An Agent-Based Simulation Framework for Clinical Management Integrating Fuzzy Logic-Based Patient Satisfaction Evaluation

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Keywords: multi-agent system, clinical management, artificial intelligence, fuzzy logic, patient satisfaction, intelligent agent, healthcare services

Received: September 10, 2025

Efficient clinical management relies on coordinated operational workflows and reliable mechanisms for assessing patient experience. This study proposes an agent-based simulation framework for clinical management that integrates a fuzzy logic-based Patient Satisfaction Evaluation Agent (PSEA) within a multi-agent system composed of twelve specialized agents. The framework was implemented using the Mesa simulation platform and evaluated through simulation-based experiments involving 100 patients over 100 simulated time steps. Prior to its integration into the multi-agent system, the fuzzy satisfaction model embedded within the PSEA was independently designed and empirically validated using real survey data collected from 80 patients. The satisfaction scores produced by the fuzzy inference system showed strong agreement with patient-reported evaluations, achieving a correlation coefficient of 0.76 and a mean absolute error of 1.12. At the system level, simulation-derived indicators reveal a balance between adaptive coordination and operational stability. The multi-agent system performed an average of 3.68 ± 1.79 resource reallocation decisions per time step, while 12 out of 100 simulated time steps involved no reallocation, reflecting the emergence of stable operational phases.Overall, the results demonstrate that combining agent-based simulation with a pre-validated fuzzy satisfaction assessment provides a coherent and interpretable framework for supporting coordinated and patient-centered clinical management. Future work will focus on interoperability through standards such as HL7 and FHIR.

Povzetek: Študija predstavlja večagentni simulacijski sistem z mehko logiko za učinkovitejše in bolj pacientu prilagojeno klinično upravljanje.

1 Introduction

The digital transformation of healthcare has become a global priority, reshaping not only hospitals but also smaller healthcare structures such as clinics [1,2]. Clinics occupy a central position in healthcare delivery because of their ability to offer specialized services and adapt quickly to patient needs [3]. However, they continue to face persistent challenges, particularly in coordinating services, managing resources efficiently, and monitoring the quality of care as experienced by patients [4,5].

Artificial intelligence (AI) has opened new possibilities for addressing these challenges by providing tools to model, optimize, and automate healthcare processes [6–8]. Within this field, multi-agent systems (MAS) have emerged as one of the most promising approaches [9]. By modeling autonomous entities that interact in dynamic environments, MAS provide a natural way to represent the complexity of clinical settings [10,11]. Each agent can be assigned a specific role or responsibility, making it possible to simulate core workflows such as admission, planning, supervision, and resource management in a flexible and distributed manner [12–14].

Yet clinical practice also involves subjective judgments and uncertain information that cannot easily be reduced to deterministic models. Fuzzy logic, introduced by Zadeh [15], addresses this gap by formalizing linguistic concepts such as "high satisfaction" or "short waiting time" into computable values. This makes it particularly well suited for evaluating aspects of healthcare that are shaped by human perception, including patient satisfaction and perceived service quality [16–18].

In this study, we propose an agent-based framework for clinical management that brings together operational efficiency and patient-centered evaluation. The architecture consists of twelve specialized agents, among which the Patient Satisfaction Evaluation Agent (PSEA) applies fuzzy logic to assess patient experience. To ensure robustness, this subsystem was validated with real clinical data collected from several departments before being embedded into the MAS. The complete system was then simulated with the Mesa platform, which allowed us to reproduce realistic workflows in admission, resource coordination, and satisfaction monitoring.

The primary objective of this study is to design and evaluate a simulation-based multi-agent framework for coordinated clinical management. To achieve this overall objective, the study pursues several specific goals. First, it aims to model core clinical workflows through the interaction of specialized agents responsible for patient admission, coordination, supervision, and resource management. Second, a fuzzy logic-based patient satisfaction model is developed and empirically validated as an independent component before being integrated into the multi-agent system. Finally, the operational behavior of the complete framework is assessed through simulation, with particular attention to coordination dynamics, resource reallocation processes, and operational stability across different clinical scenarios. By clearly distinguishing the validation of the fuzzy satisfaction model from the simulation-based evaluation of the multi-agent system, the proposed approach seeks to provide an interpretable and patient-centered perspective on intelligent clinical management.

The remainder of this paper is organized as follows. Section 2 examines the operations of clinics and their organizational challenges, and Section 3 reviews related work on multi-agent systems and fuzzy logic in healthcare. Section 4 describes the adopted methodology, while Section 5 details the organization of the proposed multi-agent system and its agents. Section 6 presents the fuzzy-based Patient Satisfaction Evaluation Agent (PSEA), and Section 7 introduces the technical implementation and simulation setup. Section 8 reports the simulation results, followed by a discussion in Section 9. Finally, Section 10 concludes the paper.

2 Operations of clinics and organizational challenges

Clinics play a pivotal role within modern healthcare systems, offering an intermediate level of care between primary outpatient services and large public hospitals. Their operational structure is built upon a delicate coordination of clinical services, patient flows, resource management, and quality-of-care imperatives [1][2].

A typical clinic is structured into several core units, including admission, consultation, inpatient care, pharmacy, medical imaging, laboratories, surgical services, and discharge planning. These are further supported by administrative departments, electronic medical record management, and interfaces with insurance providers, external laboratories, and regulatory authorities. This intricate network requires a fluid and responsive architecture in which the synchronization of clinical and logistical activities becomes a central concern [19][20]. Clinics are confronted with a range of structural and operational challenges:

- **Queue and emergency management**: Delays and overcrowding can negatively impact care quality and patient satisfaction [21].
- **Traceability of medical procedures**: Accurate documentation is essential for continuity of care and regulatory compliance [22].
- **Perceived quality of care**: Patients' perceptions of care quality significantly influence their satisfaction and loyalty [23].
- **Security of medical data**: Safeguarding sensitive health information is critical to maintaining patient trust and adhering to data protection regulations [24].
- **Optimization of human and material resources**: Efficient allocation of resources is fundamental for ensuring both financial sustainability and operational efficiency [25].
- **Integration of artificial intelligence in clinical decision-making**: AI offers new possibilities to enhance diagnostic accuracy and treatment effectiveness [26].

As healthcare systems undergo rapid digital transformation, clinics are increasingly embracing smart technologies such as electronic medical records, telemedicine, predictive analytics, and automated flow management systems. Within this broader context of AI adoption in healthcare, multi-agent systems have been identified as promising tools for improving task coordination and patient-centered service organization [27], while recent policy-oriented works emphasize the institutional and ethical frameworks required to support such technological integration in health systems [28].

3 Related work

The effective management of clinics, whether public or private, remains a critical challenge in modern healthcare systems, particularly in urban environments with limited resources. As healthcare services grow increasingly complex, involving multiple actors and a broad spectrum of patient needs, new approaches grounded in distributed artificial intelligence have begun to emerge. Among these, multi-agent systems (MAS) and fuzzy logic stand out as promising methodologies for modeling, simulating, and enhancing the functioning of clinical infrastructures [12] [29] [30].

Multi-agent systems enable the representation of autonomous entities such as departments, healthcare professionals, patients, and medical equipment that can interact, collaborate, and make decisions at a local level [10][14]. This decentralized modeling capability is particularly well-suited to clinical contexts, where processes are often fragmented, dynamic, and multidimensional [31]. For instance, Munavalli et al. developed a MAS for coordinating care within a university clinic, simulating interactions between departments to streamline patient journeys [32].

Fuzzy logic, for its part, is distinguished by its ability to model imprecise, uncertain, or subjective knowledge such as patient satisfaction evaluation, care prioritization, or risk management [15][16]. In clinical settings, where decisions are rarely binary and often rely on expert judgment, fuzzy logic offers a framework for translating qualitative expertise into operational decision-making algorithms [10] [33]. In this vein, Yager and Filev proposed a fuzzy system for assessing perceived quality of care in community clinics, using linguistic categories such as "good", "acceptable," or "unsatisfactory" [34].

Hybrid approaches that combine MAS and fuzzy logic have demonstrated particular effectiveness in designing intelligent systems capable of adapting to the realities of healthcare settings [35]. For example, Jemal et al. designed a simulated clinical environment in which intelligent agents make fuzzy decisions regarding patient prioritization, based on medical, social, and organizational criteria [36]. Similarly, Ekin et al. implemented a fuzzy-agent architecture to manage resource allocation in a multidisciplinary clinic, incorporating fuzzy constraints related to staff availability and case severity [37].

Across both primary and specialized care domains, numerous studies have highlighted the relevance of these methods for improving decision-making, enhancing coordination, and strengthening service quality. Rahmat et al. introduced a MAS-based simulation system to plan patient flows in overcrowded urban clinics [38], while Adepoju et al. explored the use of fuzzy logic to model patient satisfaction in private clinics in sub-Saharan Africa [39].

Other works have proposed decision-support tools based on fuzzy rules, deployed through software agents to guide clinical choices when precise data are lacking or when conflicting criteria must be reconciled [40][41]. These models are particularly valuable in contexts where human expertise remains essential but requires robust computational support.

Recent research has emphasized the importance of systemic approaches that integrate intelligent agents and fuzzy mechanisms to adapt to the complexity of healthcare environments [32][42][43].

Table 1 provides a comparative synthesis of representative studies, highlighting differences in architectural focus, use of fuzzy logic, patient satisfaction modeling, and validation strategies.

Table 1: Comparison of multi-agent and fuzzy approaches for clinical management and patient satisfaction

Reference	Approach Type	Main Objective	Patient Satisfaction Modeling	Validation Strategy	Key Limitations
Munavalli *et al.* [32]	Classical Multi-Agent System (MAS), no fuzzy reasoning	Optimization of outpatient scheduling	Not considered	Simulation-based	Operational focus only
Jemal *et al.* [36]	MAS enriched with fuzzy rules for task prioritization	Clinical decision support	Indirect, via fuzzy-based prioritization	Simulation	No real patient validation
Ekin *et al.* [37]	Standalone fuzzy logic model (no agent-based architecture)	Resource allocation optimization	Not considered	Mathematical modeling	No agent coordination
Adepoju *et al.* [39]	Standalone fuzzy logic system for service evaluation	Healthcare service quality evaluation	Yes, based on patient surveys	Real questionnaire data	Not operationally integrated
Rojas-Domínguez *et al.* [35]	Fuzzy Multi-Agent System (fuzzy reasoning embedded in multiple agents)	Clinical assistance systems	Partial	Simulation	Limited clinical scope
This work	MAS combined with fuzzy logic through a dedicated evaluation agent	Patient-centered integrated clinical management	Yes, explicitly modeled via a fuzzy-based agent	Real data combined with simulation	Proof-of-concept scale

Yet few models offer a unified view of clinic operations that combines organizational management with patient-centered evaluation. Our work responds to this gap by proposing a multi-agent framework that coordinates key clinical functions such as reception, scheduling, and care coordination while incorporating a dedicated Patient Satisfaction Evaluation Agent (PSEA). Unlike previous approaches, this subsystem was validated with real data from multiple clinical departments, ensuring that patient perceptions are captured in a robust and empirically grounded way.

