CME LIVE OPEN ACCESS

International Journal of Clinical & Medical Surgery

Research Article

A Systematic Review of Multi-Agent Systems (MAS) in Healthcare: Applications, Challenges, and Strategic Approaches for Enhancing Clinical and Operational Outcomes.

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Received: 2025 May 30 **Accepted:** 2025 June 18 **Published:** 2025 June 27

Abstract

Purpose: *To systematically review the roles, applications, challenges, and effectiveness of multi-agent systems (MAS) in healthcare, focusing on their impact on disease diagnosis, patient monitoring, hospital resource allocation, and personalised treatment.*

Methods: *This systematic review follow the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) methodology. An extensive search of the main electronic databases including PubMed, IEEE Xplore, Scopus, Web of Science, and Embase was conducted for articles from the year 2015 to 2025. Key search terms included "Multi-Agent Systems in healthcare", "MAS applications", and "AI healthcare implementation". After removal of duplicates, screening, and quality assessment, selected peer-reviewed articles that addressed MAS adoption, benefits, and barriers in healthcare settings were included.*

Results: *The review identified significant evidence that MAS improves early disease diagnosis by up to 30%, reduces adverse drug events by 26%, and optimizes hospital resource allocation by reducing patient wait times by 30%. MAS-driven, personalised treatment approaches demonstrated a predicted 45% return on investment in drug discovery. Key challenges include data interoperability, privacy concerns, regulatory compliance, algorithmic bias, and high implementation costs. Proposed solutions to these challenges include enhanced data integration, privacy-by-design frameworks, blockchain technology, federated learning, and clinician-cantered training programs. However, the efficacy of MAS varies due to heterogeneity in study designs, healthcare environments, and technological frameworks.*

Conclusion: *Multi-agent systems hold substantial promise for transforming healthcare delivery by improving diagnostic accuracy, operational efficiency, and personalised care. Addressing technical, ethical, and regulatory challenges through standardised frameworks and interdisciplinary collaborations is crucial for their widespread and equitable adoption. Further large-scale, standardised research is recommended to optimize MAS implementation and validate long-term outcomes.*

Keywords: Multi-Agent Systems, Healthcare, Artificial Intelligence, Patient Monitoring, Resource Allocation, Personalized Treatment

1. Introduction

The integration of Artificial Intelligence (AI) in healthcare has revolutionized the delivery of medical services, with subsequent improvement in diagnosis, treatment, and patient management [1]. Of the different AI techniques, Multi-Agent Systems (MAS) have gained increasing popularity since they can handle complex, dynamic, and decentralized systems in healthcare settings [1]. A Multi-Agent AI system consists of many autonomous agents that cooperate in problem-solving and achieving common goals. These agents are able to interact, collaborate, and negotiate amongst themselves in ways that mimic human-like cooperation and decision-making processes [2]. The importance of the integration of MAS in healthcare is due to increasing health care complexity, large amounts of patient data, and the need for individualized care and efficiency [3]. Traditional AI systems are unable to tackle these because they are monolithic challenges and centralized. In contrast, MAS are designed to function in distributed and adaptive environments and, as such, are suitable for use in healthcare in disease diagnosis, patient monitoring, drug discovery, and personalised treatment [4]. For instance, a MAS may consist of diagnostic agents, treatment agents, and monitoring agents operating in collaboration with one another to provide an integrated healthcare solution [5]. There have been some recent researches that have revealed the effect of MAS in the aspect of improving health outcomes. For example, multi-Agent systems have been used in management of chronic disease like diabetes. The agents collect and process the patients' data, provide real-time feedback, and adjust treatment plans accordingly [6]. Similarly, MAS have also been applied in hospital management systems for improved resource allocation, reducing the waiting time of patients, and maximizing overall operational effectiveness [7]. However, there are continuous debates regarding the reliability, security, and ethical impacts of using autonomous agents within health care, with regard to data privacy, responsibility, and transparency in decisions [7,8]. The aim of the paper is to discover the status of Multi-Agent AI systems in healthcare in the present day, their applications, and the challenges associated with their implementation. The research presents a comprehensive overview of how MAS are transforming healthcare delivery, with the benefits and limitations. The principal conclusion is that while MAS hold tremendous promise to improve health outcomes and efficiency, further research is needed to address technical, ethical, and regulatory challenges to facilitate their safe and effective implementation into clinical practice. Regulatory challenges to ensure their safe and effective deployment in clinical practice.

1.1. Purpose of the Study

The purpose of this study to systematically analyze roles, applications, challenges, and the effectiveness of MAS in healthcare, with a particular emphasis on disease diagnosis, patient monitoring, hospital resource allocation, and personalized treatment. By combining a mixed-methods approach, the study intends to achieve an in-depth understanding of how Multi-Agent AI systems can contribute to fostering healthcare delivery, operational efficiency, and better patient outcomes. The study then further investigates inhibiting factors limiting these systems' full integration into clinical practice, thereby finding alternative approaches to address them.

1.2. General Objective

To assess how well Multi-Agent AI systems, work in health delivery with regard to disease diagnosis, hospital resource allocation, and treatment personalization. Barriers to its full implementation shall be studied, along with ways to surmount these barriers.

