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Chapter 9: Multi-Agent Learning for Adaptive Clinical Decision-Making

9.1. Introduction

It is still a long way before Artificial Intelligence (AI) can replace human clinicians in healthcare. AI may eventually assist in every aspect of the healthcare ecosystem, but introducing an interactive and fully-fledged personal assistant capable of communicating, storing, and learning selectively as a clinician remains an uncharted journey. The interaction between clinicians and technology is, in fact, becoming more profound as the technology becomes necessary for interpreting all sorts of clinical data. Still, the final decision lies in the clinician's cognitive abilities, emotional intelligence, and life knowledge. AI, however, can contribute to any part of the decision-making process under heavy supervision, as the direct impact of a mistake can affect human lives. Therefore, AI can be considered an informative tool during the decision-making process. Nevertheless, there is still much room for improving and writing adaptive tools that can be chosen or rejected by a user or a group of users.

In healthcare settings, multiple auxiliary tasks could be performed by these adaptive AI modules or agents acting independently but in a coordinated manner without disrupting the decisions made by the clinicians. The design of autonomous agents capable of coordinating in an adaptive way opens new directions for both problem resolution and application. For certain types of problems, the decentralized nature of the functionalities provides the opportunity to obtain solution approaches not feasible with an actor-centric perspective. When healthcare practitioners are engaged in certain auxiliary tasks, the form of intercommunicative association can behave cooperatively, competitively, or completely indecisively at different times.

9.2. Background and Related Work

Existing literature on the development of multi-agent learning frameworks has primarily focused on the more applied aspect—merely enabling online and on-the-fly learning in complex dynamic environments. Few works have paid attention to the design of agent training protocols that could enhance the underlying learning process either quantitatively or qualitatively. The growing interest in multi-agent communication and coordination may also be addressed by an explicit consideration of the communication infrastructure provided in the learning process and the rules for interactions between agents. Communication is particularly important in faster-than-real-time simulations, where individuals are typically modeled as “naive players” that are assumed not to learn from past encounters.