This contribution thus represents a significant step forward in the development of integrated, intelligent, and operational systems that are transferable across diverse clinical settings.

4 Methodology

The methodology adopted in this study is based on a hybrid approach that combines multi-agent systems (MAS), fuzzy logic, and computational simulation. Its objective is to realistically model the operational processes of a healthcare clinic by accounting for patient flow dynamics, interdepartmental interactions, and the evaluation of patient satisfaction. The fuzzy logic subsystem was validated with real patient data collected from multiple clinical departments, while the complete MAS was simulated with the Python-based Mesa platform to reproduce realistic clinical workflows.

4.1 Design of a multi-agent system

The multi-agent architecture was designed to reflect the functional organization of a clinic through twelve specialized agents, each responsible for a well-defined set of tasks. This modular decomposition ensures that clinical operations such as admission, consultation, coordination, medical records management, and satisfaction monitoring are represented in a distributed yet coherent manner.

Formally, the system can be represented as:

$$MAS = \{a_1, a_2, \dots, a_{12}\} \quad (1)$$

where each agent a_i is modeled as:

$$a_i = \langle P_i, A_i, C_i \rangle \quad (2)$$

Where P_i denotes the set of perceptions an agent can process, A_i represents its possible actions, and C_i refers to its to its communication rules with other agents, inspired by the Agent Communication Language (ACL).

By distributing responsibilities across twelve specialized agents, the MAS reflects the interdependence of clinical processes while preserving coherence and adaptability. The architecture is organized into four functional layers: interface, medical, logistical and intelligence. Together, these layers ensure modularity, scalability and the flexibility needed to simulate a variety of operational scenarios, while remaining aligned with the practical realities of clinical management.

4.2 Integration of a fuzzy subsystem for patient satisfaction

The subsystem for evaluating patient satisfaction is based on fuzzy logic, which translates subjective perceptions into interpretable scores. Eight input variables covering communication and information, reception and accessibility, staff competence, infrastructure and cleanliness, perceived effectiveness of care, billing transparency, personalization of care, and intention to return were collected through structured questionnaires administered in several clinical departments, including gynecology, dermatology, and emergency services. Each response was normalized on a 0–10 scale and descriptive statistics such as mean, standard deviation, minimum, and maximum were computed to calibrate the membership functions. This empirical validation ensured that the Patient Satisfaction Evaluation Agent (PSEA) reflects authentic perceptions of care and provides a reliable basis for intelligent patient-centered assessment [44].

It is important to emphasize that the empirical validation of the fuzzy satisfaction subsystem was conducted independently of the multi-agent simulation. The objective of this validation phase was to ensure that the Patient Satisfaction Evaluation Agent (PSEA) produces scores consistent with patient-reported perceptions. The subsequent agent-based simulation does not aim to revalidate the fuzzy model, but rather to examine the behavior of the overall system when this validated component is embedded within the multi-agent architecture. In this sense, the simulation provides a complementary, system-level evaluation focused on coordination dynamics and operational interactions among agents.

4.3 Implementation and simulation

The complete system was implemented using the Python-based Mesa framework, which was used to reproduce realistic clinical workflows through agent-based simulation. Twelve agents were defined, each assigned to a distinct functional role, and their interactions were modeled within the simulated environment. Three representative scenarios were designed:

- Reduction of patient waiting times;
- Dynamic reallocation of clinical resources;
- Evaluation of overall patient satisfaction.

These simulations provided insights into the system's capacity to coordinate complex operations, adapt to evolving conditions, and generate meaningful indicators of clinic performance.

5 Operation and organization of the multi-agent system

In medical contexts, characterized by heterogeneity, dynamism, and strong interconnectivity, multi-agent systems (MAS) provide a particularly appropriate solution. Their capacity to embed intelligent functionalities within autonomous units makes them ideal for decomposing clinical functions into specialized modules, coordinating distributed activities, enhancing hospital system flexibility, and integrating artificial intelligence (AI) techniques such as fuzzy logic and expert systems [45]. Jennings et al. demonstrated how MAS can enhance coordination within complex medical systems [46]. Wooldridge underscored their suitability for simulating dynamic environments [10], and Hongqiao et al. illustrated their relevance in simulating clinical care operations [14]. Altogether, these properties make MAS a powerful tool for designing health systems that are more robust, intelligent, and responsive to the evolving needs of both patients and healthcare institutions.

5.1 System overview

The proposed system is built on a distributed and cooperative architecture composed of 12 agents, each assigned to a specific functional domain within the clinic. This organizational structure enables efficient management of internal processes while ensuring modularity, scalability, and resilience. Agents communicate using standardized protocols, exchanging critical information to maintain system coherence. The Mesa simulation platform is used to model agent behavior and environmental dynamics.

The system aims to simulate the full operational cycle of a clinic in an integrated manner, with a particular emphasis on care optimization, resource management, service quality improvement, and patient satisfaction.

5.2 Agent descriptions and functional roles

Each agent in the system represents a distinct functional entity, aligned with real-world clinical operations. Their modular design ensures faithful representation of workflows and facilitates simulation and future expansion. Table 2 provides an overview of the 12 agents, including their acronyms, names, and primary functions.

Table 2 : Functional overview of the agents

No.	Acronym	Agent Name	Functions
1	UIA	User Interface Agent	Receives input from users (patients, staff), adapts the interface accordingly, and manages initial data capture.
2	PCA	Prescription and Consultation Agent	Oversees clinical consultations, performs diagnoses, and generates prescriptions.
3	MRA	Medical Record Agent	Manages electronic health records, ensures data confidentiality, and oversees updating and archiving of medical information.
4	MPMA	Medication and Product Management Agent	Controls medicine availability, monitors inventory, and flags shortages.
5	LRA	Laboratory and Radiology Agent	Coordinates lab and imaging procedures, manages sample processing and result dissemination.
6	AOA	Admission and Orientation Agent	Manages patient admissions and assigns them to appropriate departments or available timeslots.
7	SCA	Service Coordination Agent	Oversees patient flow between departments (e.g., emergency, inpatient care, surgery), resolving logistical conflicts as needed.
8	PSEA	Patient Satisfaction Evaluation Agent	Evaluates patient satisfaction using a fuzzy logic engine based on eight key indicators (waiting time, reception, etc.).
9	SAA	Security and Access Agent	Controls access rights and identity verification, and ensures secure communication and data exchanges.
10	MIA	Medical Intelligence Agent	Supports clinical decision-making by leveraging structured medical knowledge.
11	ECA	External Communication Agent	Handles interactions with insurance providers, governmental bodies, and institutional partners.
12	PLA	Planning Agent	Coordinates the activities of all agents, resolves conflicts, and ensures overall system consistency.

5.3 Agent communication and coordination

Inter-agent communication is based on a protocol inspired by the ACL (Agent Communication Language) standard. Each message is structured with a performative type (e.g., inform, request, propose, confirm) and a clearly defined content, enabling consistent interpretation by recipient agents.

The Planning Agent plays a central role in coordinating the system’s global behavior. It identifies bottlenecks, prioritizes critical tasks, and dynamically reallocates resources. This function is particularly valuable in clinical settings, where emergencies or unexpected events may alter priorities in real time.

5.4 Conceptual model of the system

The multi-agent system is structured into four functional layers, providing a clear organizational blueprint and ensuring modularity and interoperability:

- **Interface Layer:** Manages user interactions (patients and healthcare staff) via the User Interface Agent (UIA) and External Communication Agent (ECA).
- **Medical Layer**: Includes the Prescription and Consultation Agent (PCA) and the Laboratory and Radiology Agent (LRA), focusing on diagnostic and treatment functions.
- **Organizational and Logistical Layer**: Comprises the Admission and Orientation Agent (AOA), Medical Record Agent (MRA), Medication and Product Management Agent (MPMA), Service Coordination Agent (SCA), and Security and Access Agent (SAA), responsible for core operations, logistics, and security.
- **Intelligence and Monitoring Layer**: Encompasses the Patient Satisfaction Evaluation Agent (PSEA), the Medical Intelligence Agent (MIA), and the Planning Agent (PLA), which support decision-making, real-time optimization, and strategic coordination.

This layered structure facilitates independent module updates, encourages interoperability, and enables progressive specialization based on the clinic’s specific operational needs. This architectural organization is visually synthesized in Figure 1.

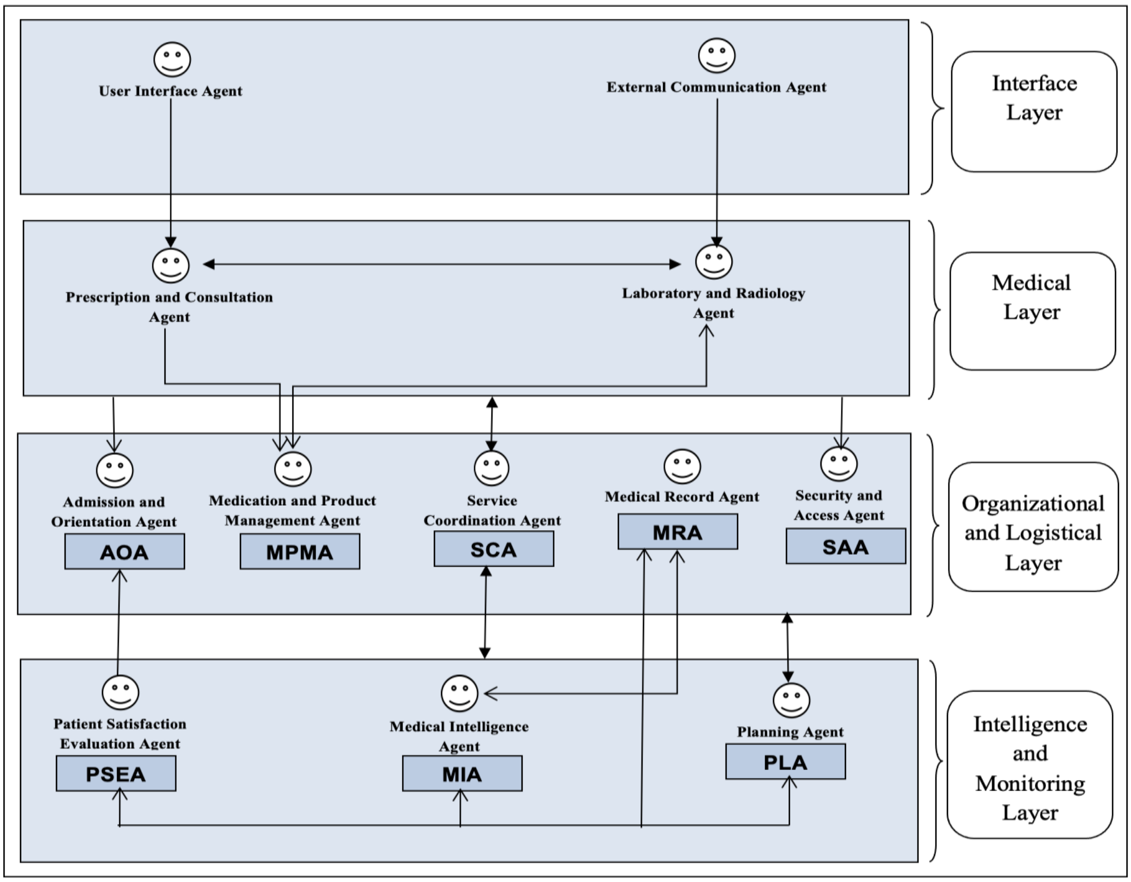

Figure 1: Layered architecture of the proposed multi-agent system for clinical management

6 Patient satisfaction evaluation module (PSEA) based on fuzzy logic

This section introduces the construction of the fuzzy logic system embedded in the Patient Satisfaction Evaluation Agent (PSEA), designed to provide a numerical satisfaction score that captures patient experiences.

