Evolution of Future Medical AI Models:
From Task-Specific, Disease Centric to Universal Health

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ABSTRACT

Medical artificial intelligence (MAI) has evolved from traditional machine learning (ML) to deep learning (DL), and from supervised methodologies to unsupervised learning paradigms. Recently, the focus has shifted from task-specific to Generalized Medical AI (GMAI) models. However, these new AI models and algorithms still need to be translated to clinical use in different medical and healthcare settings. In this paper, we discuss the foreseeable transition from specialized MAI models towards more universally applicable models. We introduce two concepts and paradigms: Universal Medical AI (UMAI) and Universal Health Artificial Intelligence (UHAI). UMAI models will be distinguished from GMAI by their capabilities in emulating critical aspects of human intelligence necessary in clinical practice, particularly physician empathy and physician intuition. UHAI further expands beyond by addressing disease states (UMAI) and covers maintenance of health and prevention of disease, and pivots from using traditional clinical data to integrating broader information from non-clinical data (e.g., socio-economic, behavioral, environmental) to allow AI to be incorporated into a more holistic understanding of human health and disease origin. We outline key research directions and future pathways from GMAI to UMAI and, subsequently, UHAI, allowing AI to be more integrated, intuitive, patient-, physician- and societal-centric.

Medical artificial intelligence (MAI) is a promising interdisciplinary field that provides AI technology for medical applications. A notable MAI research trend is shifting from task-specific models to more general ones. Generalized Medical AI (GMAI)[1] uses multi-modality data to address various medical tasks. The development of large language models (LLMs) and foundational models (FM), along with "hardware" solutions (e.g., smart healthcare devices), are additional advances in this field.

Despite these, the clinical application of MAI and the level of physician, patient, and societal acceptance remain challenging; current MAI models lack integration of "human intelligence," which is traditionally developed through years of clinical practice experience. Second, current MAI models primarily focus on disease states and overlook the comprehensive aspects of the natural history from health to disease with various overlapping intermediate stages (e.g., multiple asymptomatic subclinical disease stages). Third, current MAI models are primarily trained on the data collected from developed countries, paying less attention to medical issues in developing countries.

We propose transitioning from GMAI to Universal Medical AI (UMAI) and Universal Health AI (UHAI) to address these challenges. UMAI is distinguished from GMAI by its capabilities to emulate critical aspects of human intelligence necessary in clinical practice, particularly physician empathy and intuition. UHAI further expands beyond addressing disease and covers maintenance of health and prevention of disease and pivots from using traditional clinical data to integrating broader information from non-traditional sources (socio-economic, behavioral, and environmental factors). **Table 1** highlights the concepts and distinctions between traditional MAI, GMAI, UMAI, and UHAI for data inputs, application scopes, and capabilities.

The main features of UMAI and UHAI includes the following two parts:

Incorporating Empathy and Intuition Abilities: The dual-process theory of human cognition distinguishes between a rapid, intuitive heuristic-based system and a slower, deliberate calculating system[2]. We propose a new paradigm, UMAI, to integrate a heuristic-based approach that harnesses extensive knowledge data, building an adaptive and smart system that considers the unique structure of medical data. This approach aims to create a system that adaptively addresses various medical tasks, considering the intricate relationships and patterns within medical information. Achieving this requires algorithms that incorporate decision rules based on multiple cues and overcoming technical challenges in data imputation, efficiency, and value alignment.

Incorporating Non-traditional Non-Clinical Data for Health: Our proposed model of UHAI would incorporate non-clinical data, which offers a wealth of information and perspectives to understand a user's health comprehensively and makes UHAI capable of gaining insights into health behaviors and characteristics from multiple angles. Additionally, these continuous signals provide the potential for UHAI to offer daily feedback and support to individuals, thereby fostering a more proactive and personalized approach to healthcare.

In the following section, we discuss how different elements can be incorporated to enable UMAI and UHAI models (**Figure 1**).

Health Data Integration and Alignment: Transformer techniques have demonstrated remarkable capabilities in integrating multiple data types into a specific modality. For instance, Imagebind[3] proposed using a visual model as the core and translating other modality data into the visual space. UniVAL**Error! Reference source not found.**[4] achieved this by projecting various data types into a model in a sequence-to-sequence manner. Although these studies are not directly designed for medical tasks, they shed light on potential directions to effectively integrate non-clinical data within MAI models.

Another critical research direction involves efficient data usage through data alignment for MAI. The need for paired medical data across diverse types makes training a unified model difficult. However, there are promising approaches to address this challenge. Contrastive learning presents a potential solution to tackle data missing problems during alignment[5]. Additionally, devising novel alignment strategies specifically for medical scenarios holds considerable promise compared to conventional alignment strategies based on semantics. These strategies could significantly enhance data alignment and utilization within MAI models, contributing to more effective and accurate MAI applications.