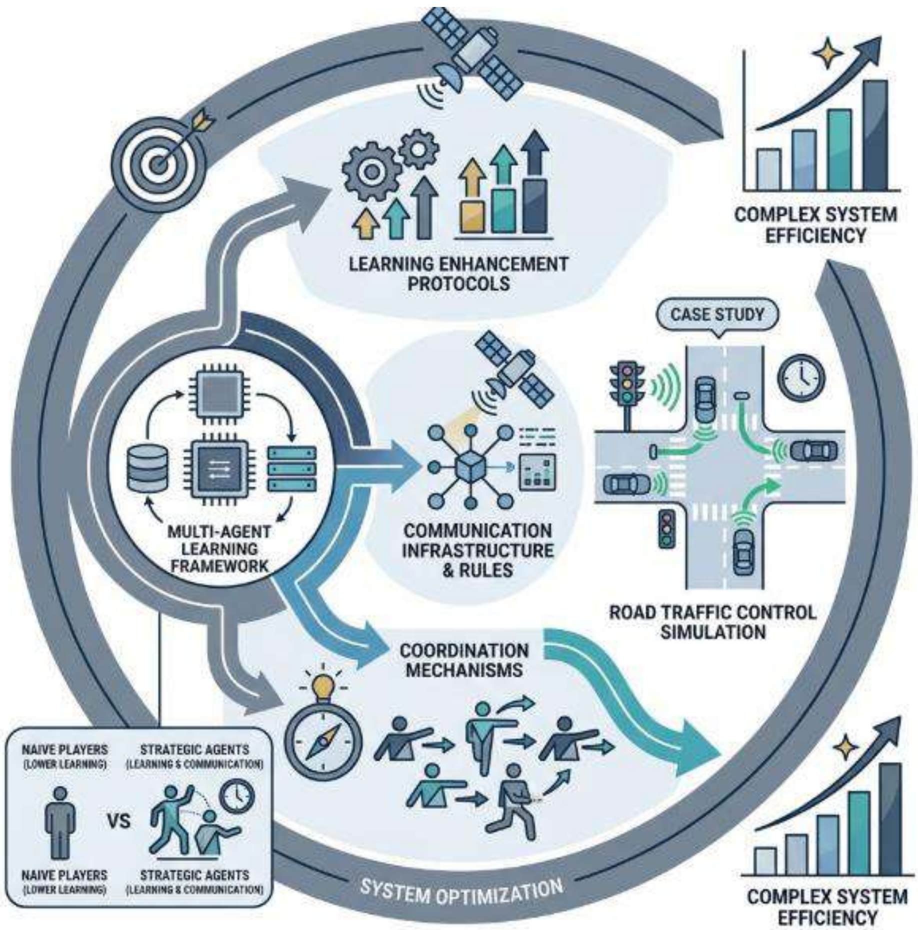

Fig 9.1: A Communication-Driven Framework for Enhancing Multi-Agent Learning and System Efficiency: Application in Intelligent Road Traffic Control

Given this foundation, the forthcoming section serves to analyze learning strategies that can be adopted in a Multi-Agent System environment to enhance the efficiency of the overall complex system. It is argued that the nature of the clinical utility functions in the specific application space considered is such that one cannot simply use any approach for the learning processes. Formalization of the learning methodology into an a priori defined communication protocol may thus be valuable. The importance of communication in accelerating learning and creating coordinated behavior is then evaluated. Road traffic control could serve as an instructive example, and simulation results are presented.

9.2.1. Review of Existing Literature and Key Insights

A literature survey indicates that mutual learning of trials via coordination can enhance the performance of different agents in setting up an academic research forum; nevertheless, the multi-agent environment setup of different agents helps different peers to engage in a learning phase. Different agents participate in different trials of dynamic resource management in self-driving car simulators, where the multiple driving cars use a reward network to reward the actions of far-away peers who do not share any samples. Afterwards, defined roles among the agents are employed to produce a knowledge-sharing protocol with a protocol-learning mechanism to facilitate the knowledge transmission. A structured action space for each agent regarding type selection is established to ease the learning complexity in cooperative-Issue-Chain-Games settings.

In a multi-user, multi-item market setting, different sellers offer different combinations of seller types and item types. Agents allocate a budget to purchase items for sale during the market's trading segment to maximize personalized utility. An academic-support management system, where agents try to decide which subject area to start (or join) the discussion in through adaptive communication and coordination, is also discussed. A multi-agent reinforcement-learning framework educates robots how to traverse mobile robots in the presence of a human being. The experiments reveal that with the assistance of other robots, even the agents that do not directly interact with their peers learn the trial more quickly than those that do.

9.3. Problem Formulation

Multi-agent learning algorithms are adaptive clinical decision-making agents utilizing mechanisms to allow learning and decision-making in production-mode environments. Partially observable Markov decision processes (POMDPs) are also a natural modeling choice for clinical decision-making problems since they effectively capture the partial observability, uncertainty, and temporal aspects of the application context. Furthermore, the clinical decision-making context has the characteristics of a multi-agent system (MAS) in that data can both be competitively and cooperatively generated by many agents with different views of the problem. Finally, an important area that has received less attention in learning in MAS settings relates to decision-making algorithms.

Multi-agent clinical decisions are formulated using a MAS architecture. The goal is to choose clinical policies that promote the fulfilment of clinical utilities which can be formally described using reward functions. The analysis is focused on policy optimization in cooperative and competitive environments and steered from a clinical perspective; that is, interactions must be explicitly clinical decision processes such as patient diagnosis and treatment recommendation rather than side processes as in a game. The resulting adaptive decision-making algorithms are finally validated both in selected simulation scenarios and with real clinical data experiments.

9.3.1. Clinical Decision-Making Context

Clinical decision-making hinges on selecting one of several interrelated actions for a patient population. Treatments often cause side effects, but failing to provide treatment may allow morbidity or mortality. In the classic decision-theoretic paradigm, outcomes of the actions and their costs or payoffs are modeled, and optimal actions are recommended for each particular attribute state of the patient population. Marginal cost-effectiveness also leads to assessments of which actions to add or drop. In a decision-theoretic framework, individual or patient-centered decision-making considers the effects of a particular treatment on a particular patient's health. In contrast, adaptive decision-making involves groups of patients who share similar attribute states by shaping action-specific symmetric attribute-related approximate state values.

