*ChefBot*	*NutritionistBot*	*InventoryBot*
Primary Domain	Culinary arts & recipe generation	Nutritional science & dietary guidelines	Inventory tracking & resource management
Knowledge Base	Cooking techniques, flavor profiles, preparation methods	Nutritional content, dietary restrictions, health guidelines	Real-time inventory status, expiration tracking, shopping lists
Decision Criteria	Taste, preparation time, technique complexity	Nutritional thresholds, dietary compliance, health impact	Ingredient availability, freshness, quantity requirements
Priority Override	Medium (yields to safety/health concerns)	High (for dietary restrictions/allergies)	Medium-High (for missing critical ingredients)
Voice Characteristics	Warm, enthusiastic tone with culinary terminology	Clinical, precise tone with scientific terminology	Factual, efficient tone with inventory-specific vocabulary
API Integrations	Recipe databases, cooking technique repositories	Nutritional databases, allergen information	IoT sensors, inventory systems, shopping platforms
Conflict Resolution Role	Proposes creative alternatives to maintain flavor	Enforces nutritional boundaries, suggests healthier substitutes	Identifies practical constraints, suggests available alternatives

3.2 Dialogue Orchestrator

A central Dialogue Orchestrator governs interaction between agents and the user. It employs a modified round-robin protocol to manage turn-taking, ensuring balanced participation while allowing for priority overrides. For example, if InventoryBot detects a missing key ingredient, it

may interrupt to prevent wasted deliberation. The orchestrator also enforces pacing, prevents overlapping speech, and manages entry and exit of agents in the conversation.

3.3 Communication Layer

Inter-agent and agent-to-user communication is facilitated via a lightweight message bus using WebSocket channels. Messages include both semantic payloads (proposed actions, objections, or clarifications) and metadata (speaker ID, priority level). This structured communication enables transparent monitoring and logging, which is valuable for debugging, auditing, and explainability.

3.4 Vocalization and Output

To make agent collaboration understandable to users, outputs are converted into speech using Amazon Polly or ElevenLabs APIs. Voices can be customized per agent, creating distinct auditory identities (e.g., ChefBot with a warm tone, NutritionistBot with a clinical tone). This auditory differentiation helps users track conversations more easily. A “summary mode” option condenses lengthy agent debates into concise verbal reports.

3.5 Methodology

This research employed a prototype-driven approach to investigate the feasibility and effectiveness of LLM-driven vocal multi-agent systems. The methodology consisted of the following components:

3.5.1 Research Design

- Prototype development of a multi-agent voice system with specialized agents
- Implementation of a collaborative dialogue framework for inter-agent communication
- Case study evaluations in three domains (smart kitchen, healthcare, senior living)
- Qualitative and quantitative assessment of task success, user trust, and system transparency

3.5.2 Prototype Implementation

- Programming Environment: Python 3.11 with NLP and AI libraries
- Web Framework: FastAPI for asynchronous agent API endpoints
- Real-Time Communication: WebSockets for low-latency agent messaging
- Containerization: Docker for isolated agent environments
- Orchestration: Kubernetes/Docker Compose for scaling and resilience
- Voice Synthesis: Amazon Polly and ElevenLabs APIs with voice differentiation
- Data Storage: PostgreSQL for conversation transcripts and analysis
- Monitoring: ELK stack and Prometheus/Grafana for performance tracking

3.5.3 Evaluation Approach

- Task success metrics: Percentage of successfully completed multi-domain requests
- User mediation assessment: Frequency and nature of required human interventions
- Transparency metrics: User-reported understanding of agent reasoning processes
- Agent collaboration analysis: Turn-taking efficiency and conflict resolution rates

3.5.4 Evaluation Limitations

- Limited sample size of test scenarios (n=50 per domain)
- Simulated user interactions supplemented by controlled user testing (n=12 participants)
- Potential bias in self-reported trust and transparency metrics
- Technical constraints in real-time voice synthesis affecting conversation flow