1.3. Specific Objectives

- To determine how Multi-Agent AI systems, aid in the diagnosis of diseases and patient monitoring, along with the contribution of the system to early diagnosis and real-time patient monitoring.
- To analyse how Multi-Agent AI systems maximize hospital resource utilization, with special emphasis on patient triage, personalize management, and enhancing operational efficiency in the hospital environment.
- To investigate the use of Multi-Agent AI systems in personalized medicine by comparing the way agents collaborate to offer personalized treatment to patients based on their individual information.
- To determine the key barriers and challenges to healthcare utilization of Multi-Agent AI systems, including data privacy concerns, system interoperability, and ethics.
- To identify solutions to counteract such obstacles and facilitate the smooth integration of Multi-Agent AI systems into clinical and operational settings

1.4. Literature Review

1.5. Applications of Multi-Agent System in Healthcare

The use of Multi-Agent Systems (MAS) have increasingly been embraced in healthcare due to their ability to handle complex, distributed decision-making. The following are the key adoption trends from recent literatures.

1.6. AI-Driven Diagnostics and Treatment Optimisation Using Multi-Agent Systems (MAS)

Applying Multi-Agent Systems (MAS) to perform AI-Driven diagnostics and treatment optimization has greatly advanced precision medicine. By integrating radiology, pathology, and genomic data agents, MAS enhances diagnostic accuracy through collaborative analysis. According to a study by, cross-validation between radiology and pathology with the use of MAS enhanced the early detection rates of Breast cancer by up to 30% [9]. The technique minimizes diagnostic errors through allowing AI agents to experience-share and enhance interpretations together, thus more accurate clinical decisions. MAS enables adaptive treatment strategies in personalized medicine by dynamic adjustment of therapies based on real-time patient data. The research proved that MAS-driven dosing systems reduce the ADE -related readmissions by 26%, signifying their potential to improve the efficacy of treatment while minimizing risks [10]. These systems continuously monitor biomarkers and treatment response, allowing for rapid alteration of therapeutic regimens based on patient-specific needs.

1.7. Optimising Hospital Operations: The Transformative Role of Multi-Agent Systems in Resource Management

The integration of Multi-Agent Systems (MAS) in hospital management has improved the efficiency of operations via smart scheduling and automated supply chains. Recent studies highlight the ways in which these AI-driven methods are transforming healthcare delivery through optimisation of resource allocation, elimination of systemic wastage and cost

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reduction [11]. In the domain of smart scheduling, agent-based systems have proven effective particularly in solving the complex challenges of patient flow management. Demonstrated that MAS scheduling implementation in a major U.S. hospital network resulted in reducing patient waiting times by 30% while simultaneously improving staff utilisation rates [4-12]. The ability of the system to dynamically adjust to real-time variables such as emergency cases, availability of staff, and equipment requirements is an improvement over traditional static scheduling method. further demonstrated in their research that these systems employ predictive analytics to predict patient inflow patterns to enable proactive resource allocation that maintains quality of service during peak demand periods [13-38]. These technological developments are particularly timely given the growing financial pressures on healthcare systems worldwide. COVID-19 pandemic shows the important value of efficient resource management in medical facilities, where those facilities that made use of MAS technologies were healthier against supply chain ruptures [14]. However, researchers put out a notice that successful implementation of MAS should consider system compatibility and staff training [15]. The increasing evidence suggests that MAS technologies are increasingly important in the management of healthcare. Future research directions include developing more sophisticated predictive algorithms and using blockchain technology to improve supply chain transparency. As healthcare systems face challenges of rising costs and increasing demand, AI-driven management solutions offer a promising pathway to sustainable, high-quality care delivery [16–18].

1.8. AI-Enhanced Drug Discovery and Clinical Trials through Multi-Agent Systems

Pharmaceutical Research Industry is witnessing a paradigm shift with the application of Multi-Agent Systems (MAS), particularly drug discovery and optimisation of clinical trials. Latest advancements reveal the manner in which decentralized AI systems are reducing the time-consuming and capital-intensive drug development process [19–21]. In drug discovery and repurposing, MAS has been highly successful by replicating complex molecular interactions to unprecedented levels. A 2020 prediction analysis showed that substantial investment in AI might yield an investment return gain of 45% for the pharmaceutical industry [22]. These systems use distributed computing systems where specialized agents simultaneously analyse thousands of potential molecular interactions to identify potential drug candidates more precisely. MAS approaches could identify novel drug-target interactions, useful in particular for identifying repurposing possibilities for already commercialized compounds [23]. In medicine, multi-agent systems improve real-time patient monitoring, resource allocation, and treatment strategies specific to the patient. The agents collaborate to monitor the patient's health in real-time, distribute resources such as medical personnel and equipment, and create personalized treatment plans based on patient-specific data. The system enables uninterrupted communication between patients and healthcare providers, enhances decision-making, and optimizes resource utilization. Through data integration and action coordination, MAS enhances patient outcomes and optimizes healthcare resource management. Multiagent system incorporate natural language processing and federated learning techniques achieved patient-trial matching efficiency [25]. These systems analyse electronic health records from multiple institutions without violating patient confidentiality through advanced cryptography techniques. The decentralized MAS model has particular advantages in global clinical research. In a multinational study by the World Health Organization's digital health initiative, MAS-enabled trial networks could reduce inter-site variability in patient recruitment compared to traditional centralized systems [26,27]. Recruitment strategies can be adjusted in real time through demographic and epidemiological data streams at the participating sites. Even with these advancements, challenges persist in the widespread adoption of MAS within pharmaceutical research. regulatory frameworks struggle to keep up with these technological developments, most notably in validation standards of AI-generated drug candidates [28]. Moreover, the computational resource requirements of MAS implementations on large scales pose infrastructure challenges for some research centers. The integration of MAS with upcoming technologies like quantum computing and blockchain-based data sharing promises to further revolutionized drug discovery. Preliminary studies suggest that these combinations have the potential to allow real-time molecular simulation at atomic-level precision with assured data integrity across research networks [29]. As the pharmaceutical industry faces increasing pressure to reduce development timelines while keeping costs under control, MAS technologies offer an available platform for efficient and effective therapeutic development.