The quality of action selection is affected by that of approximate state-action value estimates. These values can be learned from data using a number of different approaches. For example, when decision-making data for an adaptive decision-making problem are available, utility-maximizing action selections can be induced. An attractive feature of these estimates is their ability to capitalize on available individual-level data while still facilitating adaptive decisions. In simple terms, it seeks to define the prospect, value, or utility of a decision. Yet these prospects may not be the same from the perspective of a physician, patient, or health system.

9.3.2. Multi-Agent System Architecture

Multi-agent architectures for clinical decision support consider the overall process a clinical team follows to exploit information and knowledge in patient management. Two classes of multi-agent learning systems are to be developed. The first class exploits cooperative communication to create a shared model of the clinical space without the necessity of real-world interactions. The second class considers independent learning under a reward structure that reflects both individual and team performance.

An agent-based approach for developing decision support systems in clinical settings focuses on three main characteristics of the problem space. First, the overall decision-making process (patient care) is naturally decomposed into a number of sub-tasks (diagnosis, treatment, prognosis) that can be performed in parallel by many specialized agents. Second, clinical teams possess different sources of information and knowledge (expertise), and hence have different competence at performing the constituent sub-tasks. Finally, teams of agents can exploit their communication capabilities to accelerate the learning process by coordinating their interactions.

9.4. Methodology

Adaptive clinical decision-making aims to optimize treatments through an ensemble of clinical decision-making agents that automatically adapt to treatment outcomes using multi-agent learning methods. These methods can learn online based on the feedback received from the treatment decision or offline by using clinical treatment records. The underlying decision-making model resembles a multi-agent system where agents take actions that may be jointly beneficial, competitive, or collaborative. The objective is to devise a decision-making mechanism that responds to the ever-changing environment of the treatment system, in which utility maximization is the goal. While a lot of attention has been accorded to game-theoretic methods, there has been only limited work in the domain of reinforcement learning.

In complex multi-agent situations, where optimal policies are unknown to all agents, the choice of learning method is more intricate than in single-agent scenarios. Therefore, agents can be assumed to be exploring their parts of the environment using multi-agent learning methods. Cooperative multi-organ learning (i.e. tissue-wide multi-organ coordination) is also considered in this context; that is, while the learning tasks of the different agents are not synchronised, an agent is placed in the environment of other participating agents at locations (control points) where it can perceive the states of other agents and jointly maximise a state-dependent utility based on all agents' states. In other situations, agents can be considered to have opposing objectives (competitive learning) and can benefit from a mixture of imitation and reward, depending on the results of the last interaction.

9.4.1. Learning Frameworks for Multi-Agent Settings

Multi-Agent Reinforcement Learning (MARL) is a research domain that deals with the issue of how a group of agents can learn and grow together while interacting with one another and with a shared environment. The multi-agent aspect of the MARL problem arises from group-related issues like influence, communication, learning and coordination abilities of agents in interactions. The study of this problem is generally split into cooperative MA-RL methods, competitive MA-RL methods and methods able to tackle both of these cooperative and competitive environments.

In a cooperative setting, agents are assigned common goals to accomplish, motivating each agent to engage in joint actions that maximize the accumulated performance or expected behaviour of the group. Such systems are typically represented as cooperative Dec-POMDPs with a joint action space for all agents and joint observations and beliefs. The SCA and SMART approaches, the AC-NDMES framework, and the method of Yuan et al. are interesting contributions for this setting.

9.4.2. Communication Protocols and Coordination Mechanisms

Frameworks for multi-agent learning have been established in which interactions among the learning agents—including communication and coordination—can be exploited to improve training efficiency. Communication mechanisms for such multi-agent reinforcement learning settings have been proposed, and an attention-based communication protocol, which allows agents to selectively share actions and observations at each time step, has been shown to outperform a fixed communication strategy in a challenging multi-agent sequential decision-making task.

Many real-world multi-agent problems have different degrees of dependencies—some agents need to cooperate, some compete, and some may act independently. Existing deep reinforcement learning methods combine agents into a single cooperative group considering full dependency, which is not desired, and the impact of dependency relations is neglected. To exploit dependency relations, a framework has been developed that expresses learning relations among agents as a directed graph and enables actors, managers, and independent agents to learn collaboratively but effectively without communication. The framework has been adopted to implement a multi-agent competitive-cooperative environment, which serves as a benchmark for further exploring agent-dependency relations and adaptive multi-agent deep reinforcement learning algorithms.

