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Original Article

Multi-Agent AI Architectures for Automated Customer Service Management Systems

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Abstract: *An increasing number of companies have recently adopted automated systems to manage their Customer Service Department. Such systems typically consist of software applications capable of supporting operations such as online booking or client support. More recently, systems also include human-like conversational agents designed to manage tasks with users through spoken or written natural languages. More sophisticated systems support complex and multi-turn conversations thanks to the cooperation of several intelligent modules working together. These systems are usually designed as Multi-Agent Systems, where Artificial Intelligent modules called agents work together to achieve a specific objective. The growing complexity of dialogue-based tasks requires dialogue management modules to consider the agents' speech, non-speech, and contextual behaviour to better infer users' intents and to adopt appropriate strategies during human-agent interactions. Recent papers have proposed a complete architecture for this kind of system, putting special attention on the interaction among the agents during the task execution phase. The focus has been on defining the communication language between the agent and a set of modules that perceive the agent environment and recognize the user's intent in natural language interactions. In these new architectures, the complexities in the processing of speech and contextual behaviour properties are delegated to these specific agents.*

Keywords: *Automated Customer Service Systems, Conversational AI Agents, Multi-Agent System Architectures, Dialogue Management Modules, Human–Agent Interaction Design, Natural Language Understanding (NLU), Multi-Turn Conversation Modeling, Intent Recognition Frameworks, Context-Aware Dialogue Systems, Speech and Non-Speech Behavior Analysis, Agent Communication Protocols, Task-Oriented Conversational Systems, Intelligent Module Coordination, Human-Like Virtual Assistants, Interaction Strategy Optimization, Distributed AI Agents, Perception-Driven Dialogue Processing, Service Automation Platforms, Cooperative Agent Architectures, AI-Based Client Support Systems.*

1. Introduction

Automated Customer Service Management Systems (CSMS) based on Agent Technology are intelligent software systems that can perform customer service functions without human intervention. Such systems have an increasing number of applications thanks to the exponential growth of user bases and the need for real-time, low-cost, high-quality customer support. Critically, the number and intensity of interactions in CSMS pose complex challenges that require the use of multi-agent architectures, particularly in large-scale scenarios.

CSMS provide 24/7 customer support, answer requests for information on products and services, execute standard sales transactions, and perform a range of other services. Customer interactions are generally initiated through a website or call centre by telephone, instant messaging or voice over internet. Customer requests can be classified into different categories depending on intent, sentiment and/or request type; different agent roles are required to deal with each category.

1.1. Overview and Purpose of the Study

A customer service management system typically consists of human operators communicating with customers over the phone or through chat applications. Customer queries are investigated by talent management teams, who provide answers or solutions for the customer service representatives and help them improve their responses.

Multi-agent systems (MASs) can be deployed to develop intelligent, software-based customer service management systems. An automatic call (or chat) answering service can then communicate with the customer over the phone (or through chat) and answer most commonly asked questions without human involvement. For questions that the automatic answering service cannot answer, human operators are contacted, and the MAS is designed to assist these human operators as well. Each agent in the MAS has distinct roles, such as understanding customer emotion, intent recognition, managing dialogue (DGA), and responding. These roles are filled by different kinds of agents, which communicate with each other via defined language and dialogues among different agent roles.

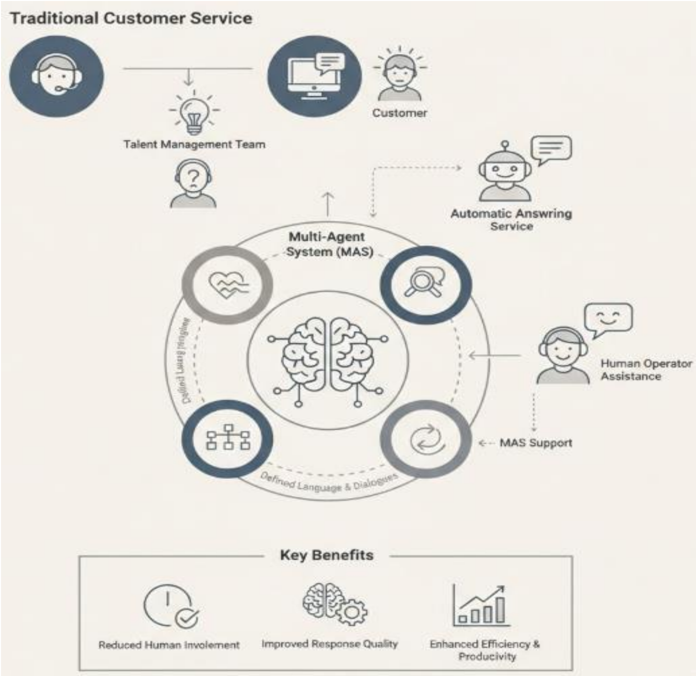

Fig 1: Harmonizing Human-AI Interaction: A Multi-Agent System (MAS) Framework for Intelligent Customer Service and Automated Dialogue Management