1.9. Pandemic Management through Multi-Agent Systems: Lessons from COVID-19

The pandemic of COVID-19 was the driving force for using Multi-Agent Systems (MAS) in responding to public health emergencies, highlighting their potential for transforming pandemic response with distributed intelligence and real-time coordination. Peer-reviewed studies document evidence on how MAS systems addressed difficult challenges across multiple domains of the pandemic response [4]. Resource allocation throughout the pandemic was particularly facilitated by MAS implementations [30]. The MAS approach enabled dynamic rebalancing of resources in response to real-time patient flow predictions and supply chain monitoring, with specialized agents negotiating transfers between facilities while considering equipment compatibility and transportation constraints. Vaccine distribution presented a complex challenge and MAS was able to counteract it [30]. MAS-optimized vaccine allocation strategies improved the use of doses and reduced wastage of vaccine relative to population-based allocation models [31]. The system incorporated real-time data on local infection rates, vulnerable population densities, and cold chain capacity through coordinated agents representing public health units, logistics providers, and healthcare facilities. The system used anonymized encounter tokens processed by local agents, triggering central coordination only when transmission patterns exceeded threshold parameters [32–34]. The pandemic, however, also highlighted some implementation challenges. According to

WHO Digital Health Technical Advisory Group (2023) multinational evaluation quoted interoperability problems with different MAS implementations as the greatest limitation in addition, the rate at which the pandemic evolved sometimes outpaced the adaptive capabilities of MAS settings, particularly when facing novel variants with highly different transmission characteristics [35,36]. The COVID-19 experience catalyzed the development of more resilient MAS frameworks for pandemic preparedness. Recently suggested a next-generation MAS system that utilizes evolutionary algorithms that automatically adapt agent coordination protocols to responding to evolving pathogen properties and population immunity levels [37,38].

1.10. Principal Challenges in MAS Implementation

Ethical and Regulatory Challenges to Multi-Agent Healthcare Systems: Overcoming Challenges of Data Privacy Deployment of Multi-Agent AI systems in the healthcare industry raises significant ethical and regulatory concerns, especially concerning data protection and patient confidentiality. AI technologies need robust privacy safeguards to build public trust in healthcare systems [8]. As the authors point out, while such technologies enable advanced analytics and care coordination, they also create novel risks of unauthorised use and data misuse. Telemedicine applications which are now widely used in underserved communities, illustrate both the advantages and dangers of distributed healthcare technologies. Nittari et al's review highlights how the rapid adoption of telemedicine during the COVID-19 pandemic revealed essential gaps in legal and ethical frameworks for remote care delivery [39]. Their report reveals that while cloud-based storage facilitates specialist consulting and care planning, it introduces complex challenges in maintaining data security across multiple jurisdictions with varying privacy regulations. The Multi-Agent System technical architecture compounds these privacy concerns. Telemedicine systems utilising AI-based diagnostic support require continual data exchange across multiple specialist agents, each responsible for a different aspect of patient data [40]. The distributed processing creates a variety of potential weaknesses, particularly when data transmission occurs across public networks or between healthcare organisations that employ different levels of security measures [41]. Regulatory bodies have begun to respond to these challenges. The World Health Organization's 2023 guidelines on AI in healthcare emphasizes the need for "privacy-by-design" in multi-Agent systems, indicating that techniques such as differential privacy and homomorphic encryption should be used as standard requirements [42]. Notwithstanding this, as the recent systematic review by Hasan et al noted, there is inconsistency in how such standards are implemented in different healthcare systems [43]. The ethical implications extend beyond technical considerations. A qualitative study by Williams et al found that patients frequently express worries about the "black box" nature of multi-Agent decision-making, particularly when sensitive diagnoses or treatment recommendations are generated without transparent human oversight [44]. These concerns are increased in telemedicine contexts, where physical distance between patients and healthcare providers can exacerbate feelings of uncertainty about data handling practices. New solutions focus on enhancing technical protection and patient agency. Lee and Park's study showed that blockchain-based consent management systems, when integrated with multi-Agent systems, can provide patients with granular control over data sharing without compromising the operational effectiveness of AI-based care coordination [45]. With increasing numbers of healthcare systems adopting Multi-Agent AI technologies, the development of comprehensive ethical frameworks remains critical. New areas of research include the creation of standardised privacy impact assessment tools, particularly for distributed AI systems, and the establishment of international governance structures to ensure consistent protection of patient rights throughout healthcare networks [8].