9.5. Adaptive Decision-Making Algorithms

Clinical decision-making problems can be understood and formulated as a multi-agent learning problem since all the involved players or roles can be modeled as agents. When players are cooperating by optimizing the same objective, cooperative reinforcement learning algorithms can be deployed. Cooperative deep reinforcement learning algorithms can also be employed in realistic environments with a larger state/action space using single or multiple centralized critics. A clinical setting that takes doctor–patient interactions among two intelligent agents has been presented for the treatment of hypertension patients. A competitive multi-agent deep reinforcement learning-based model has been elaborated, where doctors and insurance companies work against each other.

The method offers promising results using clinical data from intensive care units. Extension of the previous method, which presents a model without a patient, for realistic environments are filled by implementing the technology and using real-world data. Risk minimization for real-world depends on different utility perspectives of agents. Multi-agent deep reinforcement learning methods, using dirty information from a hospital, consider doctors' and patients' utilities. Classic utilities are discussed and optimized by using a third-party insurance company. The policy gradient method is applied due to the complexity and continuity of the utilities.

9.5.1. Cooperative and Competitive Learning Approaches

Adaptive algorithms that leverage joint learning in multi-agent systems are critical for a broad set of clinical problems that have gained attention recently due to the rise of wearable sensors, treatment and exercise reminders, personalized medicine, and adaptive patient management. In addition to knowledge transfer and two-player games, polynomial mixture games offer a special case with a naturally defined system utility that is different from the sum or product of individual agents. These techniques are thus suited to applications including the learning of communication between coordination-commuting agents and systems with subpopulations of cooperative but disconnected agents.

Many problems in clinical decision making can be modeled as a multi-agent system, where agents represent different resources used to address the same problem. Typically, a task is done by one agent during each time step, and completing the task provides immediate rewards to that agent but incurs a delay. Whenever possible, the work should be divided among the available agents to save time. For such a setup, an adaptive multi-agent learning algorithm is formulated that maintains a dynamic Q-value for each agent at each state-action pair. The algorithm relies on a coordination-aware communication protocol and two exploring but non-communicating Q-learning agents in a standard task division scenario.

