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# TOWARDS MODELING OF DISTRIBUTED INTELLIGENCE SYSTEMS IN MODERN HEALTHCARE

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**Abstract**
From the perspective of Distributed Intelligence, this study assesses the practical application of Artificial Intelligence (AI) in healthcare. It reveals that despite AI's efficacy across medical datasets, its deployment in healthcare settings is relatively limited. The research identifies a scarcity of technical studies directly focused on "Distributed Intelligence in Healthcare" and a lack of a specific developmental paradigm. It emphasizes the complex interactions between healthcare professionals (HCPs) and AI, highlighting the necessity of research on trust-building from a social value-sharing perspective and identifying gaps in technical implementation. Additionally, the study discusses the need for clear legal, operational norms, and protocols for HCPs using AI. Addressing these challenges will enable effective AI integration in healthcare, proposing a significant advancement in the field.
**Keywords**
Distributed intelligence, artificial intelligence, healthcare application, medical research, ai implementation, healthcare professionals, technical studies, developmental paradigm, trust-building, legal requirements, operational norms.

## Introduction

In the contemporary realm of healthcare, the amalgamation of Artificial Intelligence (AI) with Distributed Intelligence Systems is increasingly becoming a pivotal research trend. Utilizing the PRISMA guidelines, this study comprehensively reviews English literature to probe into the practical application of AI within healthcare settings, particularly from the perspective of Distributed Intelligence [1]. It delves into the current status and potential challenges of AI implementation in medical systems. The research reveals that despite the significant efficacy of AI tools in addressing various medical issues, their actual deployment in real-world healthcare environments remains limited.

We focused on information sharing, practice sharing, goal sharing, value sharing, trust sharing, human-computer interaction, AI regulatory role and AI regulatory architecture in the implementation of AI in distributed medical environments.

## Information sharing in distributed healthcare

In the realm of distributed medical information sharing, the Personal Health Train (PHT) addresses privacy concerns by processing data at its storage locations, while Federated Learning trains shared models without exchanging local data. Both methods demonstrate unique advantages in enhancing privacy protection and computational efficiency, and are extensively applied in handling distributed medical data, including COVID-19 detection on edge computing and IoT devices, as well as the analysis of medical image data.

## Practice sharing in distributed healthcare

In the realm of intelligent healthcare, "practice" denotes a pivotal type of knowledge, particularly in distributed systems designed for tasks such as creating optimal chemotherapy plans for various cancers. This practice is not static but evolves through continuous feedback,

adapting treatment strategies based on patient responses, thereby enhancing both therapeutic outcomes and minimizing side effects.

The concept extends beyond individual patient management; knowledge gained from one type of cancer can inform treatments across others, demonstrating how practices in medical contexts are interconnected and dynamically shared across tasks and systems. This dynamic sharing is crucial in fields like intelligent healthcare where different diseases may require distinct but interrelated therapeutic strategies. Central to this is the role of Multi-Task Learning (MTL) and Multi-Task Reinforcement Learning (MTRL). MTL allows AI agents to handle various medical tasks simultaneously by learning under a unified framework where tasks share some underlying structures or parameters, thus facilitating rapid adaptation and learning across tasks. For instance, strategies developed for managing breast cancer might overlap with those for lung cancer, particularly in responses to similar chemotherapy drugs.

MTRL, on the other hand, incorporates feedback mechanisms that adjust the learning process based on real-world outcomes, essentially learning from the environment. This is crucial in healthcare where patient responses can vary widely, and treatments must be quickly adaptable. Such systems leverage shared experiences to enhance decision-making capabilities, not just within a single task but across multiple tasks, benefiting from a repository of 'shared practices'. Moreover, these technologies apply shared learning to improve decision-making and patient management across a variety of settings.

For example, federated learning models combined with reinforcement learning can optimize treatment strategies across multiple healthcare units without compromising patient data privacy. These models learn from decentralized data sources, allowing for a broad application of learned practices without direct data transfer. In predictive healthcare, multi-source and multi-task learning frameworks utilize vast amounts of data from varied sources to enhance diagnostic accuracy and treatment efficacy.

For instance, models trained on data from electronic health records (EHRs) can predict patient outcomes more accurately, adapting to new tasks or patient groups rapidly due to the shared knowledge structures.