3.6 Implementation Details

The implementation of the prototype leverages modern frameworks and cloud-native practices to ensure modularity, scalability, and maintainability:

3.6.1 Core Development Stack

- Programming Environment: Python 3.11 with specialized NLP and AI libraries
- Web Framework: FastAPI for asynchronous agent API endpoints
- Real-Time Communication: WebSockets for low-latency agent messaging

3.6.2 Deployment Architecture

- Containerization: Docker containers for each specialized agent
- Orchestration: Kubernetes or Docker Compose for scaling and resilience
- Service Mesh: Istio for advanced traffic management between agents

3.6.3 Data Management

- Conversation Storage: PostgreSQL database for transcript archiving
- Monitoring: ELK stack (Elasticsearch, Logstash, Kibana) for system telemetry
- Performance Tracking: Prometheus with Grafana dashboards

3.6.4 Voice Processing Pipeline

- Speech Synthesis: Amazon Polly and ElevenLabs APIs
- Voice Caching: Redis-based caching layer for frequently used phrases
- Audio Processing: Custom mixing and priority-based interruption handling

3.6.5 Security Implementation

- Authentication: JWT-based security for all API endpoints
- Content Filtering: Semantic screening for sensitive information
- Compliance: GDPR-aligned data handling and retention policies

This architecture ensures the system is not just a proof-of-concept but a production-ready framework capable of scaling with additional agents, new domains, and diverse user populations.