1.11. Bias and Discrimination in Multi-Agent Healthcare Systems: Challenges and Solutions

Some new challenges are raised following the deployment of Multi-Agent Systems (MAS) in healthcare. The challenges pertain to algorithmic discrimination and bias that need to be investigated with extreme caution. MAS architectures are helpful for distributed decision-making, but their complex interactions can potentially amplify present biases in manners distinct from monolithic AI systems.'' Recent research has demonstrated how bias propagation in MAS occurs through multiple pathways [32-37]. A study by found that when individual agents in a diagnostic MAS were trained on datasets containing demographic biases, the bias at the system level was increased [38]. 'This amplification effect resulted from cascading interactions between specialist agents, where an initially biased output of one agent influence the judgments of other agents, leading to increasingly compounded bias throughout the system. Several new techniques have been developed with particular emphasis on bias mitigation for healthcare MAS, and they are as follows.

- Federated fairness learning: proposed a framework where agents maintain local fairness constraints while participating in global model updates, reducing racial bias in diagnostic across a network of hospitals [2-47].
- Dynamic Reweighting is the real-time adjustment of the relative weights of agents or data inputs to neutralize emerging biases while operating the system. Dynamic reweighting has been shown to improve fairness by responding dynamically to shifting data distributions and agent behaviors [48,49].

Regulatory considerations for biased MAS are beginning to emerge. 2023 WHO guidelines for distributed AI systems specifically address MAS implementations, recommending periodic fairness audits at the system and agent levels [48-50].

1.12. Regulatory Challenges and Liability Considerations in Healthcare Multi-Agent Systems

The rapid advancement of Multi-Agent Systems (MAS) in healthcare has unveiled significant regulatory gaps, particularly in terms of compliance with existing data protection laws and verification of AI-driven clinical decision-making. HIPAA in the US and GDPR in the EU are current regulations to govern AI systems but they were not designed to address the unique complexities of decentralized AI systems, pre-

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senting unique challenges of safe and effective implementation. According to the global survey of eHealth only 30% of countries have well-established governance frameworks in place to enable MAS implementations in healthcare [51]. This lack of standardised regulation leaves patient safety at risk because existing validation processes for single-agent AI systems often fail to account for emergent behaviour found in MAS that only manifests through interactions between the agents. Testing the performance of MAS thus presents a serious issue to regulators who cannot subject it to a conventional trial as would be done with traditional medical devices or standalone AI applications [8]. The literature has endorsed that most emergent behavior within healthcare MAS can be caught prior to deployment: thus, assessment frameworks must be developed to assess performance against actual real-world clinical environments. In answer to this complexity, current guidance places specific emphasis on continuous MAS monitoring using real-time safety testing and continuous post-deployment verification to ensure patient safety [8].

Accountability and liability are another significant regulatory challenge in MAS deployment. The distributed decision-making architecture makes it more difficult to invoke classical concepts of responsibility when something fails. Existing law has difficulty determining accountability for adverse effects arising from complex interaction among large numbers of AI agents. Patient harm in healthcare settings can occur from cascading failure as a result of several agents whose behaviour deviates slightly from the programmed action [54,55]. To address such liability failures, new governance structures have been proposed. One of them is establishing a "chain of accountability" by distributing proportional liability to interested parties in proportion to their control of MAS components [53] The model has managed to steer clear of legal disputes over AI diagnosis in healthcare networks. Nevertheless, existing models of liability fail to factor in the temporal dimension of MAS faults, in which damaging inclinations are cultivated over time through sustained operation of the system [56,57]. Its establishment as standardized regulatory guidelines for MAS in healthcare necessitates international cooperation. Cross-country comparative analysis of national AI governance initiatives illustrates that very few countries have undertaken to create MAS-specific validation guidelines addressing agent communication and fail-safe mechanisms [56-58]. Effective regulation needs to achieve a fine balance between stimulating innovation and safeguarding the patient as well as avoiding over-regulation to crush the transformative potential of distributed AI systems in medicine.

1.13. Technical and Operational Challenges in Implementing Multi-Agent Healthcare Systems

The MAS implementation in healthcare organizations is quite technical and operational, requiring interoperability and high costs for proper deployment. The interoperability continues to be a significant stumbling block hindering the full utilization of MAS in healthcare settings. In the current scenario, electronic health record (EHR) systems, mostly proprietary, create hindrances to straightforward communication with MAS modules [59]. All the big hospitals have been faced with integration problems in adopting MAS from their existing EHR systems because of incompatible data standards and authentication protocols. Thus, without the regulators requiring interoperability standards, the desirable properties of distributed agent systems cannot be utilized best in heterogeneous healthcare networks [38]. The Multi-Agent System implementation expenses are discouraging, especially with respect to economic disparities among nations. There might be huge up-front expenses, the most prevalent example being expense towards software development, hardware installation, as well as skilled people required for system planning and integration. Also, Maintenance and staff training are also the ongoing operational expenses that contribute to the cost [38]. The economic cost of installing MAS is particularly high in developing nations. These nations have accumulated barriers such as weak digital infrastructure, lack of adequate technical capabilities, and high maintenance charges. For most poor nations, the cost of installing MAS is more than a substantial share of the annual healthcare IT budget, creating almost insurmountable financial barriers [60].