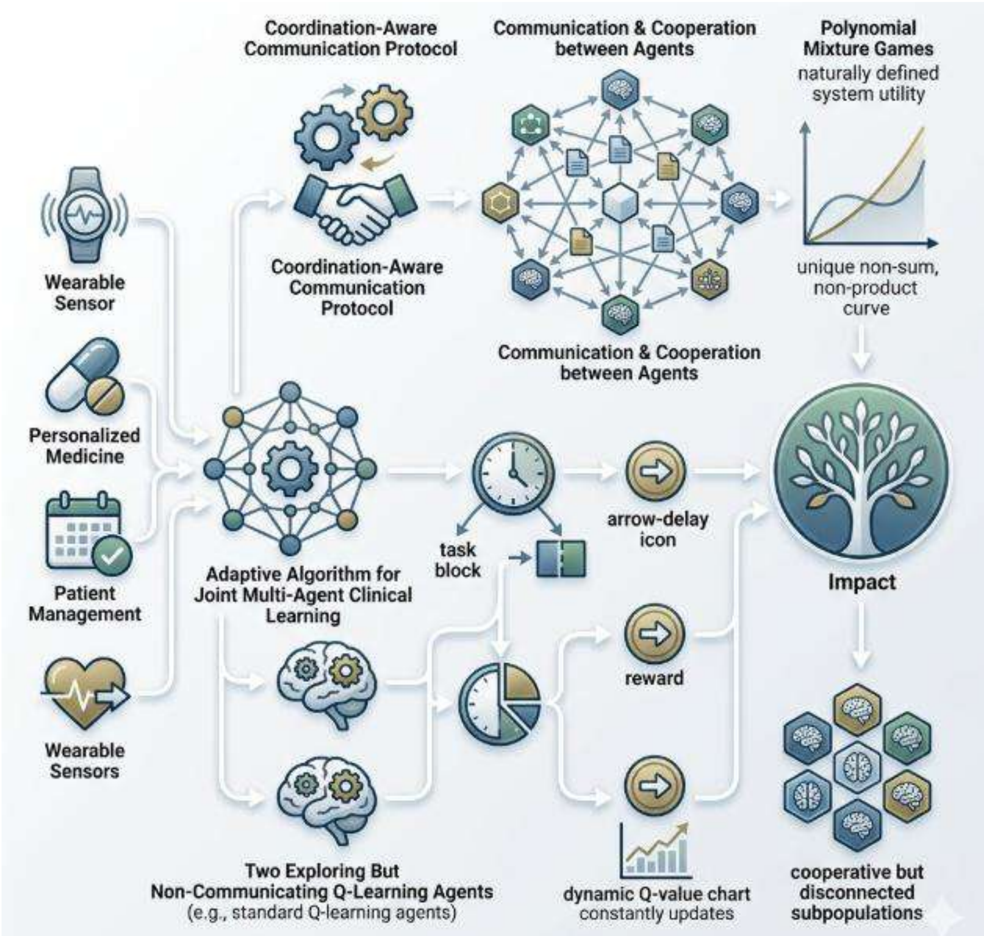

Fig 9.2: Synergistic Clinical Decision-Making: Adaptive Multi-Agent Joint Learning via Coordination-Aware Protocols and Polynomial Mixture Games

9.5.2. Policy Optimization for Clinical Utilities

Decision-making processes commonly involve recreating ideal conditions to optimize a utility. However, these methods are often limited because they obfuscate the underlying learning process of the decision-making agents when given sufficient opportunities to sample experiences, rather than recreating the ideal situation. These multi-agent learning methods offer alternative prospects to consider all possible agent interactions in the sampled data, exploring the synergies among agents.

Nevertheless, multi-agent cooperation is often left unaddressed. Decision-making in complex, high-stakes tasks – such as those found in many healthcare contexts, where an ideal decision depends on the actions of other agents that are often not explicitly controlled but are implicitly part of the environment – can incur serious harm or loss of life when agents are not dedicatedly cooperating. For such cases, modelling and solving the problem at hand in a cooperative way is crucial. Agents must be optimally coordinated (and communicative) in their activities or supporting behaviours to guarantee that, despite their individual preferences or interests, they automatically act as one for the joint benefit.

9.6. Evaluation and Validation

To validate and evaluate multi-agent learning algorithms and methods in the healthcare domain, two types of studies are conducted: 1) agent-based simulation studies to illustrate advantage and determine performance in various settings, and 2) studies using real-world clinical data sets to demonstrate the applicability of the approaches on actual data.

Agent-Based Simulation Studies—Multi-agent systems are particularly useful for problems where tractable large-scale simulations or analytic formulations can be defined but for which centralized algorithms do not exist, are impractical, or difficult to implement. Multi-agent systems can provide important insight for these settings. Multi-agent learning methods can be used to determine static or dynamic policies depending on the situation. During the coordination process, agents can either use common communication protocols throughout the learning period or adapt them according to the state of the local environment. Some learning methods address the scenario where agents may use a greedy-follow-the-greedy-picker policy. Multi-agent learning algorithms that incorporate elements of both active exploration and passive feedback can help improve the quality of solution policies. Multi-agent co-learning algorithms can also be used with trivial diagonal-shaped noise added to the agents' utility functions to encourage diverse exploration and dynamic exploitable-ness of cooperation.

The second type of study focuses on agents learning using clinical data sets, illustrating applications of the previously defined communication schemes. During the coordination process, agents use either common communication protocols throughout the learning period or adapt them according to the state of the local environment. The first data set consists of subjects who survived an acute myocardial infarction. The second data set consists of patients presenting to the emergency department with shortness of breath and presenting with a lung-protocol computed tomography scan. The third data set contains patients with high-grade blushes for prostate cancer who underwent external beam irradiation and brachytherapy.

9.6.1. Simulation Environments and Benchmarks

Various simulated environments can be designed for adaptive clinical decision-making, facilitating the evaluation of proposed algorithms. These environments include both: (a) co-operative, multi-agent POMDPs, with shared rewards, finite observation depth, and minimal state-action dependency; and (b) competing multi-agent settings, defined as non-zero-sum stochastic games, in which each agent aims to improve its local reward while maximising the global system utility. These environments serve as test beds for training cooperative communication protocols and JAMs. Existing simulation frameworks for modelling, simulation, and training of JAMs are extended to support multi-agent settings. Shared dynamics are incorporated, allowing the validation of communication protocols and coordination approaches that facilitate exploration in multi-agent JAMs without centralised controllers.