6.1. Functional role within the multi-agent architecture

Within the proposed multi-agent system for clinical management, patient satisfaction is evaluated through a dedicated module called the Patient Satisfaction Evaluation Agent (PSEA)**.** This agent activates at the end of the patient journey and operates independently of clinical outcomes. Its objective is to provide a numerical score summarizing the overall satisfaction of the patient. The empirical validation of the PSEA was carried out prior to its integration into the multi-agent simulation and was conducted independently of the simulation experiments. Unlike purely simulated models, the PSEA was empirically validated with patient data collected from several clinical departments, ensuring that its outputs reflect authentic perceptions of care. Recent studies using fuzzy agent-based approaches for hospital service quality evaluation have reported comparable advantages, further supporting the relevance of this design [47].

6.2. Input variables and rationale

The PSEA relies on eight input variables reflecting multiple dimensions of patient experience within the clinic. These variables were selected through expert consensus and literature review to ensure that they represent operational, relational, and emotional aspects of care. The selected criteria are:

- Communication and Information,
- Reception and Accessibility,
- Staff Competence,
- Infrastructure and Cleanliness,
- Perceived Effectiveness of Care,
- Cost Transparency and Billing,
- Personalization and Patient Involvement,
- Intent to Return and Recommend.

The Patient Satisfaction Evaluation Agent (PSEA) was deliberately designed around service-quality dimensions that are common to most clinical settings rather than being tied to a specific department. The input variables capture widely shared aspects of patient experience. This design choice allows the fuzzy inference structure to remain applicable across different clinical units. Adaptation to local contexts can then be achieved through the recalibration of membership functions and rule parameters to account for organizational practices and patient expectations, without altering the core structure of the model.

6.3. Linguistic mapping and membership function design

Each of the eight input variables was mapped into fuzzy linguistic categories designed to reflect patient perceptions in a structured and interpretable way. Figure 2 shows the full set of membership functions defined for the fuzzy subsystem. These functions provide the foundation for translating subjective, qualitative judgments into normalized inputs that can be processed by the inference engine

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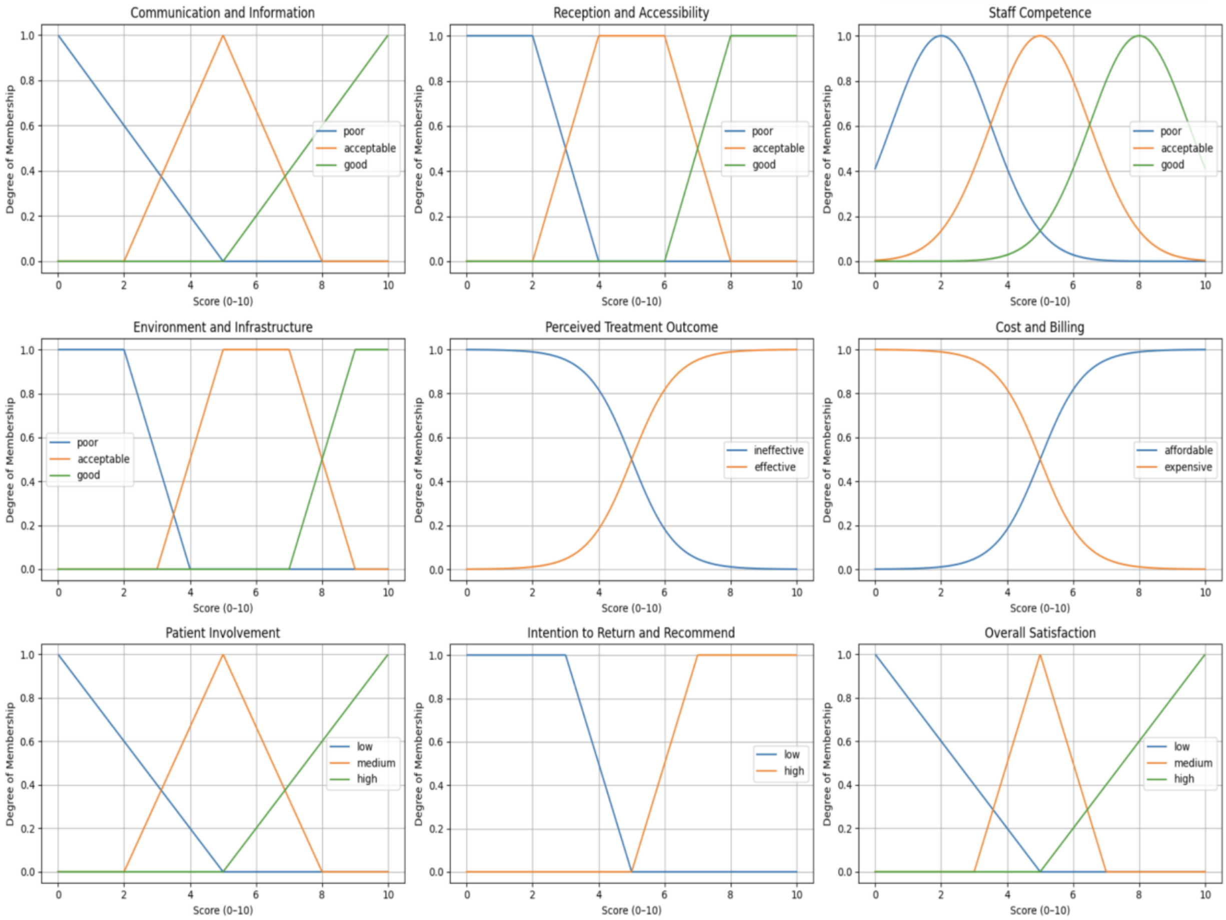

Figure 2: Membership functions for the eight input variables and the output variable

Depending on the nature of the criterion, different types of membership functions were employed, including triangular, trapezoidal, sigmoidal, and Gaussian shapes. This diversity allowed the system to capture both gradual transitions and sharper thresholds in patient evaluations. Most variables were represented with three categories, such as *poor*, *acceptable*, and *good*, while others, like billing transparency or treatment outcome, were simplified into two categories (e.g., *affordable* vs. *expensive*, *effective* vs. *ineffective*). The output variable, overall satisfaction, was modeled with three categories (*low*, *medium*, *high*) to provide a synthetic measure of patient experience on a 0–10 scale.

The output variable, overall satisfaction, was represented by three categories (*low*, *medium*, *high*), allowing the model to summarize patient experience on a scale from 0 to 10.

The general form of a membership function is expressed as:

$$\mu_A(x): X \to [0, 1] \qquad (3)$$

where $\mu_A(x)$ represents the degree of membership of x in the fuzzy set A, ranging between 0 (no membership) and 1 (full membership).

The boundaries of these linguistic categories were calibrated using responses collected through structured questionnaires. This empirical basis ensured that the fuzzy scales were not arbitrarily defined but aligned with how patients actually perceived the quality of care. For example, a high value in *Staff Competence* reflects consistently professional and reliable behavior, while a low value indicates inattentiveness or clinical errors.

6.4. Fuzzy inference mechanism and output evaluation

The core of the PSEA is a fuzzy inference system that processes the eight inputs to derive a single satisfaction score. A Mamdani-type inference system was adopted, as it supports intuitive rule construction and yields results that are easily interpretable in clinical contexts.

The rule base was constructed to capture the main patterns linking patient perceptions to overall satisfaction. Rather than listing all forty rules, two illustrative examples are given here:

- *If Communication is high and Staff Competence is high and Billing is affordable, then Satisfaction is high.*
- *If Accessibility is low and Infrastructure is poor, then Satisfaction is low.*

Formally, the degree of activation of a fuzzy rule can be expressed as:

$$\mu_R(x_1, x_2, \dots, x_n) = \min\left(\mu_{A_i}(x_i)\right)_{i=1,\dots,n} \quad (4)$$

where $\mu_{A_i}(x_i)$ denotes the membership degree of the input x_i in the fuzzy set A_1. This formulation allows the system to translate multiple linguistic conditions into a consistent fuzzy rule evaluation. In total, approximately forty rules were defined to cover the main patterns observed in patient evaluations.

Although the eight input variables could theoretically generate thousands of possible rule combinations, the system relies on about forty carefully selected rules. This reduced set was designed to capture the most clinically meaningful scenarios, combining expert insights with patient-derived data. The empirical validation showed that this compact but representative rule base was sufficient to align fuzzy-generated scores with real patient perceptions, while keeping the model both interpretable and practical.

The inference results were aggregated into an output fuzzy set and then defuzzified into a crisp satisfaction score on a 0–10 scale. For this step, the centroid method was used, defined as:

$$S = \frac{\int y\mu_B(y)dy}{\int \mu_B(y)dy} \quad (5)$$

Where $\mu_B(y)$ represents the aggregated membership function of the output variable. This method ensures that the final score provides a balanced representation of all activated rules.

To illustrate the behavior of the inference engine, fuzzy surfaces were generated. These surfaces depict how two input variables interact to influence the satisfaction outcome. The surfaces in Figure 3 demonstrate how high values in both input dimensions lead to satisfaction scores close to the maximum, whereas lowering either dimension significantly reduces the predicted outcome. These visualizations confirm that the fuzzy subsystem not only processes inputs consistently but also captures the nuanced interactions underlying patient experience.