A vital step from UMAI to UHAI is gathering additional non-clinical data to support scenarios with less/no clinical data. Integrating more AIoT devices and high-quality wearable devices is essential in providing daily data support. These data might be useful in modeling a person's health state and enhancing our comprehension of human health from multiple perspectives. This is particularly crucial for developing countries, where technological integrations can provide invaluable insights and support in health-related matters.

Aligning MAI with Human Values: Aligning mainstream human values is a crucial requirement in the domain of MAI. Apart from the need to develop efficient and reasonable value alignment methods in general scenarios (e.g., Human Feedback Reinforcement Learning[6]), special attention ought to be given to the construction of high-quality alignment data (aligned with common sense) in the medical context. Thus, it is imperative to implement corresponding mechanisms for data quality control to ensure effective training.

Injection of Medical Tacit Knowledge: UMAI proposes to combine tacit knowledge, i.e., healthcare professionals' experiences and intuition ability, presenting a challenge in injecting new knowledge. A practical yet straightforward strategy involves constructing diverse sets of human-annotated data across various medical scenarios to capture human tacit knowledge in decision-making, and training models on this annotated data can help integrate human expertise into the models. Nevertheless, this process is highly costly. Another viable approach, imitation learning[7], could capture the expertise of healthcare professionals by training machine intelligence to understand the sequential action decisions of human experts. Novel methodologies to enable MAI models to assimilate valuable tacit knowledge should be explored.

In diagnosis and treatment, healthcare professionals often need to engage in a series of sequential reasoning and decision-making to arrive at a final judgment. With the development of LLMs, research on chain-of-thoughts[8] and tree-of-thoughts**Error! Reference source not found.** has significantly enhanced the reasoning capabilities of AI models. These advancements make it possible to integrate such reasoning processes into MAI models.

Multiple Medical Agent Collaboration: Due to the intricate conditions of one patient on some occasions, it may be necessary for multiple doctors from different specialties to discuss together to devise optimal treatment plans. Multi-agent systems in LLMs[10] can effectively enable MAI models to achieve similar textual dialogues and interactions, thereby gaining a more comprehensive understanding of a patient's pathophysiological status and appropriate interventions. This will also greatly enhance the decision-making accuracy and effectiveness in complex situations by making group decisions akin to healthcare professionals.

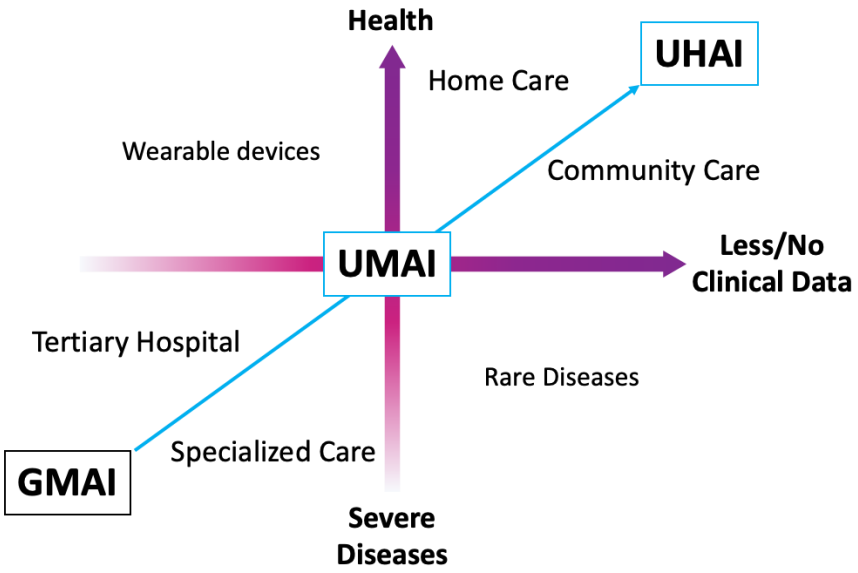
Foundation Model or New Backbone for MAI models: Transformer-based model architectures have brought about a transformative shift for MAI in recent years[11]. The advent of LLMs has spurred extensive research focused on constructing MAI models based on these foundation models. Just as Transformer is gradually superseding traditional architectures, more powerful foundation model architectures tailored for the needs of MAI scenarios hold the potential to ignite a new wave of research and development in MAI, such as NeuroAI techniques[12].