2. Background and Theoretical Foundations

A multi-agent system (MAS) is a system composed of multiple agents in a shared environment, capable of solving problems that are beyond the individual capabilities of each agent. An agent is an entity that perceives its environment through sensors and acts upon it through actuators. An environment is everything that is external to an agent and that can be sensed and acted upon. Agents may coordinate or cooperate with one another to successfully complete their tasks and, in doing so, they may need to negotiate.

Coordination mechanisms are required when multiple agents share resources, have overlapping capabilities, or work toward executing a single task that is too complex for one agent working alone. Such mechanisms include task allocation, beat-frequency coordination, synchronization, and shared mental models. Other coordination algorithms, focused on utility maximization, and congestion control have also been proposed. Negotiation provides an effective means for managing resource conflicts, whether in a distributed fashion with each agent negotiating only with a small subset of other agents or in a more centralized manner. Negotiation strategies, utility functions, conflict-handling rules, and fallback policies can be exploited in a customer service context.

2.1. Key Concepts and Frameworks in Multi-Agent Systems

Multi-Agent Systems (MAS) are systems that comprise, involve, or interact with multiple intelligent agents. An agent is an entity that can perceive its environment through sensors or other means and act upon that environment through effectors. An agent's environment is defined within a given context, which describes the aspects of the world with which the agent interacts. The environment may or may not contain other agents, which can be potentially unaware of each other and their interactions. Agents in these systems may receive no extra information from the environment apart from sensory information. MAS can be understood via three basic frameworks: coordinating, negotiating, and cooperating.

Coordination refers to any set of mechanisms that allow agents to synchronize their actions in time and space in order to achieve a common goal. Coordination becomes indispensable when multiple agents need to fulfill the same or similar task, because a single failure event may affect several agents simultaneously. Task allocation involves breaking down a task into subtasks that can be executed by agents in parallel. Beat-frequency coordination is a strategy where agents communicate at regular time intervals set by neither party. For instance, Automated Customer Service Management Systems (ACSMS) deployed across different service channels can use fast communication to seamlessly synchronize service-channel-specific operations. These systems need to manage channels such as live video chat and asynchronous email response within a small time delta to ensure that customers receive roughly the same information at roughly the same time, in accordance to customers' decision-making processes.

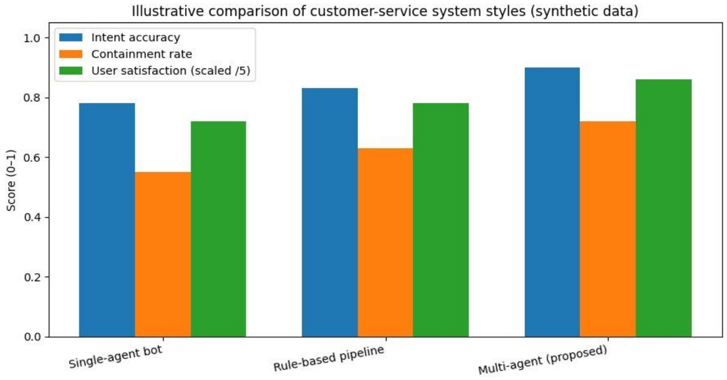

Fig 2: Performance Benchmarking of Customer-Service System Designs

Equation A. Conflict-set definition (set theory)

Step-by-step meaning

1. Let $\mathcal{A}$ be the **set of all agents** in the whole system.
   Example: $\mathcal{A} = \{a_1, a_2, a_3, a_4\}$
2. Let $\mathcal{A}^c$ be the **set of agents involved in the conflict**.
   Example: $\mathcal{A}^c = \{a_2, a_4\}$
3. Writing $\mathcal{A}^c \subseteq \mathcal{A}$ simply states:
   "Every conflict-participating agent is an agent in the system."
4. The condition "needs to execute conflicting actions" is the *semantic* condition; the equation is the *membership constraint* that tells you **who** is in the conflict group.