In addition to synthetic environments and benchmarks, adaptive clinical decision-making algorithms are validated on a publicly available, large-scale multi-agent clinical dataset. By leveraging clinical observations of renally-dosed antimicrobials, a multi-agent cooperative decision-making problem is formulated, serving as a benchmark for learning adaptive clinical decision-making algorithms. The dataset comprises 60442 episodes and 4978748 actions, with each episode containing a complete temporal sequence of drug dosing decisions over the treatment course of the patient. The actions consist of continue, pause, or stop placements of a drug. The reward for each agent is the clinical utility of its local action, equal to 1 when the drug placement is recommended and useful. Therefore, the formulated data-driven problem is a multi-agent partially observable stochastic game, with a JAM model that includes communication units and a recurrent-layered structure.

9.6.2. Real-World Clinical Data Studies

To evaluate learning-based algorithms for clinical decision-making in realistic scenarios, several studies have utilized real-world clinical data. These investigations for the first time address decision-making in scenarios with non-ideal functional agents using settings beyond single-agent control, testing various clinical decisions in the diabetic field. In these settings EmrHAbS is employed as an external reinforcement learning agent, enabling the analysis of other agents that may act in a non-cooperative manner. This includes information-receiving agents like clinicians, who aim to maximize their own reward within certain constraints or with limited information. Some settings even incorporate agents displaying other-regarding preferences, for example considering the possible reward lost by EmrHAbS during the process of attempting to help them. Finally, the learning-based algorithm is tasked with maximizing the present expected reward concerning the diabetes-related decisions, while indirectly dealing with the other non-perfect agents.

The inspired EmrHAbSim algorithm has been tested for three distinct clinical-related decision-control problems, in which the goal is to contribute efficiently to the screening and management of chronic diabetes-related diseases. A detailed screening process for diabetic-related foot lesions is considered, followed by the maintenance of nutrition status and the therapeutic adherence of patients with chronic obstructive pulmonary disease. For each decision, real-world data have been collected, ensuring that the agents controlling it do not be excessively cooperative and act mainly according to their own interests. The aim of the external reinforcement learning agent is to help these agents take a better decision without them explicitly asking for it.

9.7.Ethical, Legal, and Regulatory Considerations

As multi-agent learning systems for adaptive clinical decision-making (ACDM) hold potential for automated use in real-time medical diagnosis and treatment prediction, their ethical implications and the need for regulatory compliance must be carefully considered. Because algorithms employed in health care are currently subjected to various layers of regulation—ranging from testing for statistical existence in connection to a restrictive rule established by the Food and Drug Administration (FDA) to undergoing full premarket approval—the spectrum of ACDM for clinical decision-making may therefore deliver significant societal benefits, provided that the associated newspapers, journals and industry investment are conscientious and trustworthy. Like all areas of technology, successful machine learning in medicine requires constant vigilance to prevent misuse by irresponsible leaders, be they in the public or private sector.

Since rare cases of severe joint injuries (e.g., ruptured ligaments) can be poorly served by prediction systems trained on abundantly available large datasets, the exact contribution of core-topological, principal-geodesic-type trojan horses must be made clear. A far more compelling argument resides in the very recent demonstration of knee-arch-depth-trophy-bearing native-label distributions in Differential Geometry, where native diamonds are outnumbered by the rest.

9.7.1. Ethical Implications and Regulatory Frameworks

Within the field of artificial intelligence, specific attention must be dedicated to ethical issues arising from the social, practical, and technological characteristics of particular domains. By adopting a structured, systematic approach, the ethical analysis of practical applications within the domain of medical healthcare can help the sector progress in a coherent manner according to the broader interests of society. In the healthcare context, the deployment of Intelligent Decision-making Systems raises ethical questions principally concerned with: whether the engagement or use of computerized Machine Learning systems, or part of their chain of decision-making, is ethically acceptable; how these systems should be designed in order to avoid adverse consequences and how actors of the ecosystem should use these systems to improve their work; under which conditions would it be acceptable for these systems to make autonomous decisions without the approval and involvement of a Medical Operator, taking into account their level of accuracy; how these systems are to be certified for approval and Monitoring.