Conclusions

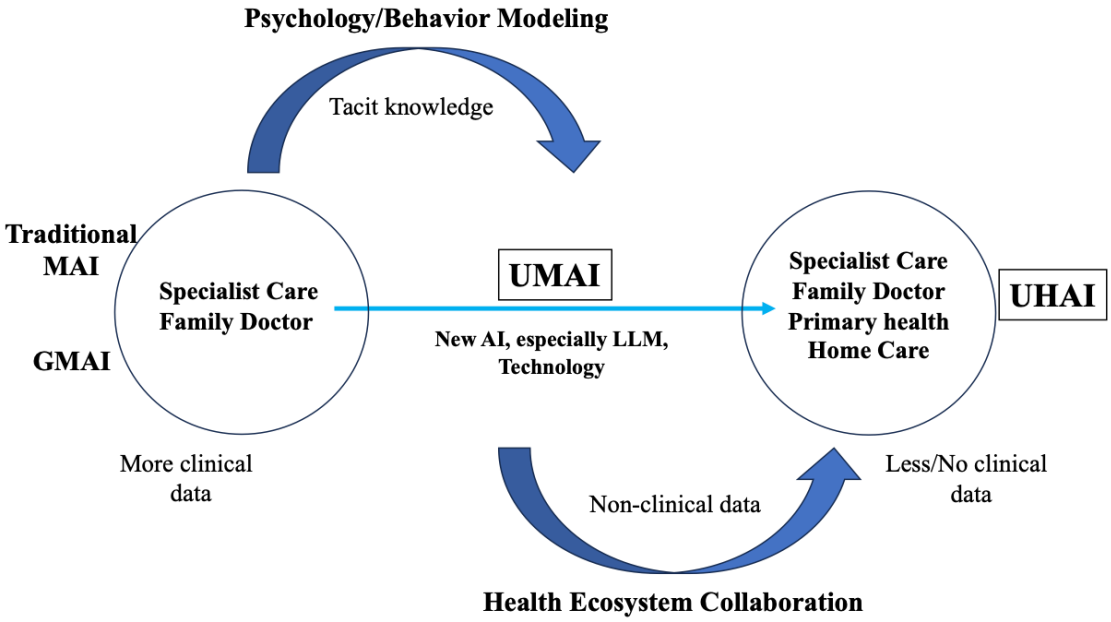
Recent research in MAI demonstrated a trend towards using multi-modality data for greater generalization across diverse medical tasks. The advent of LLMs and FM further expanded the possible applications of MAI. Despite these advancements, significant challenges must be solved in translation, adoption, and application. We propose UMAI and UHAI as innovative models to tackle these issues by integrating tacit knowledge alongside non-traditional and non-clinical data. This approach emphasizes a holistic view of health, aligning with WHO/UN goals for universal healthcare. By incorporating critical attributes of healthcare professionals, such as empathy and intuition, accrued through years of experience, into UMAI and UHAI, these new paradigms are poised to construct a more holistic MAI that addresses the broad healthcare spectrum.

Table 1. Comparison of Traditional MAI, GMAI, UMAI, and UHAI.

	Data	Tasks	Diseases	Scenarios	Abilities
Traditional MAI	Single modality data with limited domain knowledge	Single	Single	In-hospital & community settings	Perception
Generalist MAI (GMAI)	Multi-modality data with domain knowledge	Multiple	Multiple	In-hospital settings or separate healthcare settings	Perception, Cognition
Universal MAI (UMAI)	Multi-modality health data,with domain and **Tacit knowledge**	Multiple	Multiple diseases	**Healthcare system**	Perception, Cognition, **Physician and other healthcare professionals' abilities (e.g., empathy, intuition, wisdom)**
Universal Health AI (UHAI)	Multi-modality health data, with domain and **Tacit knowledge, and non-clinical data**	Multiple	Multiple diseases, Health states	**Universal health care, global health**	Perception, Cognition, **Physician and other healthcare professionals' abilities, including public health professionals**



(a)



(b)

Figure 1. (a) A Comparison Among GMAI, UMAI, and UHAI. UMAI and UHAI can deal with more health-related tasks with even less or no clinical data. (b) Roadmap from GMAI to UHAI. The development of UMAI and UHAI will require new data collation from tertiary hospitals to communities and homes, new AI techniques, and broader stakeholder engagement. More powerful AI techniques are needed in heterogeneous "messy" data integration, domain knowledge injection, and reasoning. Tacit knowledge modeling studies from the perspective of human behavioral science and psychology will be required to incorporate healthcare professionals' wisdom (e.g., empathy and intuition). These models require support from the traditional healthcare ecosystem and the broader society in providing non-clinical data on health and not just disease. This will be particularly important in developing countries with less or no clinical data.

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