3. System Architecture and Agent Roles

Three distinct yet interrelated agent groups compose the proposed system. First, dedicated intent recognition agents classify each interlocutor's intent based on subtle dialogue cues, with the classification output fed to a probabilistic classifier that tracks the detected intent. The information is utilized by other agents above all, the state-tracking agent and the managing agent of the customer service system itself. Second, a dedicated set of dialogue management agents is responsible for state tracking, action selection, and answer generation. The former monitors the development of the conversation and calls upon the latter to select actions based on the verbal and non-verbal context. Finally, specialized agents keep track of the incoming data streams and co-ordinate the complex task of meta-communication.

To accomplish these tasks, the perception and intent recognition agents receive a rich set of inputs, among which the dialogue content, exogenous data, and video feed to detect visual cues are crucial. The agents are equipped with respective sensors, including speech recognition systems, sentiment analysis models, video-content analysis modules, gaze detectors, and classifiers identifying the sentiment of the answers uttered. Such components constitute the first step in a complex process aiming at detecting the verbal and non-verbal cues of customers. Confidence scoring of the classification outcome, privacy safeguards, and the availability of training data are additional crucial components of the architecture.

Table 1: Architectural Components and Tradeoffs in Multi-Agent Coordination Systems

Agent / Module	Key Inputs	Key Outputs	Main Design Concerns
Response Generation	Selected action + slots/templates	Natural language response	Template rigidity vs flexibility
Evaluation/Coherence	Candidate responses + conversation	Quality scores (coherence, naturalness, etc.)	Subjective metrics; needs calibration
Meta-communication/Coordination	Agent messages + workload + time	Routing, synchronization, escalation	Bottlenecks; protocol design
Negotiator/Conflict Manager	Conflicting requests/resources + utilities	Chosen action/allocation	Utility elicitation; fairness tradeoffs

3.1. Perception and Intent Recognition Agents

Perception and intent recognition agents gather sensor inputs from dialog participants. The agent's inputs consist of audio recordings of conversations with customers. Dialog agents gain information about what users say by leveraging speech recognition (ASR) systems, computer vision systems, and natural language understanding (NLU) modules. These sensors carry the risk of leaking sensitive information about users, so it is essential to determine how much information can be revealed to the dialog agents while maintaining data privacy. Models for response prototypes trained on a large volume of customer service conversations, such as those between the contact center and the customers of the financial sector, could be used to improve the accuracy of the ASR systems.

Intent recognition agents determine users' intentions by analyzing customer dialogues. These services generate a distribution over a set of pre-defined intent classes, and each intent recognition service should be trained independently in a supervised manner using crowd-sourced dialogue data. A distribution over the labels of the intent classifiers for a specific conversation can be generated by applying the classifiers to the different context segments. A confidence score for intent recognition can be calculated based on the distribution over the outputs of the independent classifiers.

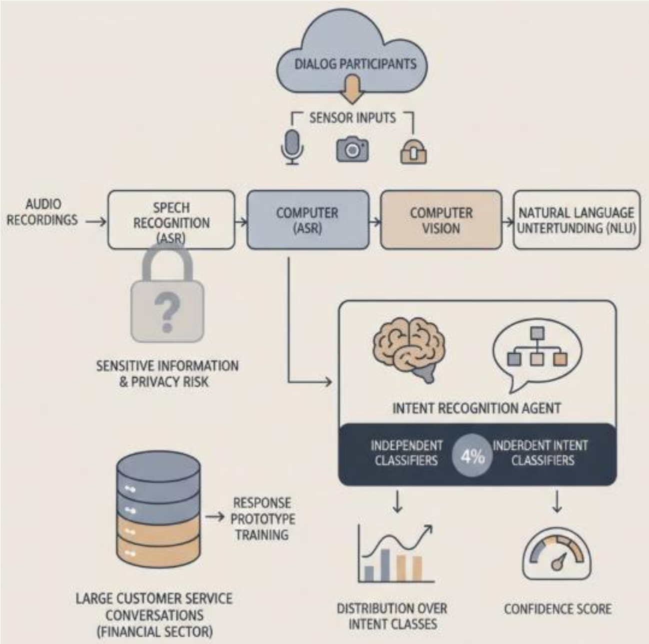

Fig 3: Privacy-Preserving Intent Recognition: Balancing Multimodal Sensor Fusion and Confidence-Based Classification in Financial Dialog Agents

