A COLLECTION OF INNOVATIONS IN MEDICAL AI FOR PATIENT RECORDS IN 2024

Yuanyun Zhang

Department of Computer Science
University of the Chinese Academy of Sciences
{yuanyun81}@ucas.ac.cn

Shi Li

Department of Computer Science Columbia University

ABSTRACT

The field of Artificial Intelligence (AI) in healthcare is evolving at an unprecedented pace, driven by rapid advancements in machine learning and the recent breakthroughs in large language models (LLMs) (Zhao et al., 2023). While these innovations hold immense potential to transform clinical decision-making, diagnostics, and patient care, the accelerating speed of AI development has outpaced traditional academic publishing cycles. As a result, many scholarly contributions quickly become outdated, failing to capture the latest state-of-the-art methodologies and their real-world implications. This paper advocates for a new category of academic publications—an annualized citation framework—that prioritizes the most recent AI-driven healthcare innovations. By systematically referencing the breakthroughs of the year, such papers would ensure that research remains current, fostering a more adaptive and informed discourse. This approach not only enhances the relevance of AI research in healthcare but also provides a more accurate reflection of the field's ongoing evolution.

1 Introduction

Artificial Intelligence (AI) has become an integral force in shaping the future of healthcare (Rajpurkar et al., 2022), with applications spanning from predictive modeling and diagnostics (Kasula, 2021) to personalized medicine and automated clinical decision support. Recent advancements in deep learning, particularly the rise of large language models (LLMs) (Zhao et al., 2023), have further accelerated innovation, unlocking new possibilities for applying large scale models to biomedical research. However, this rapid progress presents a fundamental challenge: the traditional academic publishing cycle struggles to keep pace with the speed of AI development. By the time a study is peer-reviewed and published, newer, more advanced models and techniques may have already rendered its findings outdated or incomplete.

This discrepancy raises critical concerns about the relevance and longevity of AI research in health-care. While conventional papers provide valuable theoretical and empirical contributions, they often fail to reflect the field's most current state. As AI-driven solutions continuously redefine the boundaries of what is possible, there is a growing need for an alternative publication model that prioritizes recent innovations.

To address this issue, we propose a new category of academic papers that explicitly cite the break-throughs of the year, ensuring that discussions and analyses remain grounded in the latest developments. This approach would not only improve the timeliness of AI research in healthcare but also foster a more dynamic and iterative academic ecosystem. By incorporating up-to-date references and acknowledging the fluid nature of AI advancements, such papers would enhance the accuracy, relevance, and practical impact of AI-driven healthcare research.

2 Language Models

In 2024, the field of biomedical natural language processing (NLP) witnessed significant advancements with the development of several specialized language models tailored for health and biomed-

ical applications. These models have been designed to enhance various tasks, including information retrieval, question answering, and text generation within the biomedical domain.

One notable contribution is MediSwift, introduced by Thangarasa et al. (2024). This model employs sparse pre-training techniques on domain-specific biomedical text data, achieving up to 75% weight sparsity during pre-training. This approach results in a 2-2.5x reduction in training FLOPs, leading to more computationally efficient models without compromising performance. The study demonstrates that sparse pre-training, combined with dense fine-tuning and soft prompting, offers an effective method for creating high-performing, computationally efficient models in specialized domains.

In the realm of biomedical text retrieval, BMRetriever (Xu et al., 2024b) was developed to enhance retrieval tasks across various biomedical applications. This model series utilizes unsupervised pretraining on large biomedical corpora, followed by instruction fine-tuning on a combination of labeled datasets and synthetic pairs. Experiments across multiple biomedical tasks and datasets have verified BMRetriever's efficacy, demonstrating strong parameter efficiency. Notably, the 410M variant outperforms baselines up to 11.7 times larger, and the 2B variant matches the performance of models with over 5B parameters.

Addressing the challenge of referring ability in biomedical language models, Jiang et al. (2024) introduced a method to improve this aspect by designing a pre-training sequence that enhances the model's capacity to refer to entities within biomedical texts. Empirical studies demonstrate that this approach improves both intra-sample and inter-sample referring abilities of auto-regressive language models in the biomedical domain, encouraging more profound consideration of task-specific pre-training sequence design for continual pre-training.

Another significant development is BioMedLM (Bolton et al., 2024), a 2.7 billion parameter GPT-style autoregressive model trained exclusively on PubMed abstracts and full articles. Despite its relatively smaller size compared to models like GPT-4 (Achiam et al., 2023) and Med-PaLM 2 (Singhal et al., 2025), BioMedLM demonstrates competitive performance on multiple-choice biomedical question-answering tasks. For instance, it achieves a score of 57.3% on MedMCQA (dev) (Pal et al., 2022) and 69.0% on the MMLU Medical Genetics exam (Wang et al., 2024b). This indicates that smaller, targeted models can serve as transparent, privacy-preserving, and economical foundations for specific NLP applications in biomedicine.

Additionally, BioMistral (Labrak et al., 2024) was introduced as an open-source large language model tailored for the biomedical domain. Utilizing Mistral as its foundation model and further pre-trained on PubMed Central, BioMistral has been evaluated on a benchmark comprising 10 established medical question-answering tasks in English, demonstrating its applicability in health contexts.