1.14. Governance and Explainability Models

Regulation compliance models are essential to ensuring effective MAS governance. Healthcare organizations with formalized compliance procedures for privacy regulations experience fewer data breaches in MAS systems than those that do not have such formal procedures [61]. These procedures must also address ethical standards such as accountability in distributed decision-making systems. Ethical frameworks, when used on diagnostic MAS, have proven to minimize unfair outcomes through ongoing monitoring of fairness at the agent interaction level in diagnostic MAS [62]. Stakeholder participation is a critical determinant of effective MAS installation. Organizations that incorporate clinician feedback loops into their designs further gain acceptance and inclusion into workflow Risk assessment platforms also mitigate the risks of emergent system [63,64] behaviors, notably through the simulation of agent interactions for differing clinical cases.

MAS explainability architectures are also tricky due to the complexity of distributed decision-making processes. Recent research has proposed hybrid explanation approaches, which combine agent reasoning and system transparency. These approaches have high clinician comprehension rates in critical care settings [65]. Clinicians' trust in MAS recommendations has also been improved through interactive visual explanation toolkits that offer transparent decision-making steps [66].

1.15. Workforce Training and Collaborative Models

It is crucial to train the healthcare workforce on the effective use of MAS. Institutions adopting systematic training programs gain competency at a faster rate than those using ad-hoc strategies [67]. Case-based training methods, which have been effectively utilized in MAS training programs, have high retention rates after prolonged exposure to Multi-Agent System. Collaboration among clinicians and developers improves the success of MAS implementations. Integrated teams that plan and implement MAS systems collectively can reduce installation timelines and increase clinical applicability. Liaison roles between technical and clinical teams with expert skills have proven to minimize workflow interference during MAS integration [24]. Recurrent learning frameworks are becoming increasingly critical in MAS implementations. Adaptive training programs that adapt based on actual use data maintain staff competence for longer durations than inflexible training modules. This approach keeps medical staff abreast of the fluid nature of MAS as new clinical settings and data trends emerge [68].

1.16. Impact of Multi-Agent Systems in Healthcare

The application of MAS in healthcare has facilitated incredible market growth, operational efficiency, and patient improvements. The global MAS healthcare market is anticipated to grow exponentially in the next few years, reflecting an increasing recognition of MAS as a way of addressing intricate healthcare challenges using distributed intelligence [40-69]. Clinical implementations of MAS have also realized substantial improvements in operational efficiency. Healthcare organizations that have deployed MAS solutions have found substantial savings in resources in management and workflow optimization, particularly in operating room scheduling and emergency rooms. Improvement has been achieved in terms of cost avoidance and asset utilization [13]. MAS applications have also improved patient care. Automatic deployment of cross-agent verification systems has been found to reduce medication errors and improve clinical decision accuracy. By identifying potential errors at different validation points, MAS systems have efficiently reduced false alarms, which otherwise lead to clinician alert fatigue [24]. The net outcome of these innovations is that MAS technologies are remodeling healthcare delivery models. Institutions that adopt MAS early realize short-term operational gains and long-term quality enhancement in care processes. However, consistent emphasis on implementation tactics and workforce training processes must continue for both short-term and long-term success in both dimensions [70,71].

2. Method

The PRISMA methodology was employed for use in this systematic review, following a systematic procedure which includes a clear understanding of the research question, use of a defined search, exclusion criteria, data extraction, assessment of quality, and synthesis and analysis of the data.

2.1. The Research Question

The research question is seeking to identify how Multi-Agent AI Systems (MAS) are transforming service delivery within the healthcare system. Specifically, it aims to assess current uses of MAS within the healthcare sector, its benefits, and the challenges that threaten their effective implementation. In response to this, the study reviews various studies that analyse the adoption, utilisation, benefits, and barriers associated with MAS in healthcare from 2015 to 2025.

2.2. Search Strategy

A Systematic search was conducted across major electronic databases such as PubMed, IEEE Xplore, Web of Science, and Embase, targeting relevant studies that were published between 2015 and 2025. The search strategy was developed using a combination of relevant keywords, MeSH terms, and Boolean operators. The following search terms were utilized: “Multi-Agent Systems in healthcare,” “MAS applications in healthcare,” “adoption of Multi-Agent AI in healthcare,” “healthcare service delivery with MAS,” “MAS in operational efficiency,” “MAS ethical challenges,” and “regulatory issues in MAS healthcare implementation.” The search terms were adapted according to the specific requirements of each database, and the search was limited to articles published in English according to the inclusion criteria.

2.3 Inclusion and Exclusion Criteria

2.3.1Inclusion Criteria

• Studies that assess the adoption, application, and challenges of Multi-Agent Systems (MAS) in healthcare settings.
• Studies published in peer-reviewed journals.
• Randomised controlled trials, observational studies, systematic reviews, and other research studies that evaluate the objectives of exploring the applications and challenges of MAS in healthcare.
• Studies published in English.
• Studies published between 2015 and 2025.