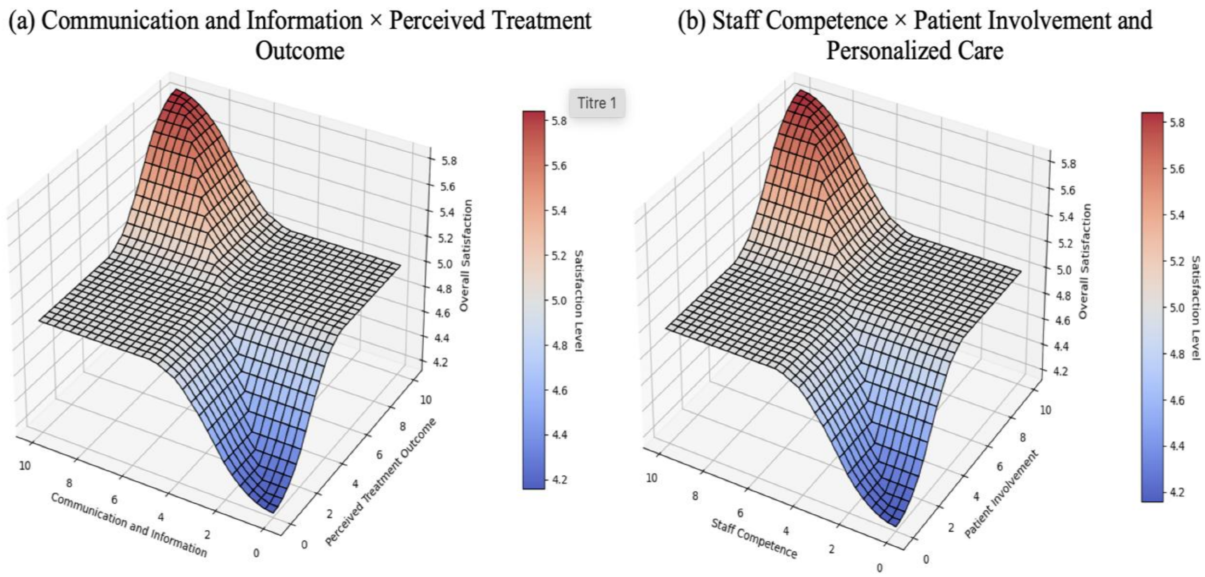

Figure 3: Representative fuzzy inference surfaces for patient satisfaction: (a) Communication and Information × Perceived Treatment Outcome and (b) Staff Competence × Patient Involvement and Personalized Care

6.5. Simulation with real patient data

To strengthen the reliability of the fuzzy subsystem, real-world data were collected through structured questionnaires administered in several hospital departments, including gynecology, dermatology, cardiology, emergency, and others. The survey covered eight core dimensions of patient experience such as communication, accessibility, staff competence, environment, treatment outcome, billing, patient involvement, and willingness to return. Overall, the mean values for these dimensions ranged from 5.8 to 6.9 on a 0–10 scale, reflecting generally positive yet heterogeneous perceptions of care.

The questionnaire used to gather patient satisfaction data was deliberately constructed to correspond to the eight input variables of the fuzzy inference system. Each item targeted a distinct aspect of patient experience and was formulated based on expert judgment, complemented by established studies on healthcare service quality. Patient responses were collected using ordinal rating scales and subsequently harmonized to ensure consistent interpretation across variables. Prior to their use for model calibration and validation, the collected responses were reviewed for completeness and internal coherence. Basic descriptive analyses were then performed to examine response distributions and to confirm that the questionnaire captured meaningful variability in patient perceptions across the clinical departments involved.

	Fuzzy-Generated Satisfaction	Patient-Reported Satisfaction
Sample Size	80	80
Mean Score	5.08	5.74
Standard Deviation	1.78	2.00
Minimum Score	2.00	1.00
Median Score	5.18	6.00
Maximum Score	8.97	10.00

Table 3: Comparative statistics of patient-reported and fuzzy-generated satisfaction scores

For each patient, two global satisfaction scores were obtained: one directly reported by the patients themselves, and another generated by the fuzzy inference system using the eight input dimensions. As shown in Table 3, both scores are closely aligned, with the fuzzy model showing a tendency to slightly smooth extreme values.

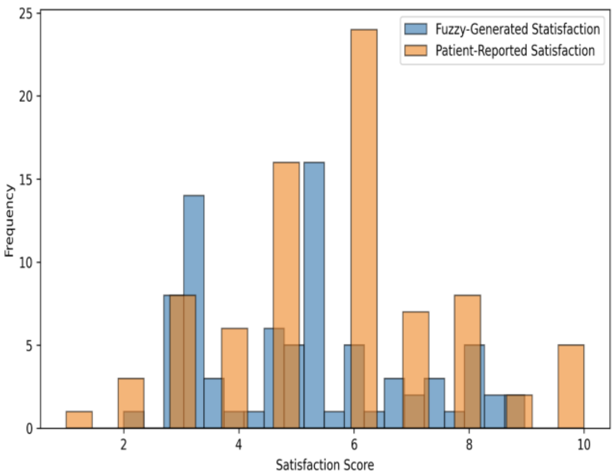

Figure 4: Comparative histograms of patient-reported and fuzzy-generated satisfaction scores

The comparative distributions, presented in Figure 4, confirm this general convergence. Patient-reported scores tend to be more dispersed, while fuzzy-generated scores appear smoother and less extreme.

Figure 5 further illustrates this relationship, highlighting a strong linear correlation between the two measures ($r = 0.76$). Prediction errors remained modest ($MAE = 1.12$, $RMSE = 1.48$), showing that the fuzzy model provides a stable approximation of actual patient perceptions.

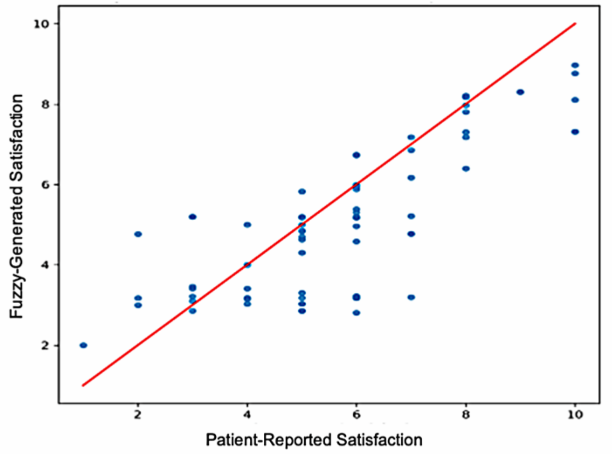

Figure 5: Relationship between fuzzy-generated and patient-reported satisfaction scores. Each point represents one patient evaluation; the solid line shows the linear trend.

Taken together, these findings demonstrate that the Patient Satisfaction Evaluation Agent (PSEA) offers a robust and empirically validated mechanism for capturing subjective perceptions of care. By grounding its inference process in real patient data, the fuzzy subsystem not only enhances interpretability but also strengthens the credibility of the overall MAS framework.

6.6. Interaction with other agents

The Patient Satisfaction Evaluation Agent (PSEA) operates as an autonomous evaluative component within the multi-agent system, responsible for synthesizing patient feedback into an interpretable satisfaction score. Validated using real patient data, this score provides a reliable assessment of perceived service quality at the end of the patient care process.

In the current implementation, the satisfaction score generated by the PSEA is recorded and made available at the system level, but it does not directly influence the behavior of other agents during the simulation. Nevertheless, the availability of this information opens several perspectives for future system extensions. For instance, satisfaction indicators could be leveraged by the Planning Agent to refine long-term strategies or resource allocation policies, by the Service Coordination Agent to inform adaptive scheduling decisions, or by the Medical Records Agent to support longitudinal analysis and continuous improvement initiatives. Similarly, the Interface Agent could exploit historical satisfaction patterns to tailor post-visit feedback mechanisms.

From this perspective, the PSEA output should be viewed as a foundational evaluative signal that enhances the interpretability of the system and provides a basis for future adaptive and learning-oriented extensions, rather than as an active driver of real-time coordination in the present study.

7 Technical implementation and simulation setup of the multi-agent system

To test the behavior of the proposed system and evaluate its performance across various clinical contexts, a dedicated simulation platform was developed. This implementation reproduces the operational dynamics of a healthcare clinic and enables the analysis of interactions among agents under different scenarios.

7.1 Tools and frameworks

The simulation was implemented in Python using the Mesa agent-based modeling framework, which provides a flexible environment for defining autonomous agents, managing discrete time steps, and simulating dynamic interactions within complex systems. Mesa was used to orchestrate agent behaviors, handle patient arrivals, and represent the evolving clinical environment over the course of the simulation.

Patient flows were generated dynamically across discrete time steps, with controlled variability introduced to reflect heterogeneous clinical demand. Service durations, routing decisions, and coordination actions were governed by agent-level behavioral rules. A limited degree of stochasticity was incorporated to avoid purely deterministic dynamics and to allow exploration of different operational configurations under comparable conditions. The resulting setup makes it possible to examine coordination mechanisms and overall system behavior under realistic yet controlled conditions, without aiming to replicate a specific clinical workflow in exact detail.

The fuzzy logic component dedicated to patient satisfaction assessment was developed using the scikit-fuzzy library. This library supports the definition of membership functions, linguistic variables, and inference mechanisms, and was integrated within the Patient Satisfaction Evaluation Agent (PSEA). The fuzzy subsystem processes subjective patient evaluations and produces an interpretable satisfaction score that complements the operational simulation of the multi-agent system.

7.2 Simulation modules

Each agent corresponds to a behavior simulated within the clinical environment. Patient admission, registration, and orientation are managed by the Admission and Orientation Agent (AOA), which also handles time-slot constraints. Coordination of clinical services and overall supervision of the care process are handled respectively by the Service Coordination Agent (SCA) and the Planning Agent (PLA), both of which are essential to workflow orchestration and conflict resolution. The clinical trajectory of each patient is modeled through specialized agents: the Prescription and Consultation Agent (PCA) oversees medical consultations, the Medical Record Agent (MRA) handles clinical documentation, the Laboratory and Radiology Agent (LRA) manages diagnostic tests, and the Medication and Product Management Agent (MPMA) dispenses treatments.

The Patient Satisfaction Evaluation Agent (PSEA) uses a fuzzy logic system to assess service quality across eight key criteria. User interaction with the system is facilitated by the User Interface Agent (UIA). While agents such as the Security and Access Agent (SAA), External Communication Agent (ECA), and Medical Intelligence Agent (MIA) do not appear in the interface, they function in the background to ensure secure communication and informed decision-making.

7.3 Simulated scenarios

To assess the adaptive behavior, coordination mechanisms, and operational robustness of the proposed multi-agent system, three representative clinical scenarios were simulated. Each scenario addresses a recurrent challenge in healthcare settings and provides a targeted perspective on system dynamics.

The first scenario focuses on patient waiting time reduction, analyzing how coordinated interactions among the User Interface Agent (UIA), the Admission and Orientation Agent (AOA), and the Planning Agent (PLA) regulate patient flow from registration to the start of clinical processing.

The second scenario examines adaptive resource allocation, evaluating the system's ability to dynamically redistribute clinical resources through coordinated decisions involving the Service Coordination Agent (SCA) and the Planning Agent (PLA) under fluctuating demand and availability.