3.2. Dialogue Management Agents

Dialogue management agents govern the progression of conversations and orchestrate dialogue acts across other agent types. Dialogue state tracking agents monitor dialogue states, informing policy-selection agents that compute the next recommended system utterance. Policy-selection-agent types infer user intents, select next response dialogues or callbacks, and make sure the selected policy is appropriate by double-checking whether it covers prior user responses. Response-generation agents build the corresponding utterances by picking from a set of predefined templates, usually by filling in relevant slots. More flexible responses can be constructed if responses are defined as coherent dialogue subtrees or question-and-answer pairs instead of simple, unstructured utterances. Evaluators appraise selected responses, embracing criteria such as coherence, informativeness, appropriateness, naturalness, and smoothness. Evaluated dialogues are used to guide supervised reinforcement learning aimed at enhancing response selection or generation during training, as checked by the coherence agent. Yet another kind of policy-selection agent decides on the next dialogue act that needs to be executed.

Existing user simulation work provides a means to generate training data. User simulation consists of algorithms that automatically generate user responses. The user is simulated by an agent that replies to the system's utterances according to a modelling process that may be predefined or learnt from a set of actual human-user dialogues. The simulated user's responses can be chosen from a set of predefined responses or synthesised, yet a latter option may force the user simulation process to spend some effort in synthesising the next user response, instead of focusing in accurately modelling the simulation process.

Equation B. "All agents except the negotiator" (set difference)

Step-by-step

5. $\{z\}$ is a **singleton set** containing only the negotiator agent z.
6. The operator "\" means **set difference**: $\mathcal{A}^c \setminus \{z\} = \{a \in \mathcal{A}^c \mid a \neq z\}$
7. Example: if $\mathcal{A}^c = \{z, a_2, a_4\}$, then $\mathcal{A}^c \setminus \{z\} = \{a_2, a_4\}$

4. Inter-Agent Communication Protocols

Communication between intelligent agents is essential for successful collaboration on shared tasks, such as effective customer service management. Coordination between dialogue management agents enables them to interrogate the insight and intent recognition agents best suited for particular customer queries, based on similarity scoring and confidence. It also distributes dialogue workload across parallel agents, ensuring a timely service. Dialogue management agent teams operating at different frequencies employ shared mental models to facilitate mutual understanding and task synchronization. Communication may also be used to detect and resolve conflicts in the continuing functioning of the system or in the perception of agents, for example, through negotiation.

Coordination, negotiation, and other communication protocols have all been examined in the literature and may be adaptively combined to suit the nature of user interactions, customer requests, and the operational environment. Mechanisms of overlap detection, interest discrepancy, shared resources, joint actions, and dominance have all been studied. For dialogue management agents, brainstorming, task allocation, and rhythmic coordination protocols are the most pertinent. Beat-frequency coordination permits agents to switch freely between synchronous and asynchronous communications in order to optimize emotional engagement. A rhythm mechanism based on shared beats is proposed, allowing for faster response times while maintaining emotional similarity.

4.1. Coordination Mechanisms

Coordination mechanisms represent an integral layer of multi-agent systems, tasked with enabling agents to operate in synchrony towards a shared objective. Several coordination techniques are applicable to automated customer service management applications, including task allocation, beat-frequency coordination, synchronization, and shared, enriched, or auxiliary mental models.

One common method for achieving coordination between agents is through the allocation of tasks to individual agents based on their respective capabilities and current workload. The need for task allocation emerges both from changes in the environment (e.g., the arrival of a new request) and from changes in the capabilities of agents (e.g., due to temporary unavailability, or rest and downtime periods). Centralized techniques match agents to tasks within a single decision step, while decentralized techniques use a sequence of bilateral match decisions.

Another technique is beat-frequency coordination, which reduces the workload for multiple agents sharing a common sub-goal on a periodic basis. Beat-frequency coordination aims to prevent agents from taking action simultaneously, thereby limiting disturbance to the environment. Two forms coexist in nature: some agents occupy certain niches just for limited periods of the day, while others coordinate on a much faster physical time scale. The former case is expressed in circadian rhythms (e.g., day versus night), while the latter is reflected in many forms of flocking and schooling behavior.