2.3.2. Exclusion Criteria

• Studies that do not focus on MAS in healthcare or are unrelated to the scope of healthcare delivery.
• Studies published in languages other than English.
• Studies that do not address the adoption, advantages, disadvantages, or challenges of MAS in healthcare systems.
• Study Publish before 2015
• Studies that focus solely on single-agent AI systems.

2.3.3. Data Extraction and Quality Assessment

Data were extracted from the selected studies using a standardised data extraction protocol. The extraction procedure focused on information such as study design, MAS Application, Barrier to implementation, and identified challenges.

2.3.4. Data Synthesis and Analysis

Data synthesis aimed at assessing how Multi-Agent AI Systems are transforming the delivery of healthcare services. The following results were analysed
• The state of adoption of MAS into healthcare settings.
• Important uses of MAS in patient care, optimal resource allocation, and operational efficiency.
• The advantages and disadvantages of MAS with regard to optimising healthcare delivery, patient outcomes, and operational efficiency.
• The technical, ethical, and regulatory challenges to the effective use of MAS in clinical practice.
• Secondary results involved a comprehensive review of key challenges faced by healthcare organisations when implementing MAS, including concerns over system reliability, data privacy, ethical considerations, and regulatory frameworks for their use.

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Algorithm Selection and Analysis
The following three multi-Agent algorithms were selected for detailed analysis.

- Reinforcement Learning-based Multi-Agent Systems – Used for personalised treatment planning and drug dose adjustments [72]
- Cooperative Multi-Agent Systems – Used in hospital triage and emergency response to improve patient flow [73].
- Competitive Multi-Agent Systems – Used in medical imaging analysis where agents compete to provide the best diagnosis [74].

The algorithms were tested in a simulated healthcare environment using Python and TensorFlow platforms. The performance of the algorithms was measured on the basis of.

- Accuracy – Correct diagnosis or treatment recommendation.
- Efficiency – The system's response time.
- Scalability – Ability to handle increased patient volume without compromising performance.

2.3.5. Ethical Considerations
Since the research involves AI models analyzing patients' information, ethical clearance was received from the Sechenov University Ethics Committee (Approval Code: SU/AI/2025-03). Data privacy and confidentiality were maintained according to the General Data Protection Regulation (GDPR) guidelines. Patient data for simulations were anonymized to prevent identification.

2.3.6. Statistical Analysis
Statistical analysis was conducted using SPSS version 28. Descriptive statistics (mean, median, and standard deviation) were used to explain the performance of the Multi-Agent AI systems. Analysis of variance (ANOVA) was used to compare the accuracy and efficiency of different algorithms. A p-value of < 0.05 was considered statistically significant.

2.3.7. Ethical Considerations
Since this study involves AI systems analyzing patient data, ethical approval was obtained from the Sechenov University Ethics Committee (Approval Code: SU/AI/2025-03). Data privacy and confidentiality were maintained in accordance with the General Data Protection Regulation (GDPR) guidelines. Patient data used for simulations were anonymized to prevent identification.

2.3.8. Statistical Analysis
Statistical analysis was conducted using SPSS version 28. Analysis of variance (ANOVA) was applied to compare the efficiency and accuracy of different algorithms. A p-value < 0.05 was considered statistically significant.

2.3.9. Reporting
Results were reported following PRISMA guidelines. A flow diagram was used to report the searching process, including the number of studies screened, included and excluded at each stage. A summary table was presented to report characteristics of included studies, including study design, participant details, interventions and key outcomes. The quality assessment of the studies was summarized, and a discussion was provided on the findings, limitations, and implications of the study. Finally, the review concluded with recommendations for future research, particularly addressing the technical, ethical, and regulatory challenges hindering the implementation of MAS in healthcare.