The third scenario addresses patient satisfaction assessment, where subjective feedback is processed by the Patient Satisfaction Evaluation Agent (PSEA) using a fuzzy inference mechanism to compute a composite satisfaction score at the end of the care pathway.

Detailed operational descriptions and agent interaction logic are provided in Appendix D, while the corresponding quantitative and qualitative results are analyzed in Section 8.

7.3.1 Performance indicators

To evaluate system performance, several operational and qualitative indicators were tracked, including flow efficiency, resource usage, coordination complexity, and service quality. Table 4 summarizes these indicators and their associated agents. While all indicators were recorded, only those relevant to the scenario-specific objectives are discussed in the results section. These selected metrics allow for in-depth analysis of system performance in regulating patient flow, allocating resources, and ensuring patient satisfaction.

Table 4: Key performance indicators and responsible agents

Indicator	Description	Responsible Agent(s)
Average waiting time	Time between patient registration and first consultation	UIA, AOA, SAA, PLA
Fuzzy satisfaction score	Score derived from eight fuzzy logic criteria	UIA, PSEA, MRA
Resource utilization rate	Proportion of clinical resources actively used	SCA, MPMA, PLA
Coordination workload	Number of planning decisions and conflicts resolved	PLA, SCA
Allocation conflicts	Frequency of resource competition (e.g., room, physician)	AOA, SCA, PLA, MRA
Completed care pathways	Percentage of patients completing all treatment steps	All care-related agents

8 Simulation results analysis: global and scenario-based evaluation

This section presents a comprehensive analysis of the simulation outcomes of the proposed Multi-Agent System (MAS), which models the operations of a clinical environment. A total of 100 patients were simulated across 100-time steps, interacting with 12 specialized autonomous agents. The evaluation encompasses both the global behavior of the system under standard operating conditions and its targeted performance in the three key scenarios. Together, these analyses offer a multidimensional understanding of the system's robustness, adaptability, and overall effectiveness. The configuration of the simulation, as detailed in Table 5, delineates the principal parameters and methodological approaches employed throughout the evaluation process.

Table 5: Simulation setup and parameters

Parameter	Value / Description
Number of patients	100
Number of agents	12 specialized autonomous agents
Simulation duration	100 time steps
Key scenarios	1. Waiting Time 2. Resource Allocation 3. Satisfaction
Evaluation methods	Quantitative (Scenarios 1 & 2), Fuzzy logic (Scenario 3)

8.1 Comprehensive overview of the simulated system

This subsection examines the overall behavior of the simulated multi-agent system under standard operating conditions, ahead of the scenario-focused analyses that follow. Its purpose is to offer a general perspective on how responsibilities and coordination processes are distributed among agents as the simulation unfolds. Agent activity is therefore analyzed over time to shed light on workload dynamics and interaction patterns that reflect the internal functioning of the system. Figure 6 offers a qualitative view of how agent workloads are distributed over the course of the simulation.

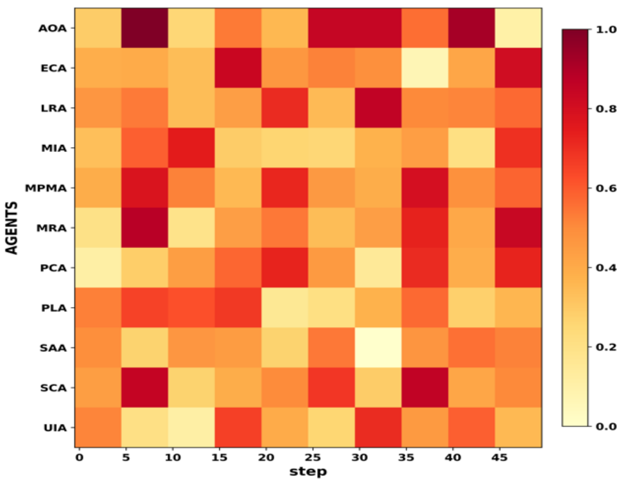

Figure 6: Agent workload heatmap

Rather than serving as a quantitative performance metric, it is intended to support the interpretation of coordination dynamics within the multi-agent system. Clear differences in activity patterns emerge depending on agent roles and the different phases of the scenario. During the early simulation steps, higher activity levels are observed for the Admission and Orientation Agent (AOA) and the User Interface Agent (UIA), which is consistent with the initial influx of patients and the associated intake and interaction processes. As patient routing becomes more stable, coordination-oriented agents such as the Planning Agent (PLA) and the Service Coordination Agent (SCA) exhibit more pronounced activity, reflecting adaptive task redistribution and ongoing resource management.

Temporary increases in workload for specific agents tend to coincide with periods of intensified coordination rather than prolonged overload. This suggests that workload peaks are primarily linked to operational adjustments required by changing conditions, rather than to systemic congestion. Overall, the heatmap illustrates the progressive evolution of agent responsibilities throughout the simulation and highlights the distributed nature of decision-making within the proposed architecture, without implying direct performance optimization.

The Patient Satisfaction Evaluation Agent (PSEA) is not shown in Figure 6, as it does not produce continuous operational activity across simulation steps. Instead, its function is confined to episodic satisfaction assessment and outcome evaluation, which are examined independently from agent workload dynamics.

8.2 Scenario 1: minimizing patient waiting times

This scenario explores how the proposed multi-agent system regulates patient flow and limits delays between arrival at the clinic and the first clinical interaction. It relies on coordinated decision-making among the Planning Agent (PLA), the Admission and Orientation Agent (AOA), the Security and Access Agent (SAA), and the User Interface Agent (UIA). Together, these agents dynamically guide patients through the system based on the current availability of resources and operational constraints.

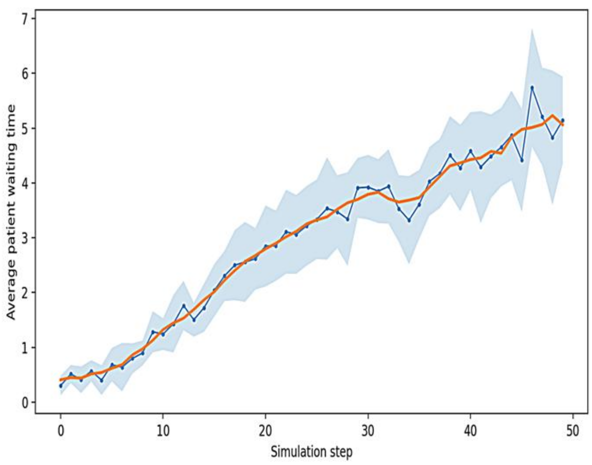

Figure 7: Evolution of average patient waiting time over simulation steps. The blue curve represents the mean waiting time per simulation step, the orange curve shows a smoothed representation of the same measure, and the shaded area indicates variability. Waiting time is expressed in simulation time units.

System behavior is evaluated through the analysis of the average patient waiting time over successive simulation steps. Waiting time is expressed in simulation time units and corresponds to the interval between a patient's arrival and the initiation of clinical processing.

As illustrated in Figure 7, waiting times are higher during the initial stages of the simulation, reflecting the early influx of patients into the system. Over time, the waiting-time curve becomes more stable, suggesting that the agents progressively adapt their coordination strategies to accommodate incoming demand. Although fluctuations persist due to the dynamic nature of arrivals and resource usage, waiting times remain within a bounded range, indicating sustained operational continuity.

Overall, these observations highlight the ability of the proposed architecture to manage patient flow in a coordinated and adaptive manner under varying load conditions. The results are intended to illustrate system behavior rather than to claim optimal performance or calibrated real-world predictions.

8.3 Scenario 2: dynamic allocation of clinical resources

This scenario evaluates the MAS's capacity to adaptively manage clinical resources, including consultation rooms, hospital beds, and medical personnel, in response to variable patient demand. It emphasizes the collaborative functioning of the Service Coordination agent (SCA) and the Planning Agent (PLA), whose shared objective is to optimize allocation while minimizing conflicts and disruptions. The principal performance indicators pertaining to the dynamics of resource allocation are consolidated in Table 6, offering a detailed quantitative perspective on the system's operational behavior amidst fluctuating clinical demands.

Metric	Value (Mean ± Std Dev)	Interpretation
Rooms used per time step	2.36 ± 1.34	Indicates moderate variability in room usage
Doctors mobilized per time step	2.32 ± 1.20	Reflects adaptive responsiveness of staffing
Reallocation decisions per time step	3.68 ± 1.79	Suggests high coordination activity
Peak simultaneous resource allocations	6	Denotes upper threshold of system capacity
Time steps without reallocation	12/100	Indicates periods of operational stability

Table 6: Summary of Key Resource Allocation Metrics

These data illustrate the MAS's ability to maintain a responsive and balanced resource allocation strategy. On average, more than two rooms and two physicians were mobilized concurrently. The standard deviations indicate that the system accommodated variability without compromising infrastructure limits. Frequent reallocation decisions (mean = 3.68) reflect proactive planning, while the 12-time steps without any reallocation signal temporary equilibrium within the clinical workflow.

Figure 8 further highlights the system's adaptive mechanisms. Room usage fluctuates between 3 and 6, often peaking at 6, indicating consistent pressure on spatial resources. Physician deployment remains relatively stable, between 3 and 4 per step, demonstrating measured staffing control. Reallocation decisions range from 0 to 3 per step, confirming the system's capacity to flexibly respond to shifts in demand without overextending its infrastructure.

Overall, the MAS exhibits a dynamic yet stable resource management approach, capable of maintaining service continuity under variable conditions.