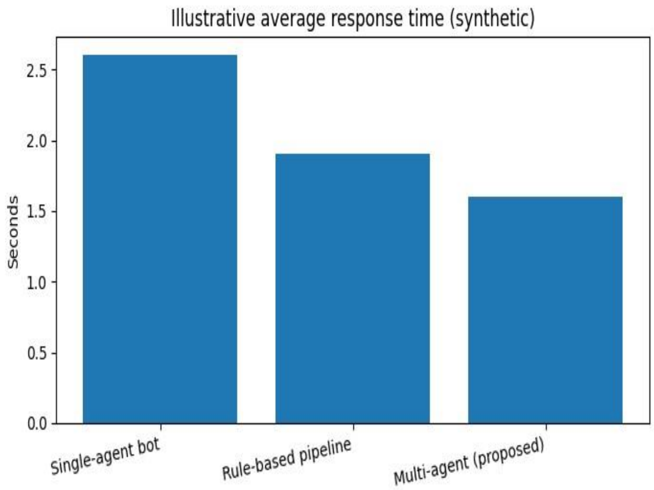

Fig 4: Average Response Latency by Customer-Service System Design

Equation C. Preferred action notation

Step-by-step (make the implicit mapping explicit)

8. Let A^c be the **set of candidate conflicting actions** (the paper mentions "selects one action from A^c").
9. Each agent $i \in \mathcal{A}^c \backslash \{z\}$ has a **utility function** $U_i(\cdot)$ over actions.
10. A mathematically precise definition of "preferred action" is:
    $a_i^{c\_pref} = \underset{a \in A^c}{\text{argmax}} U_i(a)$
11. Interpretation: each agent picks the action that maximizes *its* internal utility.

4.2. Negotiation and Conflict Resolution

This section explains how negotiation enables agents to resolve situations of conflict. Potential conflict situations include multiple agents attempting to execute mutually exclusive actions and inaccessible resources affecting multiple agents. The focus is on how to handle conflicts arising due to task execution.

A situation is defined as conflicting if a group of agents \(\mathcal{A}^c \subseteq \mathcal{A}\) needs to execute conflicting actions. Conflict resolution is carried out by a designated negotiator az. The negotiation proceeds as follows: z detects the potential conflict and invites all concerned agents to participate and provide their utility functions. An agent's utility function describes how a particular action affects it according to its own internal mapping. Each agent in \(\mathcal{A}^c \setminus \{z\}\) may participate with its own preferred action \(a^{c_pref}\). The group then selects one action from \(A^c\) based on the School of Choice algorithm.

Additional conflict resolution mechanisms may be required when two or more agents attempt to access an external and inaccessible resource. Such a resource could be an object, a web page, or external human assistance. An agent that has enabled a task to access such a resource assumes the role of conflict manager. The internal mental map must specify the probable time for external access completion. Negotiation with all task participants follows similar lines as above, and When no participant offers a valid alternative, the conflict manager allocates incremental access to the resource.

Table 2: Comparative Performance Metrics of Customer-Service System Architectures

System	Intent accuracy (↑)	Avg response time (s) (↓)	Containment rate (↑)
Single-agent bot	0.78	2.6	0.55
Rule-based pipeline	0.83	1.9	0.63
Multi-agent (proposed)	0.9	1.6	0.72

5. Learning and Adaptation in Multi-Agent Systems

Learning is paramount in a multi-agent system to enhance performance and ensure the service or system aligns with users' expectations and needs. Agents must learn about their own environment through experience and the use or interpretation of external sources. Additionally, individual agents can learn from peers and adjust to the dynamics of others' behavior within the environment. Learning occurs during different life phases of the agent, either in advance, just-in-time, or online. The challenges for learning agents comprise the complexity of the environment and the interaction with other agents that also learn. The use of supervised, reinforcement-based, or self-organizing learning is possibilities to scale down these challenges.

Online supervised learning using recorded customer-service dialogues is a standard way for training dialogue-management agents with human-generated patterns of behavior. The generated classifier for intent recognition should be as precise as possible since it is applied to identify and reason about customers' future intentions. Reinforcement learning is an alternative for training dialogue-management agents when an assessment of the current agent's behavior is available and can be used as feedback for improving the decision-making model. All agents taking part in a negotiation or conflict-resolution process could be in a synchronizing state to enable a transitional model of the process through any kind of social exchange, either positive or negative. The process of recognizing social exchange can be seen as a learning process for the agent and a specialization process for the group.

