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Framework for 10X Acceleration of Open Clinical AI Science

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Abstract

Although generative AI (GenAI) is transforming healthcare, it may take decades for its clinical impact to be fully realized due to inefficiencies in clinical science. Here, we propose a new vision for open clinical AI science and present a practical framework that provides free GenAI prediction services for all doctors worldwide. This approach enables widespread participation in the generation and dissemination of new evidence for the responsible use of GenAI in clinical care across all diseases. Broad adoption of responsible use of open GenAI services by physicians will lead to more timely diagnoses and treatments, facilitate the sharing of synthetic data and fine-tuned AI models, and thus accelerate open clinical AI science by a factor of ten.

1. Identification of challenges facing GenAI transformation in healthcare

It is widely anticipated that GenAI will rapidly transform healthcare. A key driver is GenAI's intrinsic ability to democratize healthcare, as highlighted in our review on GenAI democratization (Chen et al., 2024). However, since ChatGPT demonstrated high accuracy in a variety of healthcare tasks, few published studies have generated evidence from real clinical settings (Bedi et al., 2025). This reality check raises questions about the time required to generate the clinical evidence needed for GenAI transformation.

1.1 Inefficiency in clinical evidence generation and dissemination

Developing medical knowledge is notoriously costly and slow. By some estimates, a single scientific breakthrough may require more than $1 billion and over a decade to progress from lab concept to clinical bedside. A major contributor to this inefficiency is the antiquated structure of clinical science, which still relies heavily on time-consuming and expensive clinical trials, slow publication cycles, and additional steps for clinical translation. Although large-scale initiatives such as NIH's All of Us program aim to accelerate clinical research, these efforts have not fundamentally improved the efficiency of clinical science.

1.2 Timeline challenges

Within the current clinical science infrastructure, GenAI clinical research faces the same challenges as before: (1) only a small number of researchers participate, (2) the generation of new clinical AI evidence is very slow, and (3) the clinical deployment of AI has a high failure rate. By the current pace, we estimate that it may actually take decades to generate the necessary evidence for all clinical tasks required to transform healthcare - a timeline that is unacceptable.

1.3 The danger of repeating the history of failed AI revolutions in healthcare

Since 2000, three technological attempts to revolutionize healthcare have failed. The traditional AI revolution in healthcare ended in 2011, exemplified by the IBM Watson chatbot. The first wave of genomics industry for precision medicine revolution collapsed in 2000, while the second wave derailed in early 2025. We believe the prolonged timeline for clinical validation was among the root causes of these failures. With these issues unresolved and overlooked, the slow pace of clinical science may cause GenAI to repeat past failures in transforming the healthcare industry.

2 A new vision for open clinical AI science (OCAIS)

To overcome timeline challenges, clinical science must undergo fundamental changes to achieve the efficiency required by GenAI while maintaining rigorous clinical evaluation and patient data protection.

2.1 Vision for 10X acceleration in the healthcare GenAI revolution

We propose a new vision for OCAIS, in which every clinician worldwide can contribute to and benefit from responsible use of GenAI. By sharing synthetic patient data and fine-tuned models, this vision enables a tenfold acceleration in the generation and dissemination of new clinical evidence. The vision establishes a foundation for automating clinical research processes using GenAI and synthetic data. Notably, OCAIS does not mean opening and sharing patient data directly. Instead, it creates a new framework for generating and sharing synthetic patient data, thereby protecting privacy and ensuring data security.

2.2 Improved version of the learning health system (LHS) vision focused on clinical science

The OCAIS vision builds upon the LHS vision from the US National Academy of Medicine (NAM), which aims to fix the inefficiencies in knowledge generation and dissemination (McGinnis et al., 2024). However, we recognize that mainstream LHS approaches often focus on large, complex systems requiring substantial resources, making them difficult to implement. In contrast, our previous pioneering study demonstrated that a minimal ML-enabled LHS unit for a single task can be implemented by any clinical team to achieve the two main objectives of LHS: rapid generation and dissemination of clinical AI evidence (Chen et al., 2022). We believe the convergence of GenAI and the LHS unit offers a scalable solution that can shift the timeline from decades to years for generating the clinical evidence required to transform healthcare.

2.3 Significance of the OCAIS vision

Realizing the OCAIS vision will have significant worldwide impact, enabling a tenfold acceleration in healthcare GenAI transformation. This time savings has the potential to save millions of lives, as GenAI will improve the timeliness of diagnosis and treatment in routine care.

3 A new framework for open clinical AI science

To realize the OCAIS vision, we propose a new framework composed of the following key components:

3.1 Providing free GenAI prediction services to all clinical teams worldwide

By leveraging baseline predictions for any clinical tasks, efficient techniques for fine-tuning large language models (LLMs), the high performance of open-source LLMs, and technologies for generating synthetic patient data, the framework can fine-tune LLMs to accurately predict all diseases at low cost. This enables free GenAI disease prediction services for all clinical teams worldwide, ensuring equitable access to high-accuracy GenAI across all populations, including underserved populations in low-resource and rural regions, and promoting health equity.