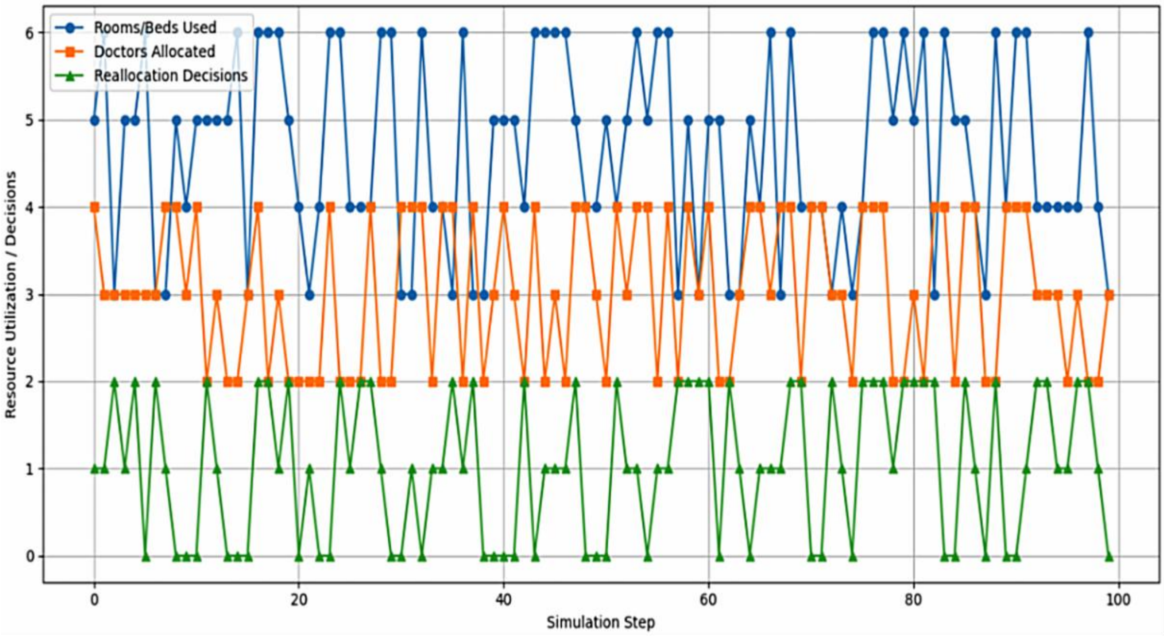

Figure 8: Dynamics of resource allocation over time

8.4 Scenario 3: assessing patient satisfaction

This scenario centers on the evaluation of perceived service quality using a fuzzy logic-based satisfaction index generated by the Patient Satisfaction Evaluation Agent (PSEA).

Patient Category	Number of Patients	Average Satisfaction Score
Consultation	32	7.84
Emergency	23	6.42
Follow-up	22	8.03
Hospitalization	23	7.02

Table 7: Patient satisfaction by category

The satisfaction score is computed at the end of each patient's clinical trajectory, based on eight key input criteria such as waiting time, reception, comfort, and perceived care outcomes. The stratification of satisfaction scores by patient category, as detailed in Table 7, provides meaningful insight into the relationship between the nature of clinical pathways and patients' perceived quality of care.

The results reveal significant variations in satisfaction across patient categories. Patients in follow-up care recorded the highest average score (8.03), likely reflecting continuity of care and familiarity with the clinical environment.

Consultation cases also scored well (7.84), suggesting strong performance in routine service delivery. Conversely, emergency patients reported the lowest satisfaction (6.42), potentially due to the urgency and unpredictability of their situations. Hospitalized patients displayed intermediate scores (7.02), but with a higher standard deviation, indicating diverse and sometimes mixed experiences.

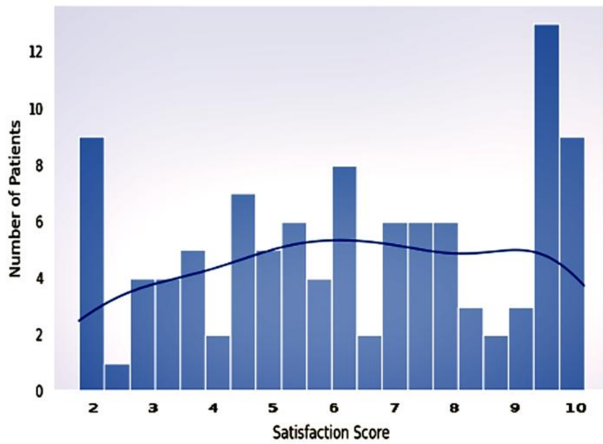

Figure 9: Distribution of patient satisfaction

Figure 9 shows a mildly left-skewed (negative) distribution of satisfaction scores. The density peaks near 9–10, with only a short tail toward lower ratings, indicating that most patients reported high satisfaction while a minority expressed dissatisfaction. The few low scores (< 4) remain important for quality improvement as potential signals of unmet expectations. Because Figure 9 is purely descriptive, it cannot be used to infer causal effects of waiting time or coordination. Nevertheless, the concentration of scores near 9–10 suggests generally high satisfaction, while the few low ratings highlight potential cases for targeted quality review.

9 Discussion

This section presents the main insights from the study, focusing on the strengths of the proposed system, its interpretability and clinical value, as well as its limitations and future perspectives.

9.1 Strengths of the proposed system

This study introduced an intelligent information system for clinic management, based on a multi-agent architecture supported by twelve specialized agents. The design captures the interdependence of clinical workflows while maintaining modularity and adaptability [10][12], qualities that are essential in healthcare settings where processes are multidimensional and constantly changing [14].

The originality of this work lies in combining a MAS for operational coordination with a fuzzy logic module dedicated to patient satisfaction assessment. Recent reviews highlight the growing importance of fuzzy logic–based CDSS (Clinical Decision Support System) in supporting healthcare decision-making [48], further underscoring the relevance of including such a module in the proposed architecture.

This integrated approach provides a unique contribution, bridging a gap in the literature where multi-agent systems for operational coordination [32] and fuzzy logic for satisfaction assessment [39] have typically been developed in isolation. Unlike most existing MAS-based clinical systems that primarily focus on operational coordination, the proposed framework explicitly integrates a patient-centered evaluative layer as a core architectural component.

In contrast with conventional clinic management approaches that often rely on static task allocation or stand-alone satisfaction surveys, the proposed framework embeds a validated patient satisfaction agent within a coordinated multi-agent architecture. In this study, such traditional approaches are considered as an implicit point of reference rather than an explicit benchmark. This qualitative comparison helps clarify the added value introduced by dynamic agent coordination and patient-centered evaluation, while remaining consistent with the study's focus on simulation-based system behavior rather than quantitative performance benchmarking against external systems.

Furthermore, the fuzzy module was validated with real data collected from several clinical departments, which ensured that the evaluation process is empirically grounded and aligned with patient perceptions. This hybrid configuration provides a unique contribution, demonstrating that the system is both operationally reliable and clinically meaningful, and offering a transferable model for broader healthcare applications. Notably, this modular design ensures transferability to diverse clinical environments, from emergency departments to long-term care facilities, by adapting specific agents while retaining the core coordination and evaluation engines.

9.2 Interpretability and clinical value

The fuzzy logic component was not conceived to rival predictive models but to complement the multi-agent system by introducing transparency and interpretability. Its main role is to capture subjective aspects of patient experience and translate them into structured indicators that can be used by other agents. Previous studies have highlighted the relevance of fuzzy logic in formalizing linguistic knowledge and expert judgment in healthcare contexts, and similar systems have already shown promising results in supporting early disease diagnosis [49][50][51].

In the proposed system, this targeted integration reinforces the MAS without diverting its operational focus. The fuzzy module ensures that patient perceptions, often difficult to quantify, are systematically incorporated into the decision-making process managed by the agents. In this way, the architecture balances automated coordination of clinical operations with an empirically validated, patient-centered assessment mechanism. Beyond its contribution to interpretability and decision support, the fuzzy-based satisfaction module also enhances the adaptability of the proposed framework, as its reliance on generic service-quality dimensions allows the model to be reused across different clinical departments through context-specific recalibration rather than structural redesign.

This hybrid configuration also enhances the system's scalability. Thanks to its modular design, the framework can be adapted to different clinical contexts, ranging from small private clinics to larger hospital settings. This ensures that the system remains not only technically reliable but also clinically meaningful, offering an interpretable bridge between patient perceptions and managerial decisions.

From a scalability perspective, the proposed system was conceived as a modular multi-agent architecture, in which agents operate autonomously while interacting through well-defined coordination mechanisms. This design allows the framework to be extended by adding or replicating agents without altering the overall system logic. Although large-scale deployments were not simulated in this study, the architecture naturally supports adaptation to larger patient volumes or more complex clinical environments, such as multi-department or multi-site settings, through incremental extension rather than structural redesign.

9.3 Limitations and future directions

Some limitations should nevertheless be noted, though they do not diminish the significance of the study.

The fuzzy satisfaction model was validated using data from 80 patients, which provides a reasonable basis for initial assessment, while broader validation on larger and more diverse datasets would further strengthen the generalizability of the results. The behavior of the multi-agent system was examined through simulation, with the objective of analyzing coordination mechanisms rather than reproducing real-world clinical operations. From this perspective, the proposed framework is best viewed as a proof of concept illustrating the feasibility and internal coherence of the approach within a controlled setting.

The agents of the MAS were designed to comprehensively represent the essential functions of clinic management, ensuring that the system captures the core processes of clinical operations in a coherent and operational way. This provides a strong foundation for simulating clinical workflows, while still allowing the flexibility needed to adapt the system to different organizational contexts [10][14][52]. This balance between completeness and adaptability makes the system both robust and scalable.

Looking ahead, future work could expand validation through broader and more diverse patient populations, integrate the architecture with electronic medical records to ground simulations in actual clinical trajectories [53], and explore cloud-based deployment to support multi-site scalability and distributed management [54]. Recent work has also pointed to human digital twins as a conceptual framework with potential relevance for future developments in personalized healthcare systems [55]. Such perspectives may inform subsequent research efforts aiming to extend agent-based approaches beyond the scope of the present study. The addition of mobile or connected interfaces (e.g., patient terminals, wearable sensors) also offers promising opportunities to increase accessibility and enable real-time intelligent coordination [56].

10 Conclusion

This study set out to design an intelligent clinical information system grounded in a multi-agent architecture and complemented by fuzzy logic. The framework was conceived to mirror the reality of clinical operations by accounting for medical, administrative, and organizational processes in an integrated way.

The system brings together twelve specialized agents, each responsible for a specific domain of activity. Within this architecture, the Patient Satisfaction Evaluation Agent (PSEA) applies fuzzy logic to capture subjective perceptions of care. Its robustness was ensured by validation with real data from several clinical departments, while the complete MAS was evaluated through simulation with the Mesa platform, reproducing realistic workflows such as admission, coordination of resources, and satisfaction monitoring.

The results show that the proposed system is capable of coordinating complex processes, maintaining service continuity, and adapting to changing conditions. By embedding a validated fuzzy subsystem into a distributed agent-based model, the framework demonstrates both reliability and flexibility, qualities that are essential for modern clinical environments.

Looking ahead, further work will involve testing the MAS with real operational data, extending the architecture to cloud environments for multi-site deployment, and enriching it with additional AI modules for advanced decision support. Aligning the system with interoperability standards such as HL7 and FHIR will also be an important step toward seamless integration into digital health ecosystems.

In short, this study highlights the relevance of combining multi-agent systems with fuzzy logic to address the complexity of clinical management. It provides not only a proof of concept but also a foundation for future developments in intelligent and patient-centered healthcare.

Ethics statement

This study did not involve clinical interventions, medical procedures, or experiments conducted on patients. The patient satisfaction data used to validate the fuzzy evaluation model were collected through voluntary questionnaires and processed in an anonymized manner. No personally identifiable information was accessed, stored, or disclosed at any stage of the research.
The evaluation of the multi-agent system was performed exclusively through simulation-based experiments using synthetic interactions generated within a controlled computational environment. In view of the non-interventional nature of the study, the use of anonymized data, and the absence of any risk to participants, formal ethical approval was not required.