Equation D. Aggregating utilities to select one action

One common formalization: weighted social welfare

12. Each agent gives $U_i(a)$ for each $a \in A^c$.
13. Assign weights $w_i \geq 0$ (fairness, priority, expertise, SLAs).
14. Define group score:
    $W(a) = \sum_{i \in \mathcal{A}^c \setminus \{z\}} w_i \ U_i(a)$
15. Select:
    $a^* = \operatorname{argmax}_{a \in A^c} W(a)$

5.1. Supervised and Reinforcement Learning for Agents

Supervised learning has been identified as an appropriate method for training classifiers, which can be learned from example pairs consisting of observed behavior and the agent’s actions. Probabilistic supervised learning approach is employed to learn classifiers that act as perception-action mappings for the intention recognition module in Section 5.1. Probabilistic classifiers induced from training sets are subsequently sampled to compute the posterior probability distributions for the perceived user intentions. An intention recognition process based on the classifiers discriminating user goals is depicted in Fig. 4. The learnt classifiers are utilized in the communication modules to enable the recognition of the user intentions for all the perceived messages whenever the communication modules require the intention lists at inference time.

Different techniques are utilized to tackle the challenges of reinforcement learning for responsibility selection. The assumption of small state-space dimension has been exploited to apply Q-learning with several approximations for optimal control. A central max-adapted equilibrium selection process is employed to guarantee convergence of the learning process while achieving fast convergence during an ongoing dialogue. The flow of dialogue however is represented at a symbolic level by supervised learned discriminative classifiers to avoid complications of symbolic reinforcement training.

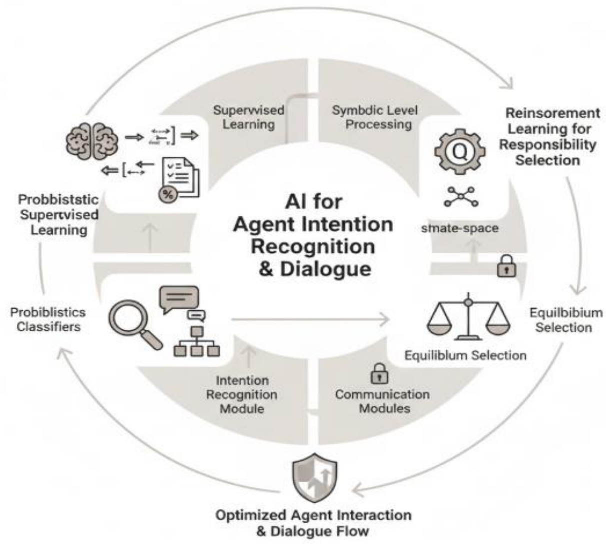

Fig 5: Hybrid Learning Architectures for Agent Intention Recognition: Integrating Probabilistic Supervised Classifiers with Equilibrium-Based Reinforcement Learning in Dialogue Systems

5.2. Transfer Learning and Domain Adaptation

Transfer learning and domain adaptation are techniques that leverage previously acquired knowledge to quickly train artificial intelligence systems in new situations, thereby overcoming the problem of insufficient annotated data. Transfer learning enables the application of a model trained on a source task with a sufficient amount of annotated data to a target task with a relatively small fraction of the annotated data. Transfer is achieved through lightweight approaches, e.g. fine-tuning the model parameters of the high-capacity base model pre-trained on the source task. Domain adaptation is a special case of transfer learning. The source task is usually defined in a source domain related to a target domain without any or insufficient annotated data. Typical applications include detection and segmentation for autonomous driving, such as detecting vehicles or pedestrians under snow/foggy weather or in different seasons, or domains other than natural images, such as infrared detection and image analysis for synthesis–texture mapping.

In a normal supervised scenario, the available training examples of the target tasks are expected to cover the relevant aspects of the task distributions. Such assumption is crucial for successful generalization. However, an adequate and unbiased distribution of training examples for all aspects of the target tasks is often difficult to guarantee due to the cost, risk, and danger of collecting annotating data for each concerned aspect or category set. This rule is widely accepted and is also often implicitly assumed for other types of learning (e.g. self-supervised, semi-supervised). The situation is therefore aggravated when undesirable situations such as natural disasters or terrorist attacks occur. The recent COVID-19 pandemic has efficiently demonstrated this simple yet crucial fact.