Meta-learning, or learning to learn, further refines this approach by enabling systems to apply learned knowledge to new but similar tasks quickly and effectively. This approach is particularly beneficial in healthcare, where rare diseases or unusual patient presentations require rapid adaptation of existing knowledge. Practical implementations of these concepts have shown significant promise.

For instance, systems designed to learn optimal treatment strategies for individual patients can pool data across similar patient groups to enhance learning speed and treatment accuracy. Such systems not only adjust to individual needs but also continuously evolve as more data becomes available, exemplifying the dynamic nature of practice sharing in medical settings.

Overall, the integration of MTL, MTRL, and meta-learning into intelligent healthcare systems exemplifies how modern educational technologies and approaches can revolutionize medical practice. By enabling the dynamic sharing and application of practices across different tasks and conditions, these technologies not only improve immediate patient care but also contribute to the broader field of medical knowledge, making healthcare more adaptive, personalized, and effective.

## Goal sharing in distributed healthcare

In distributed healthcare, goal sharing significantly enhances multi-agent systems by aligning various components towards common objectives. This concept underpins collaborative efforts in healthcare environments, where multi-agent systems, swarm intelligence, and related algorithms play crucial roles. Studies demonstrate that shared goals facilitate efficient resource management and improved patient outcomes by coordinating actions among diverse agents

managing complex healthcare tasks, from surgery scheduling to chronic disease management and emergency interventions [7].

### Value sharing and Trust Relationship in distributed healthcare

In distributed healthcare, the exploration of trust relationships and value sharing is pivotal for integrating AI effectively. While trust in AI is influenced by its transparency and explicability, genuine integration requires respecting patient-centered values which are sometimes overlooked in the drive for efficiency [8]. Studies highlight complex trust dynamics involving institutional trust, socio-economic backgrounds, and the veracity of patient information. While theoretical studies abound, practical implementations in this area are scarce, indicating a significant untapped potential for future research. This research gap underscores the opportunity for developing models that can genuinely accommodate the nuanced aspects of trust and value sharing in healthcare [5].

### Human-computer interaction in distributed healthcare

In distributed healthcare, the interplay between human and AI intelligence is critical for enhancing collaborative and individual healthcare delivery. Various studies have explored methods to integrate artificial intelligence with natural intelligence to optimize healthcare processes. Techniques like Agent-Based Modeling, System Dynamics Modeling, and advanced AI paradigms like deep learning and machine learning have been employed to address specific healthcare challenges including infection control, patient monitoring, diagnostic assistance, and resource management.

Notable research illustrates the dynamic interaction between AI technologies and human intelligence, emphasizing the necessity for effective collaboration in diverse medical settings. This integration faces challenges, particularly in achieving a seamless and trustworthy interaction where AI assists healthcare professionals and patients without supplanting them. For instance, studies have shown that technologies enabling real-time collaborative decision-making, like those modeled on swarm intelligence principles, have successfully enhanced the capabilities of healthcare teams more than individual efforts or traditional AI models alone.

Moreover, novel multi-agent systems have been proposed for various specific healthcare applications, such as post-stroke monitoring and support for cancer survivors, demonstrating the practical benefits of AI in managing complex medical conditions effectively at home.

The broad array of studies underscores the immense potential and ongoing challenges in the field of human-computer interaction within distributed healthcare systems. The research is pivotal in advancing the understanding and implementation of AI technologies that complement human medical practice, ensuring that AI supports rather than overrides human expertise, thereby enhancing the overall quality of healthcare delivery [10].

### AI regulatory role and AI regulatory architecture in the implementation of AI in distributed medical environments

In distributed healthcare, the integration and regulation of AI involve adapting it to complement human intelligence effectively. Studies show that AI can optimize healthcare practices by assisting in areas like chronic pain management through cognitive-behavioral therapy interventions and improving medication adherence. Conversational agents in telemedicine systems exemplify AI's ability to enhance patient care by providing personalized support, demonstrating the regulatory role of AI agents in patient-oriented applications. Further discussions on AI's regulatory roles emphasize the need for a robust framework that addresses the ethical, legal, and operational challenges faced by Healthcare Professionals (HCPs). This includes ensuring AI systems are underpinned by evidence-based, rigorous regulatory standards

and adapting healthcare practices to keep pace with AI developments and regulations. The collaboration between human healthcare providers and AI systems underscores the necessity for continuous assessment and integration of AI tools within healthcare settings, ensuring that AI supports rather than undermines professional healthcare delivery.

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