Data and code availability

The Python code developed for the agent-based simulation, implemented using the Mesa framework, as well as the fuzzy logic system implemented with the scikit-fuzzy library, is openly available in a public GitHub repository at: *https://github.com/amadoudiabagate/mas-fuzzy-simulation*
Due to privacy and ethical considerations related to patient data, the raw questionnaire responses used to validate the fuzzy satisfaction model cannot be publicly shared. However, anonymized and aggregated data supporting the findings of this study may be made available by the corresponding author upon reasonable request, in accordance with applicable data protection regulations.

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Appendix A – Fuzzy rule base and additional decision surfaces

A.1 Complete fuzzy rule base

This appendix reports the complete set of fuzzy inference rules used by the Patient Satisfaction Evaluation Agent (PSEA). The rule base consists of forty expert-defined rules that map combinations of patient-related service quality indicators to an overall satisfaction score.

The rules are expressed using linguistic variables associated with the eight input dimensions described in Section 6.4, namely: Communication and Information, Reception and Accessibility, Staff Competence, Environment and Infrastructure, Perceived Treatment Outcome, Cost and Billing, Patient Involvement, and Intention to Return and Recommend. The output variable corresponds to Overall Satisfaction.

All rules were implemented using a Mamdani-type fuzzy inference mechanism. While only a limited subset of representative rules is discussed in the main text for readability purposes, the full rule base is provided here to ensure transparency and reproducibility of the proposed fuzzy evaluation model. Each rule follows the general structure:

IF (combination of linguistic conditions on input variables) THEN Overall Satisfaction is {Low, Medium, High}.

Table A1: lists the complete set of forty rules.

Rule	IF Clause (Predicates)	THEN Satisfaction
R1	IF Communication and Information is good AND Perceived Treatment Outcome is effective AND Reception and Accessibility is good	High
R2	IF Patient Involvement is high AND Communication and Information is good	High
R3	IF Intention to Return and Recommend is high AND Environment and Infrastructure is good	High
R4	IF Communication and Information is good AND Cost and Billing is affordable AND Perceived Treatment Outcome is effective	High
R5	IF Staff Competence is good AND Reception and Accessibility is acceptable	High
R6	IF Environment and Infrastructure is good AND Perceived Treatment Outcome is effective	High
R7	IF Communication and Information is good AND Patient Involvement is high AND Intention to Return and Recommend is high	High
R8	IF Intention to Return and Recommend is high AND Cost and Billing is affordable AND Perceived Treatment Outcome is effective	High
R9	IF Communication and Information is acceptable AND Perceived Treatment Outcome is effective AND Patient Involvement is high	High
R10	IF Communication and Information is good AND Environment and Infrastructure is good	High
R11	IF Intention to Return and Recommend is high AND Patient Involvement is high	High
R12	IF Staff Competence is good AND Perceived Treatment Outcome is effective AND Communication and Information is acceptable	High
R13	IF Communication and Information is good AND Staff Competence is good AND Cost and Billing is affordable	High
R14	IF Communication and Information is acceptable AND Perceived Treatment Outcome is ineffective	Medium
R15	IF Reception and Accessibility is acceptable AND Perceived Treatment Outcome is ineffective	Medium
R16	IF Cost and Billing is affordable AND Communication and Information is acceptable	Medium
R17	IF Patient Involvement is medium AND Staff Competence is acceptable	Medium
R18	IF Environment and Infrastructure is acceptable AND Cost and Billing is affordable	Medium
R19	IF Staff Competence is acceptable AND Intention to Return and Recommend is high	Medium
R20	IF Communication and Information is acceptable AND Patient Involvement is medium AND Perceived Treatment Outcome is ineffective	Medium
R21	IF Reception and Accessibility is acceptable AND Intention to Return and Recommend is high	Medium
R22	IF Communication and Information is acceptable AND Cost and Billing is expensive	Medium
R23	IF Reception and Accessibility is good AND Perceived Treatment Outcome is ineffective	Medium
R24	IF Environment and Infrastructure is good AND Cost and Billing is expensive	Medium
R25	IF Patient Involvement is high AND Perceived Treatment Outcome is ineffective	Medium
R26	IF Communication and Information is poor OR Perceived Treatment Outcome is ineffective	Low

R27	IF Environment and Infrastructure is poor AND Reception and Accessibility is poor	Low
R28	IF Cost and Billing is expensive AND Perceived Treatment Outcome is ineffective	Low
R29	IF Communication and Information is poor AND Reception and Accessibility is poor AND Cost and Billing is expensive	Low
R30	IF Intention to Return and Recommend is low OR Environment and Infrastructure is poor	Low
R31	IF Patient Involvement is low AND Reception and Accessibility is poor	Low
R32	IF Communication and Information is poor AND Environment and Infrastructure is poor	Low
R33	IF Communication and Information is poor AND Cost and Billing is expensive	Low
R34	IF Perceived Treatment Outcome is ineffective AND Intention to Return and Recommend is low	Low
R35	IF Patient Involvement is low AND Perceived Treatment Outcome is ineffective	Low
R36	IF Cost and Billing is expensive AND Reception and Accessibility is poor	Low
R37	IF Communication and Information is poor AND Patient Involvement is low	Low
R38	IF Intention to Return and Recommend is low AND Cost and Billing is expensive	Low
R39	IF Reception and Accessibility is poor AND Perceived Treatment Outcome is ineffective	Low
R40	IF Environment and Infrastructure is poor AND Cost and Billing is expensive	Low

Table A1. Expert-Defined Fuzzy Rules Applied in the Proposed Patient Satisfaction Evaluation System

A.2 Additional decision surfaces

To complement the decision surfaces discussed in the main text, this appendix presents three additional input–output mappings that illustrate the behavior of the fuzzy inference system under alternative configurations of input variables. These surfaces were selected to reflect organizational, relational, and behavioral dimensions of patient experience, while avoiding redundancy with the combinations already analyzed.

Each surface depicts the variation of the Overall Satisfaction score as a function of two input variables, with all remaining inputs fixed at representative intermediate levels. The purpose is to provide qualitative insight into the aggregation mechanisms of the fuzzy rule base rather than to perform a quantitative sensitivity analysis.

Figure A1 illustrates a fuzzy inference variation surface where access conditions and infrastructural quality jointly shape patient satisfaction. When both dimensions are favorably assessed, satisfaction levels rise accordingly, whereas shortcomings in either access or infrastructure are reflected in lower satisfaction outcomes. Figure A2 presents a related variation surface highlighting the interplay between professional competence and organizational accessibility. It suggests that strong staff competence can partly mitigate moderate access constraints, while inadequate reception conditions tend to undermine satisfaction even in the presence of acceptable clinical competence. Finally, Figure A3 portrays a variation surface linking economic perception and patient loyalty, where satisfaction improves when reasonable billing aligns with a strong intention to return and recommend the service, and declines when unfavorable cost perceptions coincide with weak loyalty expectations.

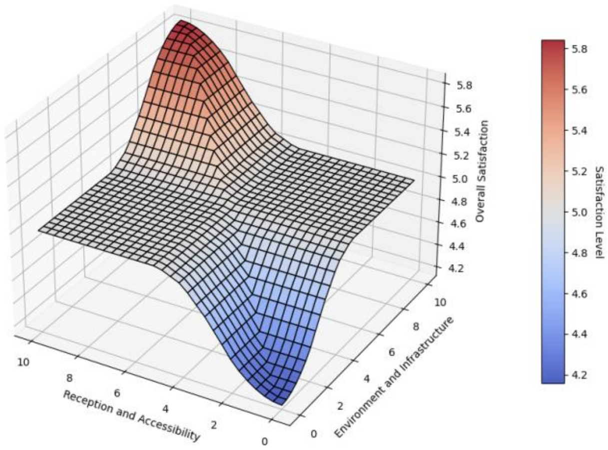

Figure A1: Fuzzy inference surface relating (Reception and Accessibility) and (Environment and Infrastructure) to overall patient satisfaction.

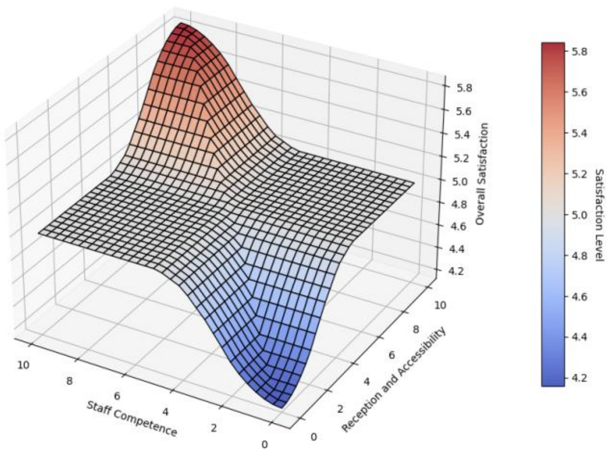

Figure A2: Fuzzy inference surface relating (Staff Competence) and (Reception and Accessibility) to overall patient satisfaction

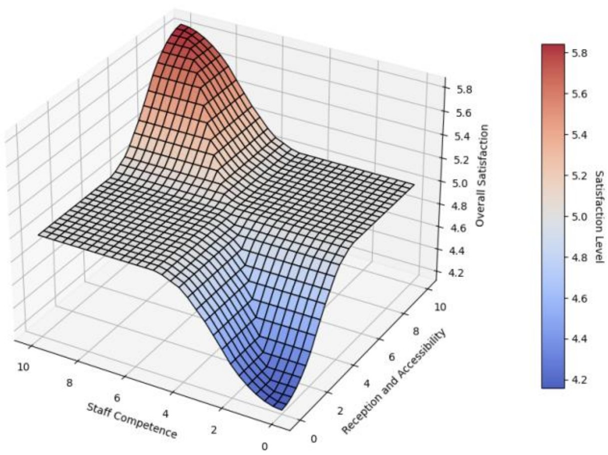

Figure A2: Fuzzy inference surface relating **(**Intention to Return and Recommend) and (Cost and Billing) to overall patient satisfaction

Together, these additional decision surfaces provide complementary perspectives on the nonlinear relationships encoded in the fuzzy rule base and contribute to a clearer understanding of the model's input–output behavior.

APPENDIX B: Evaluation metrics

This appendix summarizes the evaluation metrics used to assess the consistency between the satisfaction scores generated by the Patient Satisfaction Evaluation Agent (PSEA) and the
satisfaction levels reported by patients. To maintain readability in the main body of the paper, only high-level descriptions of these metrics are provided there, while their formal definitions are presented in this appendix.

B.1 Mean absolute error (MAE)

The Mean Absolute Error quantifies the average absolute difference between the fuzzy-generated satisfaction scores and the corresponding patient-reported values. It is computed as:

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|y_i - \hat{y}_i|$$

Where y_i denotes the satisfaction score reported by patient $i, \hat{y}_i$ represents the satisfaction score produced by the fuzzy inference system, and N is the total number of evoluted observation.
This metric provides a straightforward and interpretable measure of the typical deviation between estimated and reported satisfaction scores, expressed on the same scale as the original data.