3 EHR FOUNDATION MODELS

In 2024, foundation models for Electronic Health Records (EHRs) have seen remarkable advancements, addressing long-standing challenges such as computational efficiency, handling long patient histories, and adapting across diverse clinical tasks (Evans, 2016). As EHRs continue to serve as a vital source of patient information, these new models are pushing the boundaries of predictive accuracy and clinical decision-making by better capturing the complex, heterogeneous nature of medical data.

One of the key innovations in this space is the push for more scalable architectures that can handle longer patient histories without sacrificing computational efficiency. EHRMamba (Fallahpour et al., 2024) exemplifies this trend by leveraging the Mamba architecture, which allows it to process sequences up to four times longer than traditional models while maintaining linear computational complexity. By introducing Multitask Prompted Finetuning (MTF), EHRMamba is capable of learning multiple clinical tasks simultaneously, making it an efficient choice for deployment across different healthcare applications. Its use of the HL7 FHIR data standard further enhances its interoperability with existing hospital systems, making it easier to integrate into real-world clinical workflows. Benchmarks on the MIMIC-IV dataset (Johnson et al., 2020) confirm its strong performance across six key clinical prediction tasks, positioning it as a state-of-the-art model in EHR forecasting.

Table 1: Summary of Foundation Models for Electronic Health Records (EHRs) in 2024

Table 1: Summary of Foundation Models for Electronic Health Records (EHRs) in 2024		
Model	Key Features	Applications
EHRMamba	Scalable architecture us-	General-purpose EHR model, clinical
(Fallahpour et al.,	ing Mamba, supports	forecasting, multi-task learning in health-
2024)	long sequences, Multi-	care
	task Prompted Finetuning	
	(MTF), HL7 FHIR standard	
MOTOR	Time-to-event foundation	Risk stratification, chronic disease man-
(Steinberg et al.,	model, explicit modeling of	agement, ICU monitoring
2023)	event likelihood and timing	
Context Clues	Evaluates long-context	Long-term patient record analysis, tempo-
(Wornow et al.,	models for clinical pre-	ral modeling in EHRs
2024)	diction tasks, balances	
ĺ	computational cost with	
	predictive accuracy	
CORE BEHRT	Fine-tuned and optimized	Disease prediction, patient trajectory mod-
(Optimized)	version of BEHRT for EHR	eling
(Odgaard et al.,	data, rigorous evaluation	
2024)	, 2	
CEHR-GPT	Clinical text generation us-	Automated report generation, clinical doc-
(Pang et al., 2024)	ing large-scale pre-training	umentation, discharge summaries
	on medical text data	, 6
Event Stream GPT	GPT-based model capturing	Disease progression modeling, treatment
(McDermott et al.,	sequential dependencies in	pathway optimization
2023)	EHR data	1 3 .1
Retrieval-Enhanced	Integrates retrieval mecha-	Context-aware clinical decision support,
Medical Prediction	nisms to dynamically re-	lifelong patient record modeling
(Kim et al., 2024)	trieve past patient events	81
MEME (Lee et al.,	Converts multimodal EHR	Emergency department decision support,
2024b)	data into pseudo-notes,	multimodal learning for EHRs
	uses embedding models for	
	modality separation	
MetaGP (Liu et al.)	13-billion-parameter gener-	Rare disease diagnosis, emergency condi-
	ative model integrating EHR	tion management, biomedical research
	data and medical literature	management, oromodical resourch
EHRAgent	LLM-powered agent with	Few-shot learning for EHR reasoning,
(Shi et al., 2024)	code interface for au-	multi-tabular medical problem solving
(Sili Ct al., 2027)	tonomous data analysis	mata abatai medicai problem solving
	tonomous data allarysis	

Beyond general-purpose EHR models, several efforts have focused on temporal modeling, as predicting the timing of future medical events is critical in clinical practice. MOTOR (Steinberg et al., 2023) is one such time-to-event foundation model designed to improve risk stratification and proactive patient management. By explicitly modeling the likelihood and timing of future clinical events, MOTOR enhances real-time monitoring capabilities, making it particularly valuable for chronic disease management and intensive care settings. This focus on long-term patient history is further explored in Context Clues: Evaluating Long Context Models for Clinical Prediction Tasks on EHRs (Wornow et al., 2024), which examines how well different architectures handle extended patient records. The study highlights both the benefits and limitations of incorporating long-term data, providing insights into how models should be optimized to balance computational cost with predictive accuracy.

Another key area of improvement has been the refinement of existing architectures to better fit EHR-specific challenges. Building on the BEHRT framework (Li et al., 2020), A Carefully Optimized and Rigorously Evaluated BEHRT (Odgaard et al., 2024) presents an optimized version of this transformer-based model. The study demonstrates how careful fine-tuning and rigorous evaluation lead to superior performance across multiple clinical tasks, emphasizing the importance of domain-specific adjustments when adapting foundation models for healthcare.