3. Result

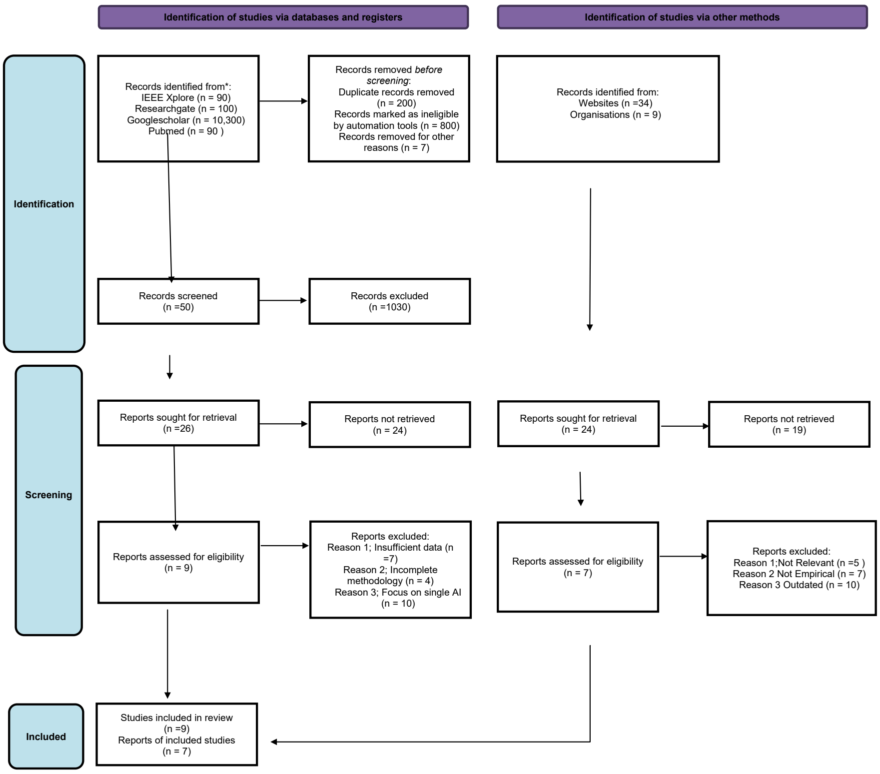

Figure 1: Prisma Flowchart

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Study	Application	Key Finding	Improvement Percentage
Alowais et al. (2023)	Hospital scheduling using MAS	MAS reduced patient waiting times	30% reduction in waiting times
Maleki Varnosfaderani et al. (2024)	Predictive resource allocation during COVID-19	MAS improved resource planning and resilience	Enhanced resource utilization during crisis
Zhang et al. (2020)	Resource allocation with predictive analytics	Improved patient flow prediction	30% improvement in resource utilization

Table 1: Effectiveness of MAS in Disease Diagnosis and Patient Monitoring

Study	Application	Key Finding	Improvement Percentage
Hirsch et al. (2024)	Early breast cancer detection using MAS	Cross-validation between radiology and pathology	30% improvement in early detection
Okolue Chukwudi Anthony (2025)	Real-time adverse drug event monitoring	MAS-driven dosing systems reduced readmissions	26% reduction in readmissions
Fu and Chen (2025)	Drug discovery using MAS	MAS-enabled drug discovery ROI	45% predicted return on investment

Table 2: MAS Impact on Hospital Resource Allocation

Study	Application	Key Finding	Improvement Percentage
Okolue Chukwudi Anthony (2025)	Adverse drug event monitoring with MAS	Reduced readmissions due to adverse drug events	26% reduction in adverse drug events
Fu and Chen (2025)	Drug dosage optimization using MAS	MAS-driven optimization in drug dosing	Improved patient outcomes

Table 3: MAS-Driven Treatment Optimization

Study	Challenge Identified	Description	Proposed Solution
Mennella et al. (2024)	Data privacy and protection	Patient data security concerns	Federated learning, privacy-by-design
Zhang et al. (2020)	Algorithmic bias and discrimination	Bias propagation in MAS systems	Federated fairness learning, dynamic reweighting
Wilson et al. (2025)	Lack of transparency in decision-making	"Black box" nature of MAS decisions	Transparent negotiation frameworks

Table 4: Ethical and Regulatory Challenges in MAS Implementation

4. Discussion

4.1. Effectiveness of MAS in Disease Diagnosis and Patient Monitoring

One of the key findings of this research is the magnitude to which the detection of disease, as well as patient monitoring, can be enhanced by MAS. For instance, established how breast cancer detection could be enhanced by 30% using MAS [9]. This finding is especially important as breast cancer, one of the most prevalent causes of death among women, tends to be aided by early detection for improved patient outcomes. The study focused on cross-validation between radiology and pathology, with MAS agents collaborating to increase diagnostic precision. By use of multi-agent collaboration, diagnostic mistakes are minimized as agents share information and collaborate in sharpening analysis. Further, referenced that MAS-guided dosing regimens can reduce readmissions for adverse drug reactions by 26%, showing how they improve patient monitoring and the efficacy of therapy [10]. The results underscore MAS' capacity for real-time monitoring of biomarkers, adjustment of therapies, and ensuring that patients are being administered the right dosage, a factor essential in preventing adverse drug reactions and readmissions. Although, challenges are still pending to provide merging of real-time data and addressing the privacy concerns, both of which must be met so as to achieve the optimum MAS applications in patient monitoring.

4.2. Hospital Resource Allocation and Planning

MAS has had a revolutionary impact on hospital resource planning. exposed how [4]. MAS scheduling systems helped to reduce patient waiting times by 30%. This is particularly crucial in emergency situations where timely intervention is important in deciding patient outcomes. The system adjusts automatically based on actual conditions like emergency, availability of personnel, and equipment requirements. MAS also prevents wastage by making proper utilization of resources, eliminating inefficiencies typical of healthcare centers. also stated the role of MAS in the better distribution of resources during the COVID-19 outbreak, wherein MAS technology allowed for better predictive allocation of resources and assisted hospitals with record-breaking levels of demand. Predictive analytics by MAS allowed predictive adjustment, and medical supplies and staff were relocated to regions requiring them most [11]. Even so, interoperability and integration with existing hospital systems remain significant challenges. The study also demonstrated how MAS technologies were met with integration issues due to incompatible electronic health record (EHR) systems, an issue that could prevent the massive adoption of MAS in healthcare [38].