At present, many countries propose legislation regulating AI applications which heavily draws on the emerging European regulation on AI, yet focus on distributing obligations among actors of the AI ecosystem based on their respective roles. The principle thrust of this approach lies in proposing a level of ethical responsibility proportional to the level of ethical risks respective actors incur while inspiring the obligation of actors to be diligent in their employment of surveillance and monitoring tools throughout the entire chain of decision-making of AI itself, including the externalization of part of the decision-making of these systems towards external actors and organizations.

9.8. Challenges and Limitations

Several challenges and limitations must be considered in the proposed multi-agent learning for adaptive clinical decision-making. First, during the learning process, agents may not fully agree on the input feature function of the surrounding state and thus learn different policies for clinical decision-making based on these features. It is essential to reveal the potential clinical differences and challenges that different agents may encounter (e.g., treatment allocation imbalance) when performing clinical decision-making in an increasingly competitive or cooperative environment.

Second, different hospitals often adopt different disease diagnosis systems and regulation terminology, which can lead to very different treatment methods or even medical treatment errors in clinical practice. As the learning progresses, decisions may deviate further away from the optimal one with respect to the change of agents' trustworthiness. Multi-agent policy optimization algorithms that can effectively overcome the aforementioned communication and clinical decision-making issues are demanded. Furthermore, the privacy and security of patient-related data and clinical information must be ensured, and relevant control measures should be taken in the actual deployment of such a learning framework.

9.8.1. Potential Obstacles and Constraints

Several challenging issues directly or indirectly related to the characteristics of the multi-agent learning setup may hinder achieving the most preferred outcomes. For example, lack of trust may complicate the learning or cooperation process. Incentives may not be properly calibrated to foster desired cooperative behaviors. External factors or agents with potentially adversarial interests may not be addressed. Systemic inequities may detract from the equitable sharing of benefits. Coordination or communication disruptions may stall workflows. Cognitive bias and processing limitations may impair the quality of obtained or exchanged information. Distrustful, hostile, or ill-suited partners may yield poor, unsafe, or nongeneralizable combined policies regardless of their potential. These or other weaknesses may demand further exploration and mitigation through appropriate safeguards, tradeoff considerations, adversarial training, or the like.

Satisfying legal or regulatory requirements, such as in healthcare or financial domains, also presents an intrinsic complexity. Validating clinical policy improvement methods requires not only the balancing and addressing of competing objectives but also that regulatory mandates be met in the process. For example, a given treatment policy under parsimony or equity constraints may be optimal under a specific utility function but still lead to severe adverse factors under external regulations. Careful tradeoff exploration and validation through actual policies learned from real-world data may naturally provide some assurances that regulatory rules are respected.

9.9. Future Directions

Future research will likely focus on the use of heterogeneous multi-agent systems with specialized learning subcomponents, underlying architectures for other training paradigms, and emotion-driven agents that imitate psychological or physiological phenomena. The use of multi-agent systems based on different training paradigms is also becoming popular.

The potential of multi-agent systems has been recognized for some applications, such as Internet-of-Things-assisted wireless communications. During a gaming process, agents can learn from a better-performing agent. In addition to coordination and communication, adaptive decision-making should be studied in a more general way. For example, clinical decision-making is a decision-making area with a profound impact on patient health because abnormal models produce abnormal consequences. If one of the agents behaves abnormally, all agents will benefit from the abnormal event. Therefore, it is also valuable to assess the cost, benefit, and even trend for supporting the adaptive decision-making process.