3.2 Supporting equitable GenAI-enabled clinical care

Any clinician, anywhere in the world, can use the free GenAI prediction services in diverse clinical settings to improve care quality according to high standards. The initial focus is on timely and accurate diagnosis across all diseases, particularly the complex, uncommon or rare diseases where GenAI can clearly assist doctors. GenAI support will be provided primarily through free online services for individual doctors, while human assistance will be available as needed. For clinical teams requiring on-premises GenAI deployment, the support team can help integrate GenAI into local clinical workflows.

3.3 Enabling every doctor to conduct embedded clinical GenAI research

Unlike traditional research, the OCAIS framework enables embedded clinical GenAI research for all.

3.3.1 Using RWD to generate RWE in routine healthcare

With free training in the comparative effectiveness research, any doctor can conduct observational studies using real-world data (RWD) during routine care. These studies enable all doctors to generate real-world evidence (RWE), improving care quality and supporting publication in peer-reviewed journals.

3.3.2 Using synthetic patient data to accelerate GenAI research

While top general-purpose LLMs such as ChatGPT-4.1, Gemini-2.5, Llama-4, Qwen-3 have high accuracy for many tasks, fine-tuning is often needed for specific clinical applications. To remove technical barriers for doctors, the framework generates synthetic data from de-identified patient cases for fine-tuning open-source LLMs and provides preclinical validation data. After verification, LLMs are further fine-tuned with more synthetic data and deployed with chatbot interface for clinical evaluation.

3.3.3 Sharing synthetic clinical data to accelerate evidence generation

To fine-tune LLMs for higher accuracy, doctors will need to pool synthetic patient data from multiple clinical sites, especially for rare and uncommon diseases. The framework provides free tools for doctors to easily generate and share synthetic data with others in research networks or medical communities.

3.3.4 Sharing task-specific fine-tuned LLMs for evidence dissemination

In this framework, fine-tuned LLMs become executable forms of evidence or knowledge. Unlike traditional medical guidelines, new evidence from embedded GenAI research can be disseminated instantly by sharing fine-tuned LLMs within networks, allowing doctors to apply this knowledge directly in healthcare.

3.3.5 Automating research processes for clinical GenAI science

To further accelerate OCAIS, the framework is able to increase automation of the embedded research processes, enabling doctors to more conveniently generate and disseminate clinical AI evidence.

3.4 Ensuring responsible use of AI for OCAIS

Aligned with the principles for the AI Code of Conduct recently released by NAM (Gonzalez et al., 2025), OCAIS prioritizes: (1) patient privacy and data security, (2) patient safety, (3) high efficacy at low cost, (4) preclinical validation, (5) equitable access, and (6) data biases reduction.

4 Progress of the OCAIS framework

NAM envisioned a future LHS capable of rapid generation and dissemination of clinical evidence, while our initial work pioneered an enhanced vision of equitable LHS units enabled by ML/AI. With LLM/GenAI, scalable implementation of LHS becomes practical, forming the foundation of OCAIS framework.

(1) **Feasibility proven**: We developed the first ML-LHS unit for disease prediction and shared synthetic patient data (Chen et al., 2022). After testing ChatGPT as a training copilot (Chen et al., 2023), we benchmarked ChatGPT's high prediction accuracy across 194 diseases with synthetic patient data (Chen et al., 2024). Recently we fine-tuned open-source Llama3.1-8B LLMs, increasing prediction accuracy from <60% to >90% for certain diseases in oncology, neurology, and immunology (Table 1), demonstrating the feasibility of providing free GenAI prediction services for all diseases. Our GenAI solution for navigators monitoring cancer care quality also won an award in a recent global challenge sponsored by Robert Wood Johnson Foundation (RWJF 2025).

(2) **Testing clinical integrations**: In collaboration with clinical teams, we are evaluating how physicians can effectively incorporate GenAI predictions into routine care delivery. Initial findings indicate that our GenAI diseases predictions enable physicians to rapidly identify uncommon or rare disease diagnoses that may benefit from GenAI support in retrospective studies, and subsequently validate these findings progressively in real clinical settings for evidence generation and publication. Our collaborators plan to rapidly share and disseminate the resulting executable evidence through clinical research networks, accelerating the generation of additional evidence supporting the timely diagnosis and treatment of rare diseases.

(3) **Expanding reach**: We are applying for funding to extend free GenAI prediction services to more low-resource clinics worldwide. Broader global collaborations are welcome.

Prediction of Example Diseases	Accuracy Before SFT	Accuracy After SFT
Lung Cancer	84%	98%
Nasopharyngeal Carcinoma	60%	97%
Lewy Body Dementia	45%	98%
Tethered Cord Syndrome	57%	96%
Rheumatoid Vasculitis	58%	99%

Table 1: Prediction accuracy before and after supervised fine-tuning (SFT) Llama3.1-8B models

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