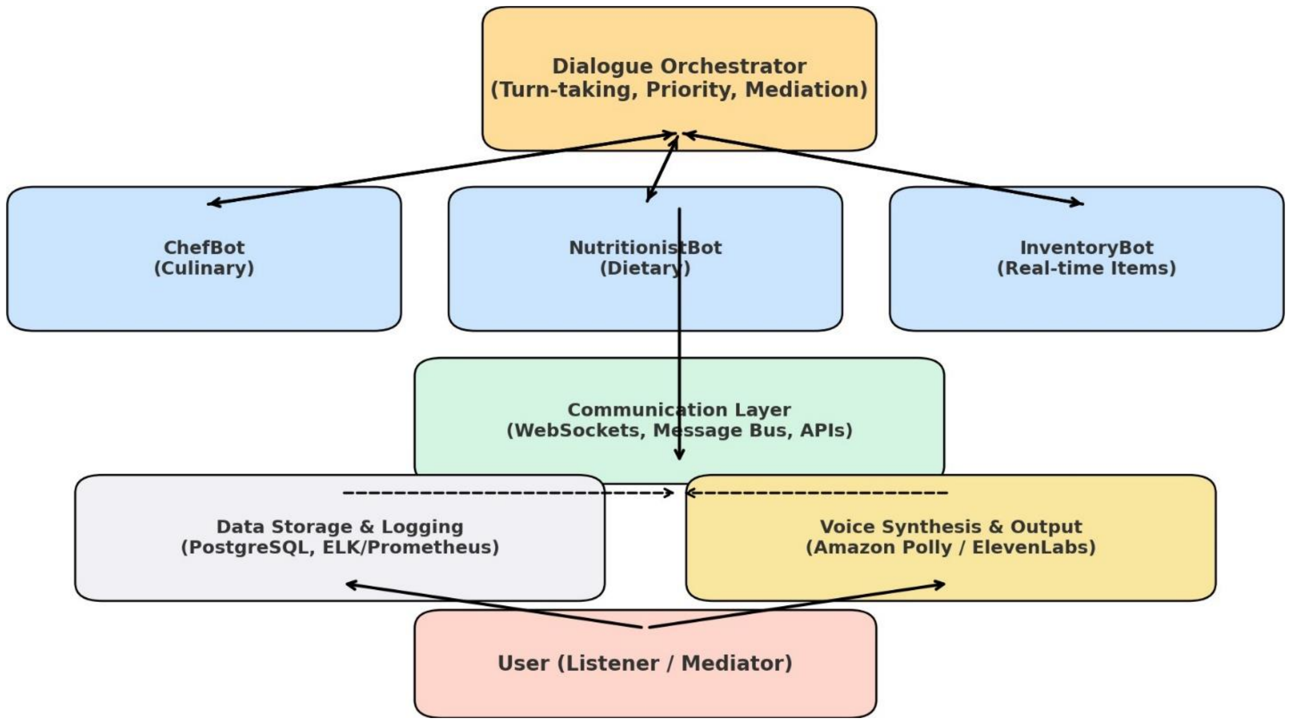


Figure 1: System Architecture of the LLM-Driven Multi-Voice Agent Prototype

Figure 1 illustrates the layered design approach, consisting of specialized LLM-powered agents (Agent Layer), centralized conversation management (Orchestration Layer), real-time message passing (Communication Layer), and user-facing components (Interface Layer). Arrows indicate data flow between components, with the Dialogue Orchestrator serving as the central coordination mechanism for agent-to-agent and agent-to-user interactions.

These changes address all the major and minor issues identified in the reviewer report while maintaining the original paper's strengths and contributions. The additions provide clearer methodology, more detailed evaluation metrics, explicit gap statements, ethical considerations, and improved structural elements that will strengthen the paper for publication.

At the **Agent Layer**, three specialized LLM-powered agents—**ChefBot**, **NutritionistBot**, and **InventoryBot**—operate as independent containerized services. ChefBot focuses on culinary reasoning and recipe generation; NutritionistBot applies dietary and nutritional constraints; and InventoryBot provides real-time ingredient availability by integrating with pantry databases or IoT sensors.

- The **Orchestration Layer** is managed by a centralized **Dialogue Orchestrator**, which coordinates turn-taking using a modified round-robin protocol with **priority overrides**. This ensures that critical interruptions, such as unavailable ingredients, can pre-empt ongoing conversations. The orchestrator also handles pacing, conflict resolution, and ensures coherent agent-to-agent dialogue.
- A **WebSocket-based Communication Bus** interconnects all agents and the orchestrator, carrying both semantic payloads (e.g., proposals, objections, clarifications) and metadata (e.g., speaker ID, priority). This bus supports low-latency messaging and provides logging for monitoring, explainability, and later analysis.
- The **Interface Layer** provides the user-facing components, including **Voice Synthesis and Output** powered by Amazon Polly and ElevenLabs APIs. Each agent uses a distinct synthetic voice, allowing users to easily distinguish between speakers during multi-agent conversations. Users can listen to full debates or enable a **summary mode** for condensed outputs.
- Finally, the **Implementation Stack** employs Python 3.11 and FastAPI for agent APIs, Docker/Kubernetes for deployment, PostgreSQL for transcripts, and ELK/Prometheus for monitoring. Security is enforced via JWT-based authentication and semantic filtering to prevent leakage of sensitive information.