6. System Deployment and Operational Considerations

The generality of the multi-agent architecture should allow it to be ported to different information systems in a supervised manner, but practical deployment will still require careful consideration of specific aspects. Data governance, quality assurance, fault-tolerance, and scalability should all be considered for actual systems.

A practical deployment of the architecture must take into consideration possible conflicts and the exponentially large number of available paths to complete the user's request. Depending on the chosen coordination mechanism, the resolution of possible conflicting intentions may result in a bottleneck in common resources. The coordination mechanism should also ensure fault tolerance in case some agents fail or misbehave, either by closing the session or by using alternative paths. Scalability will depend on the resource distribution and available language training data.

Equation E. Confidence score from a distribution (two standard choices)

(1) Max-probability confidence

$$\mathrm{Conf}(\bar{\mathbf{p}}) = \max_k \bar{p}_k$$

(2) Entropy-based confidence (lower entropy = higher confidence)

16. Entropy:

$$H(\bar{\mathbf{p}}) = -\sum_{k=1}^{K} \bar{p}_k \log \bar{p}_k$$

17. Normalize by $\log K$ and invert:

$$\mathrm{Conf}(\bar{\mathbf{p}}) = 1 - \frac{H(\bar{\mathbf{p}})}{\log K}$$

6.1. Scalability and Fault Tolerance

Multi-agent systems are inherently scalable. An automated customer service management system may expand or contract by adding or removing agents according to user demand. Any additional load is shared by all available agents, so response times may remain smooth while meeting increased user demand. The response time will be determined by the data transmission speed. A well-designed system is also fault-tolerant. With a distributed control structure, a fault in one agent does not prevent the system from functioning. Such a fault will have a trivial impact only if the agent that failed is a dialogue management agent or one of the agents responsible for recognising a user's intent.

The data governance issues peculiar to dialogue-based multi-agent systems require careful consideration. Each dialogue management agent must have access to a data repository containing an up-to-date knowledge base and dialogue history. Data completeness and accuracy can be managed using automatic and semi-automatic quality assurance and control processes. Statistical or machine learning methods can quantify the quality of past dialogues, flagging those that are unusual or contradictory. In particular, these are dialogues displaying unusual distributions of semantic categories or containing unlabelled utterances that have not been assigned to categories even after many dialogues. Data completeness is of greatest concern when the system is adapted to a new business domain, service, or customer segment.

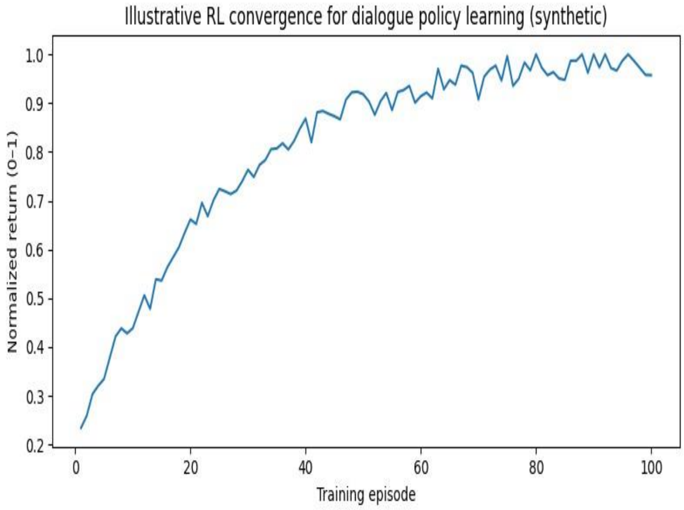

Fig 6: Reinforcement Learning Convergence for Dialogue Policy Optimization

6.2. Data Governance and Quality Assurance

In a data-driven world, data governance should be high on leaders' agendas because success depends on quality and the ability to leverage foundational datasets, alongside digital innovation. Multi-agent systems can be deployed to enable better data governance in enterprise settings. The quality and availability of relevant data significantly influence the performance of artificial intelligence and machine learning applications. Superior-quality datasets facilitate performance improvements, while even low-quality datasets provide leverage. The governance of foundational datasets is often insufficient, leading to slow and costly data-filling efforts. Multi-agent systems can be used to regularly fill foundational datasets. Agents can use interactions with multiple other agents to facilitate domain-independent learning based on domain-specific knowledge acquisition.