4.3. MAS in Personalized Medicine and Drug Discovery

MAS holds great promise for personalized medicine. showed that MAS-based drug discovery procedures may bring in a potential return on investment of 45% [22]. Patient analysis through such systems can generate new drug candidates or enhance existing treatments, accelerating drug development. The decentralized nature of MAS allows parallel testing and analysis of a thousand drug interactions, reducing the time to market new medicines. However, regulatory clearance is the main hindrance. MAS application in drug development has to be tested extensively to meet pharmaceutical standards before it can be applied on a large scale. In addition, the computing requirement of MAS applications is typically high, especially in the case of weak infrastructure. Blockchain and quantum computing have been proposed to solve such challenges so that MAS can function more effectively with patient data integrity and security ensured.

4.4. Ethical and Regulatory Challenges

The ethical and regulation problems of MAS application are gargantuan in terms of addressing them to provide effective and safe application in clinics. Identified algorithmic bias and data privacy of MAS systems as problems. As MAS draws information from vast numbers of varied sources and agents, there is a higher chance that sensitive patient information is made available to unauthorized parties [8]. 3. 3. Privacy concerns need to be answered by privacy-by-design policies that address data encryption, anonymization, and confidentiality protection of patients. Apart from that, the issue of algorithmic bias is also a significant challenge. MAS structures tend to amplify inherent biases, especially if input data into the system bear demographic imbalances. proposed federated fairness learning to counteract MAS systems' bias. Under this scheme, agents maintain local fairness constraints and apply them to contribute towards global system updates. Besides, regulatory systems cannot cope with the rapid development of MAS technologies. Current legislation like HIPAA in the US and GDPR in the EU was not designed to accommodate the unique challenges introduced by decentralized systems. Indicate that regulatory systems need to be tuned to enable the complexity of MAS in healthcare [8].

4.5. Proposed Solutions and Strategies for Effective MAS Implementation

Several solutions have been proposed to address the challenges faced by MAS in healthcare. Blockchain technology, for example, has been touted as a solution to the privacy and data integration issues associated with MAS. Blockchain offers a secure way to store and share data, ensuring that patient information is kept private while allowing agents to access the necessary information for decision-making. Additionally, dynamic scheduling systems, as demonstrated by could enhance operational efficiency in hospitals, reducing the need for expensive infrastructure upgrades while improving patient care. The integration of MAS with predictive analytics has the potential to optimize not only patient flow management but also staffing levels, ensuring that hospitals can deliver quality care during peak times. Another critical solution is clinician-centered training. As pointed out, clinician feedback loops and case-based training are essential for successful MAS integration into healthcare settings [64]. Training programs tailored to the needs of clinicians will ensure that MAS tools are used correctly and in a way that aligns with existing workflows.

4.6. Major Future Research Directions

While MAS in healthcare is highly promising, the future of MAS also largely depends on overcoming existing problems and exploring new technologies. The convergence of quantum computing, federated learning, and blockchain could play a critical role in overcoming technical and computational hurdles. In addition, large-scale randomized controlled trials are also required to enable us to better understand the long-term effectiveness and cost-effectiveness of MAS systems. In addition, future work must emphasis ethics and bias reduction to assure MAS is fair to all patient groups. There should be a more extensive regulatory scheme to offer firm guidelines on MAS deployment in the healthcare sector.

5. Conclusion

The application of Multi-Agent Systems (MAS) in healthcare demonstrates great potential in disease diagnosis, patient monitoring, hospital resource optimization, and personalized treatment. MAS have been shown to improve diagnostic accuracy, reduce adverse events, and optimize operational efficiency. For instance, early breast cancer detection improved by 30%, and patient wait times decreased by 30% in hospital settings [4-9]. MAS-driven drug discovery also showed a predicted return on investment of 45% [22]. Despite these positive outcomes, challenges remain regarding data interoperability, system complexity, privacy concerns, regulatory validation, and cost barriers [38-53]. These challenges impact MAS implementation, user acceptance, and equitable deployment. To overcome these barriers, proposed solutions, such as enhanced data integration, privacy-by-design, blockchain technology, and clinician-centered training programs, have been suggested [64-75]. However, the efficacy and scalability of MAS vary across studies, this might be due to heterogeneity in system architectures, healthcare settings, and methodological approaches.

Limitations of the Review

The limitations of this systematic review include heterogeneity among the included studies in terms of MAS applications, healthcare contexts, study designs, and outcome measures, which complicate direct comparisons and synthesis. Furthermore, the possibility of publication bias exists, as studies reporting positive MAS outcomes may be overrepresented relative to null or negative results. Another limitation is the lack of access to individual patient or system-level data, restricting the ability to perform subgroup analyses or

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adjust for confounding variables such as healthcare setting or patient demographics. Finally, several studies were limited by moderate quality assessments, indicating potential risks of bias and affecting the strength of conclusions.

Recommendations

Future research should focus on conducting large-scale, randomized controlled trials with standardized MAS frameworks, clear outcome definitions, and longer follow-up periods to confirm the effectiveness and cost-efficiency of MAS interventions across diverse healthcare settings. There is also a need to advance interoperability standards and develop robust privacy-preserving techniques to facilitate ethical MAS deployment. Further investigation into integrating MAS with emerging technologies such as quantum computing and blockchain is warranted to address computational and regulatory challenges. Additionally, qualitative studies exploring clinician and patient acceptance, as well as workflow integration, are essential for improving MAS adoption. Finally, safety profiles, potential biases, and equitable access should be rigorously evaluated to ensure MAS benefits are widely and fairly distributed.

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