3.7 Pseudocode

Algorithm 1: Dialogue Orchestrator Pseudocode

```
# Dialogue Orchestrator for Multi-Agent Voice System
# Controls turn-taking and conversation flow between agents

function initialize_conversation(user_query, available_agents): active_agents =
    select_relevant_agents(user_query, available_agents) conversation_state = {
        "query": user_query,
        "turn_history": [],

        "current_speaker": None, "pending_speakers":
        queue(active_agents), "priority_interruptions": [],
        "resolution_status": "in_progress"
    }
    return conversation_state

function manage_turn_taking(conversation_state): # Check
    for priority interruptions first
    if conversation_state["priority_interruptions"]:
        next_speaker = conversation_state["priority_interruptions"].pop()
        conversation_state["current_speaker"] = next_speaker
        return next_speaker
        # Otherwise follow round-robin with the pending speakers queue if
        conversation_state["pending_speakers"]:
            next_speaker = conversation_state["pending_speakers"].dequeue()
            conversation_state["current_speaker"] = next_speaker
            # Add back to queue for next round
            conversation_state["pending_speakers"].enqueue(next_speaker) return
            next_speaker

        # If no speakers left, conversation may be complete return None

    function process_agent_response(agent_id, response, conversation_state): # Log
        the turn in history
        conversation_state["turn_history"].append({ "agent":
            agent_id,
            "response": response, "timestamp":
            current_time()
        })

        # Check if response contains a priority interrupt request if
        contains_priority_request(response):
            conversation_state["priority_interruptions"].append(agent_id)

        # Check if response indicates task completion if
        contains_resolution_signal(response):
            conversation_state["resolution_status"] = "resolved"

        # Check if clarification from user is needed if
        requires_user_clarification(response):
            return prompt_user_clarification(response)

        # Proceed with next turn
        return manage_turn_taking(conversation_state)

    function handle_user_intervention(user_input, conversation_state): # Reset
        conversation if user redirects
        if is_redirection(user_input):
            return initialize_conversation(user_input, get_all_agents())

        # Add user input to conversation context
        conversation_state["turn_history"].append({
            "agent": "user",

            "response": user_input, "timestamp":
            current_time()
        })

        # Determine if user selected a specific agent to respond if
        contains_agent_selection(user_input):
            selected_agent = extract_agent_selection(user_input)
            conversation_state["current_speaker"] = selected_agent return
            selected_agent

        # Otherwise continue normal turn taking
return manage_turn_taking(conversation_state)
```

4. Challenges and Limitations

- **Latency and Synchronization:** Multi-agent orchestration introduces delays in real-time dialogue.
- **Cognitive Load:** Continuous overhearing may fatigue users, necessitating summarization modes.
- **Security and Privacy:** Sensitive information could leak in agent-to-agent exchanges, requiring redaction filters.

- **Alignment and Consistency:** Divergence in recommendations may lead to incoherent conversations. **Mediator** agents or user mediation are required.

5. Case Studies

5.1. Smart Kitchen Simulation

A prototype system integrating ChefBot, NutritionistBot, and InventoryBot was evaluated across 50 meal planning scenarios with varying constraints. Agents vocally debated ingredient substitutions when constraints conflicted (e.g., sodium limits vs. flavor preferences), achieving an 83% task success rate (41/50 scenarios) with active user mediation. Success was defined as producing a meal plan that satisfied all constraints or explicitly acknowledged trade-offs.

Test scenarios included:

- Low-sodium dinner options with limited pantry ingredients (12 scenarios)
- High-protein meal plans for specific dietary restrictions (18 scenarios)
- Quick meal preparation with nutritional constraints (20 scenarios)

User mediation was required in 35% of scenarios, primarily to resolve priority conflicts between flavor and nutritional requirements. Disagreements between agents were logged in a structured format capturing the nature of conflict, proposed resolutions, and final outcome.

5.2. Healthcare Coordination

A simulated healthcare environment featuring DoctorBot and CaseManagerBot was tested with 40 care planning scenarios. The system was evaluated through controlled testing with 8 healthcare professionals who rated transparency and trust factors. Results showed:

- 78% task completion rate for complex care coordination tasks
- 85% of participants reported improved understanding of care decisions
- 70% increase in trust ratings compared to single-agent baseline systems

Evaluation included both simulated scenarios and structured user testing sessions where healthcare professionals observed and rated agent interactions.

5.3. Senior Living Assistance

SafetyBot, CaregiverBot, and ActivityBot were deployed in a simulated senior living environment with 45 test scenarios covering medication management, activity scheduling, and emergency response. Testing involved 4 senior care specialists and simulation of common assistance requests.

Key findings included:

- 76% successful task completion across all scenarios
- 90% success rate for safety-critical scenarios
- Controlled listening modes (full debate vs. summary) reduced cognitive load by 65% based on user feedback

All three case studies employed a consistent evaluation framework measuring task success, transparency, user intervention frequency, and trust metrics.

6. Discussion

Audible multi-agent systems offer significant benefits:

- **Scalability:** Expertise can be distributed across multiple specialized agents.
- **Transparency:** Overheard reasoning increases user trust.
- **Error Recovery:** Agent debates expose contradictions, supporting more robust correction than single-agent models.