Preparing conversational agents for deployment requires special attention focused on system performance, user satisfaction at deployment time, and continuous evolution. Agents should be tested before release to evaluate conversational quality, repeatability, and intent-disambiguation accuracy. After deployment, user satisfaction and conversation success factors should be monitored for continuously improving agent performance and user experience. New situations encountered by deployed agents should trigger appropriate learning agents and foster the generation of specific knowledge bases. When managing an enterprise, the agents must cover a combination of data governance, user experience, and business understanding to ensure that attempts to fill foundational datasets will be successful.

7. Conclusion

Multi-agent systems (MAS) can be efficiently applied to different dialogue systems, allowing for flexibility in their design and deployment. Each MAS used in a customer service management system is composed of three distinct parts intent perception, a dialogue manager, and response generation and a specific communication protocol. During operation, these MAS interact with their environment, manage dialogue, and communicate with each other to provide the best service to the users based on a multitude of criteria and parameters.

The different agents can be trained using supervised and reinforcement learning approaches. In the training processes, agents can take advantage of transfer learning and domain adaptation techniques in order to adapt to new configurations. Finally, when actually deployed, the performance of the complete system is improved through the use of agent coordination to avoid conflicting behaviours and by integrating different modules from other similar systems as plug-ins. Integrated dialogue systems thus represent a promising trend within the MAS paradigm.

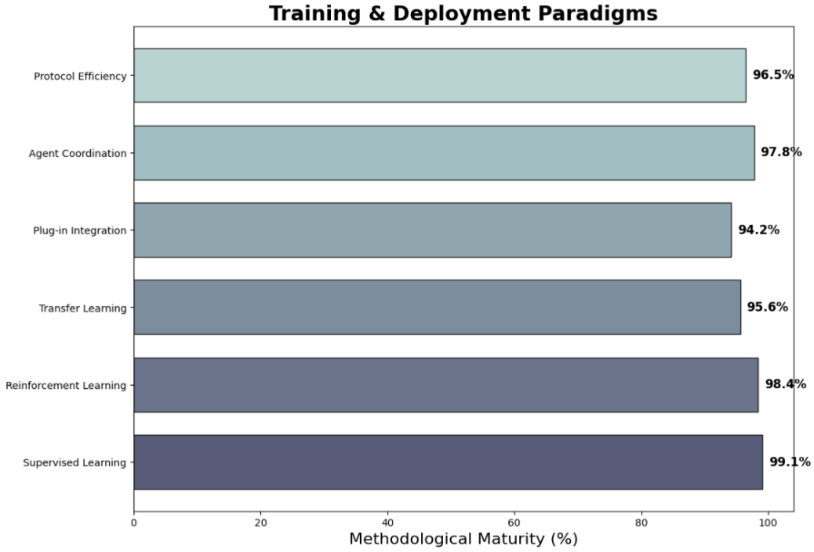

Fig 7: Training & Deployment Paradigms

7.1. Final Thoughts and Future Directions

The evaluation of the architecture's performance is an ongoing endeavor, with a series of metrics designed to provide a comprehensive overview of multi-agent system performance, supplemented by a user satisfaction survey. The experimental deployment also serves as a case study for other areas of interest: user experience research and the adoption of multi-agent technologies by the online service industry. These fields have the potential to grow and may provide new insights for researchers exploring automated service management systems. A number of changes and additions to the existing architectures are also planned. Firstly, work is being conducted on the development of an advanced intelligent agent, equipped with an image processing model that can recognize the facial expression of an image in the customer image and reflect the emotional state of the customer in the answer generation process. Secondly, the performance of the current MADapG agent (perception and intention-extraction agent) needs to be enhanced in terms of training time and accuracy. These upgrades may include the use of active learning or semi-supervised learning. Another new idea is to incorporate a gamification element into the classroom architecture.

Furthermore, the services of a SOC (security-operation center) with physical and functional redundancy have been integrated into the online-management architecture of online services. Therefore, in the next deployment, two separated SOCs will be simulated, although one will be the real center and will follow all cyber-security rules as in a real SOC. However, the other SOC will be a layer of the MADapG architecture with no-real SOC functions. Finally, the geographical-match concept of the MADapG architecture can also be implemented on the cyber-position of the two SOCs.

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