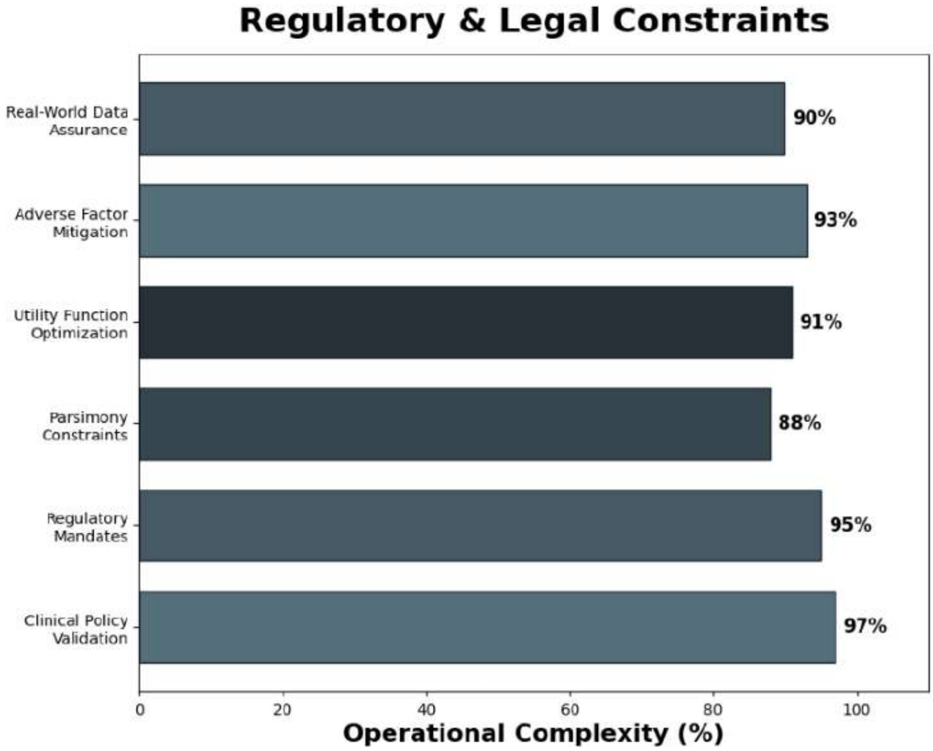

Fig 9.3: Regulatory & Legal Constraints

9.9.1. Emerging Trends and Prospective Research Avenues

Progress in the research of multi-agent systems for adaptive clinical decision making involves developing novel learning algorithms that optimize composite objective functions in a novel clinical environment more realistically modeled as a continuous multi-agent setting. Future work can also be extended to other real-time patient monitoring and control applications in critical care, such as dispensation of intravenous fluids and vasopressors, where agents adaptively learn to communicate with each other to provide timely medical intervention. The system has interesting legal implications as the communication model can be based on the physician-patient relationship in real-world clinical settings and its validity and safety in making decisions without physician supervision and communication can be analyzed based on the learning process. Simulation of these care problems with real data sets using such multi-agent adaptive learning AI environments would provide additional evidence for these agents' clinical applicability in future critical-care scenarios. Consequently, future investigation involves building clinically applicable AI simulation environments based on real clinical data that can guide real-time patient monitoring and critical behaviour.

The focus in future work is assessing these assistants as tools for triage and need detection in multi-agent settings. In this context, a triage agent is a system that coordinates the assistance of other agents communicating among themselves and adapts the level of need in each agent based on its performance. These triage agents can be thought of as non-player characters in a video game responsible for controlling the game environment, monitoring it, and notifying other players when assistance or intervention is needed. Just as those triage agents coordinate the players' actions to respond to the game environment, these agents can provide the same role in clinical settings, identifying when other agents require assistance and communicating properly to increase the success rate.

9.10. Conclusion

Recent years have seen the emergence of agent-based architectures and artificial intelligence methods for adaptive health-care decision-making. These advances go beyond the traditional technology-enhanced decision-support systems, mainly characterized by diagnosis and prescription tasks, within which the clinical decision remains ultimately dependent on health-care experts. In contrast, recent proposals focus on establishing an entirely agent-based system in which sets of interacting agents learn decisions and work in cooperation to improve system performance. More specifically, the proposed architectures address situations in which a combination of cooperating and competing agents is required, with learning and decision-making capabilities provided by reinforcement-learning techniques.

A multi-agent concept increases the number of possible chats between the agents, allowing the learning technique to converge faster and more robustly. In contrast, a competing perspective forces the agents to optimize their own decisions without violating ethical and fiduciary responsibilities. Ultimately, Artificial Intelligence and Machine Learning for Health enhance and empower mainstream health services by providing practical and operational support for health professionals. Multi-Agent-Simulated Reinforcement-Learning systems address the most complex components of patient health-care treatment.

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