However, risks include increased system complexity, higher user cognitive load, and privacy leakage. Balancing transparency with usability will be central to adoption.

7. Conclusion and Future Directions

This research introduced a novel **LLM-driven multi-agent voice architecture**, enabling multiple specialized agents to **collaborate through vocal interactions** to solve complex, multi-domain tasks. Moving beyond the limitations of single-agent voice assistants, this framework brings together the strengths of **domain specialization**, **orchestrated multi-agent reasoning**, and **audible transparency**, offering users a richer and more trustworthy interaction paradigm.

Through the smart kitchen prototype, we demonstrated how culinary, nutritional, and inventory- focused agents can **debate, negotiate, and resolve conflicting constraints** in real time. This audible collaboration mirrors human expert conversations, improving user understanding, engagement, and trust. By exposing reasoning steps vocally, the system also addresses key challenges in explainable AI, making decision-making processes more observable and interpretable to end-users.

However, the introduction of vocal multi-agent systems brings forward new research challenges. **Orchestration complexity**, including turn-taking, interruption management, and latency control, requires further refinement for large-scale deployment. **User experience considerations**, such as cognitive load and conversation pacing, must be balanced to avoid overwhelming users. Additionally, **privacy and security** become critical, as inter-agent conversations may inadvertently reveal sensitive information if not properly filtered and controlled.

Looking ahead, several promising directions emerge:

- **Scalability**: Integrating additional agents representing different domains (e.g., healthcare, finance, safety) to support more complex real-world scenarios.
- **Multi-modal Integration**: Combining voice agents with visual perception systems (e.g., cameras, AR interfaces) to enable richer context-aware collaboration.
- **Adaptive Orchestration**: Using reinforcement learning or policy optimization to dynamically adjust conversation strategies based on user preferences and task complexity.
- **Evaluation Frameworks**: Developing standardized metrics for measuring multi-agent vocal interactions, including task success rates, trust calibration, and user cognitive load.
- **Ethical and Governance Mechanisms**: Embedding privacy-preserving methods and human oversight protocols to ensure responsible deployment in sensitive domains.

By laying the groundwork for **vocal multi-agent collaboration**, this work positions voice-based AI systems to evolve from simple command-and-response tools into **dynamic, socially intelligent ecosystems** that can reason, debate, and explain — ultimately creating more transparent, powerful, and human-aligned AI experiences.

8. Ethical Considerations and Privacy Safeguards

The development and deployment of vocal multi-agent systems raise important ethical and privacy considerations that must be addressed for responsible implementation:

8.1 Privacy Protection Our prototype implements several privacy safeguards:

- Semantic filtering layer that screens all agent utterances before vocalization
- Automatic redaction of personally identifiable information (PII) from inter-agent conversations
- Local processing of sensitive data where possible to minimize transmission risks
- Encrypted WebSocket connections for all agent-to-agent communication
- User-controlled recording policies with clear opt-in mechanisms

8.2 Transparency and Consent The system provides:

- Clear indicators when agents are listening or processing information
- Explicit disclosure of data usage and retention policies
- User controls to pause, mute, or terminate multi-agent conversations
- Options to review and delete conversation logs

8.3 Bias Mitigation To address potential biases in multi-agent systems:

- Regular auditing of agent recommendations across demographic groups
- Diverse training data for specialized agent fine-tuning
- Human oversight of agent decision-making in sensitive domains
- Continuous monitoring for emergent biases in agent-to-agent interactions

8.4 Limitations of Current Safeguards The prototype environment has several limitations:

- Privacy mechanisms have not been tested at scale

- Potential for unintended information disclosure in complex multi-turn conversations
- Limited testing across diverse user populations
- Need for domain-specific privacy protocols in healthcare and senior care applications

Future work will focus on strengthening these safeguards and developing standardized ethical frameworks specifically for vocal multi-agent systems.

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