B.2 Root mean squared error (RMSE)

The Root Mean Squared Error complements the MAE by assigning greater weight to larger deviations between predicted and reported satisfaction values. It is defined as:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}$$

Because squared errors are averaged before taking the square root, RMSE is particularly sensitive to larger discrepancies, making it useful for identifying cases where the fuzzy model deviates more substantially from patient-reported assessments.

B.3 Pearson correlation coefficient

In addition to error-based metrics, the Pearson correlation coefficient was used to examine the degree of linear association between fuzzy-generated satisfaction scores and patient-reported values. It is computed as:

$$r = \frac{\sum_{i=1}^{N}(y_i - \bar{y})(\hat{y}_i - \bar{\hat{y}})}{\sqrt{\sum_{i=1}^{N}(y_i - \bar{y})^2}\sqrt{\sum_{i=1}^{N}(\hat{y}_i - \bar{\hat{y}})^2}}$$

Where $\bar{y}$ and $\bar{\hat{y}}$ denote the mean value of the patient-repoted and fuzzy-génératif satisfaction scores, respectively
This coefficient captures the extent to which variations in the fuzzy-generated scores align with variations in patient-reported satisfaction, without implying any causal relationship.

B.4 Scope of interpretation

The metrics reported in this appendix are intended to provide an empirical characterization of the coherence between the fuzzy satisfaction model and patient-reported evaluations. They are not used to claim predictive optimality or statistical generalization beyond the studied sample, but rather to support a validation of consistency within the proposed framework

Appendix C – Inter-agent communication examples (ACL-Style)

This appendix complements Section 5 by illustrating representative inter-agent communication mechanisms implemented in the simulation. The system is developed within a Mesa-based discrete-time environment, where interactions are not handled through a dedicated networked messaging middleware, but rather through event-driven exchanges mediated by shared coordination structures such as service queues, agent states, and lightweight logging mechanisms.
For clarity and reproducibility, these interactions are described using an ACL-style abstraction, specifying the sender, receiver, performative, message content, and expected operational effect. This representation reflects the effective communication logic implemented by the agents while remaining consistent with the underlying simulation framework.

C.1 Communication principles

Inter-agent coordination follows an event-oriented communication pattern. Messages are triggered when agents detect relevant state changes, such as patient arrival, completion of a processing step, or the need for coordination adjustments. In practice, communication is realized through a combination of (i) updates to patient attributes (e.g., status, assigned service), (ii) transfers of patient entities between service queues, and (iii) the recording of traceable events in agent-level or model-level logs.
This design choice ensures lightweight and transparent communication while remaining well aligned with the discrete-step nature of the simulation. Rather than emphasizing protocol complexity, the approach focuses on preserving interpretability and reproducibility of coordination behavior within the multi-agent system.

C.2 Representative message types

Table C1 summarizes representative ACL-style messages used to support patient routing, service allocation, and satisfaction assessment. Performative labels are introduced for conceptual readability (inform, request, propose, confirm, alert), while the actual implementation relies on explicit state updates and queue operations consistent with the simulation model.

Table C1: Representative ACL-style inter-agent messages used in the simulation

Sender Agent	**Receiver Agent**	**Perfor-mative**	**Message content (illustrative)**	**Operational effect in the simulation**
User Interface Agent (UIA)	Security and Access Agent (SAA)	inform	New patient registered: patient identifier, category, basic information	Patient entity is created and made available for security screening.
Security and Access Agent (SAA)	Admission and Orientation Agent (AOA)	confirm	Security check completed: patient identifier, access status	Patient is forwarded to the admission and orientation workflow.
Admission and Orientation Agent (AOA)	Service Coordina-tion Agent (SCA)	inform	Triage outcome: patient identifier, assigned service, priority level	Patient is placed into the appropriate routing queue.
Service Coordina-tion Agent (SCA)	Prescription and Consulta-tion Agent (PCA)	request	Consultation scheduling request: patient identifier, service, priority	Patient is transferred to the consultation queue subject to capacity constraints.
Planning Agent (PLA)	Service Coordina-tion Agent (SCA)	propose	Coordination policy update: reprioritization or resource adjustment	High-level guidance is recorded and reflected in subsequent routing decisions.
Prescription and Consulta-tion Agent (PCA)	Medical Record Agent (MRA)	inform	Clinical outcome available: patient identifier, summary	Patient record is updated through a traceable medical entry.
Prescription and Consulta-tion Agent (PCA)	Patient Satisfaction Evaluation Agent (PSEA)	request	Satisfaction evaluation request: patient identifier, questionnaire-derived inputs	Satisfaction input vector is registered for fuzzy inference.
Patient Satisfaction Evaluation Agent (PSEA)	Medical Record Agent (MRA)	inform	Satisfaction score produced: patient identifier, score (0–10 scale)	Satisfaction outcome is stored alongside the clinical record.
External Communica-tion Agent (ECA)	User Interface Agent (UIA)	inform	Patient-facing notification: appointment or follow-up information	Communication event is logged, supporting end-to-end workflow completeness.
Medical Intelligence Agent (MIA)	Planning Agent (PLA)	alert	Resource or risk signal: congestion indicator, anomaly, recommendation	Strategic awareness is enhanced and may influence planning decisions.

APPENDIX D Detailed Description of the Simulated Scenarios

This appendix provides additional details on the simulation scenarios presented in the main body of the paper. It complements the core analysis by further clarifying agent interactions, coordination mechanisms, and execution flow, without introducing new experiments or altering the interpretation of the reported results.

D.1 Reducing patient waiting time

This scenario examines the system's capacity to reduce the time interval between a patient's registration and their initial medical consultation, a critical quality indicator in clinical operations. The scenario involves coordinated interactions among three key agents:

- The User Interface Agent (UIA), which captures patient information upon arrival;
- The Admission and Orientation Agent (AOA), responsible for triaging and directing patients to appropriate services;
- The Service Coordination Agent (SCA), which ensures smooth distribution of patient flow across available resources in real time.

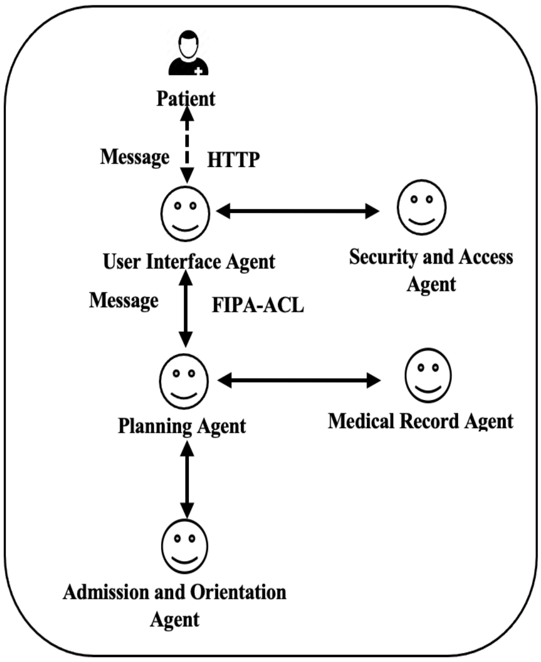

Figure D1: Communication Flow of Agents during the Waiting Time Minimization Scenario

These agents collaboratively allocate time slots and resources dynamically, accounting for workload fluctuations and service availability. The goal is to prevent bottlenecks and maintain service continuity, particularly during periods of high patient influx. The underlying communication dynamics that enable this coordinated process are visually represented in Figure D1, which delineates the structured interplay among the relevant agents engaged in the execution of the patient waiting time reduction scenario.

Beyond average workload trends, the system demonstrates an adaptive response to sudden changes in patient arrivals through coordinated agent interactions rather than predefined reaction rules. The Service Coordination Agent (SCA) and the Planning Agent (PLA) adjust resource allocation priorities in response to local congestion, while the Admission and Orientation Agent (AOA) and the User Interface Agent (UIA) regulate patient flow by dynamically managing admission sequencing and interaction timing.

Through incremental, distributed reallocation decisions, the system absorbs temporary demand peaks and progressively restores operational balance without centralized control. These mechanisms reflect general coordination principles embedded in the multi-agent architecture.

D.2 Managing adaptive resource allocation

This scenario tests the system's ability to respond dynamically to unexpected variations in resource availability such as limited consultation rooms, absent staff, or equipment shortages. In this context, the following agents are primarily involved:

- The Service Coordination Agent (SCA), which detects imbalances and redistributes workloads across service units;
- The Planning Agent (PLA), which supervises the overall distribution strategy and reallocates resources according to emerging priorities.

D.3 Assessing patient satisfaction through fuzzy logic

In this scenario, the system evaluates patient satisfaction at the conclusion of each care episode, integrating subjective feedback into its quality monitoring processes. After completing their care journey, patients are prompted, via the User Interface Agent (UIA), to respond to the questionnaire.

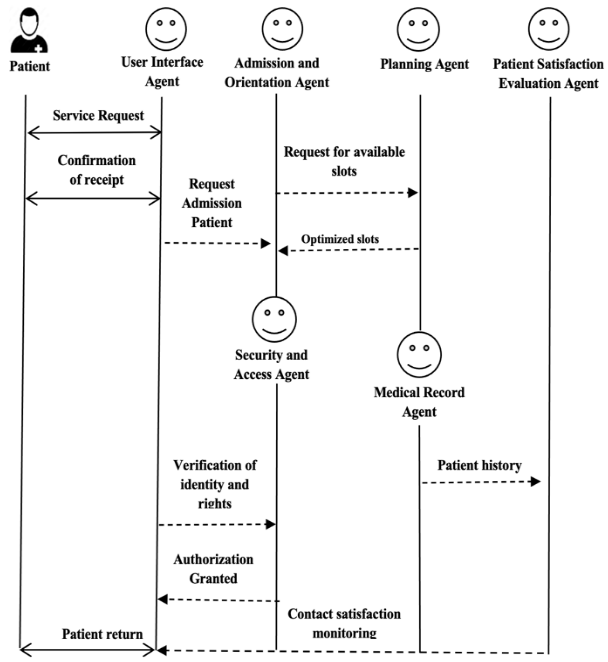

Figure D2: Sequence Diagram for the Patient Satisfaction Evaluation Process

The Patient Satisfaction Evaluation Agent (PSEA) processes these inputs using a fuzzy logic inference system, converting linguistic responses into a composite satisfaction score on a normalized scale. This output is then stored by the Medical Record Agent (MRA) for longitudinal analysis and institutional reporting. This mechanism provides a nuanced and data-driven perspective on service quality from the patient's standpoint. The sequential interactions facilitating the satisfaction assessment process are depicted in Figure D2.