While many models focus on structured EHR data, there has also been an increasing interest in bridging the gap between structured and unstructured clinical notes. CEHR-GPT (Pang et al., 2024), for instance, is designed to generate high-quality clinical text, automating documentation tasks such as discharge summaries and radiology reports. By training on a diverse corpus of clinical narratives, CEHR-GPT produces more coherent and contextually accurate reports, reducing the documentation burden on healthcare professionals and improving standardization across medical records.

In parallel, models like Event Stream GPT (McDermott et al., 2023) have focused on capturing the sequential nature of clinical events. By leveraging a GPT-based architecture, this model learns dependencies between events in a patient's medical history, aiding in disease progression modeling and personalized treatment planning. This approach allows for a deeper understanding of patient trajectories and could prove useful in complex conditions where interactions between multiple factors play a crucial role in disease evolution.

Another promising trend is the integration of retrieval mechanisms to enhance medical predictions. The General-Purpose Retrieval-Enhanced Medical Prediction Model Using Near-Infinite History (Kim et al., 2024) exemplifies this direction by leveraging extensive patient histories to inform clinical predictions. Unlike conventional models that process patient data sequentially, this model retrieves relevant past events dynamically, ensuring that long-term patterns are incorporated into decision-making. Such retrieval-based architectures underscore the importance of lifelong patient records in developing more robust and context-aware clinical models.

Recognizing that much of EHR data is heterogenous, new models have emerged to tackle the challenge of integrating diverse data types. The Multiple Embedding Model for EHR (MEME) (Lee et al., 2024b) takes an innovative approach by converting many data sources from the EHR and turns them into pseudo-notes, effectively mimicking clinical text. This enables pretrained foundation models to process structured EHR data more naturally while preserving categorical relationships. By encoding embeddings separately for each modality, MEME achieves superior feature representation and has demonstrated strong performance in Emergency Department decision-support tasks (Chen et al., 2023) across multiple hospital systems. Its success in outperforming traditional machine learning models and even some EHR-specific foundation models suggests that multimodal fusion strategies will play a critical role in the next generation of EHR-based AI.

Meanwhile, generative models are making significant strides in medical research applications. MetaGP (Liu et al.), a 13-billion-parameter generative foundation model, integrates both EHR data and medical literature to provide diagnostic support across a range of clinical scenarios, including rare disease identification and emergency condition management. By training on over ten million EHRs and an extensive corpus of medical literature, MetaGP demonstrates the potential of multimodal generative AI to bridge gaps between clinical practice and biomedical research.

Another innovative approach comes from EHRAgent (Shi et al., 2024), which introduces an LLM-powered agent with a built-in code interface for EHR reasoning. Unlike traditional models that passively predict outcomes, EHRAgent actively generates and executes custom analytical scripts to derive insights from EHR data. This few-shot learning capability enables it to handle complex, multi-tabular reasoning tasks with minimal labeled examples, making it a highly flexible tool for real-world medical problem-solving.

Collectively, these advancements reflect a broader trend in EHR modeling—moving beyond static, one-size-fits-all architectures toward more adaptive, context-aware, and multimodal approaches. Whether through scalable architectures like EHRMamba, temporal models like MOTOR, retrieval-enhanced frameworks, or generative models like MetaGP, 2024 has witnessed a fundamental shift in how AI systems engage with EHR data. These innovations pave the way for more intelligent, real-time, and clinically meaningful AI applications that are better equipped to meet the challenges of modern healthcare.

4 Data Standards and Evaluations

In the rapidly evolving field of healthcare AI, the establishment of robust data standards and comprehensive evaluation frameworks is crucial for ensuring the reliability, reproducibility, and applicability of machine learning models in clinical settings.

4.1 DATA STANDARDS

Medical Event Data Standard (MEDS) The question "Do we need data standards in the era of large language models?" is addressed in a study (Brat et al., 2024) examining the interplay between LLMs and existing medical data standards. The authors argue that, despite the advanced capabilities of LLMs, standardized data remains crucial for ensuring interoperability, accuracy, and reliability in healthcare applications. They suggest that LLMs should be designed to work within these standards to maintain consistency and trustworthiness in medical data processing. A significant advancement in this area is the introduction of the Medical Event Data Standard (MEDS) (Arnrich et al., 2024), a lightweight schema designed to facilitate machine learning over electronic health record (EHR) data. Unlike traditional common data models, MEDS offers a minimalistic yet highly interoperable framework that bridges various datasets, tools, and model architectures. By providing a simple standardization layer, MEDS enhances the reproducibility and robustness of machine learning research in healthcare.

Building upon this foundation, the MEDS Decentralized, Extensible Validation (MEDS-DEV) Benchmark has been developed to establish reproducibility and comparability in machine learning applications for health (Kolo et al., 2024). MEDS-DEV provides a decentralized framework that allows researchers to validate and compare their models across diverse datasets, promoting transparency and consistency in model evaluation. To streamline the extraction of meaningful cohorts from event-stream datasets, the Automatic Cohort Extraction System (ACES) (Xu et al., 2024a) has been introduced. ACES automates the identification of patient cohorts based on specific clinical criteria, thereby accelerating the research process and reducing the potential for human error in cohort selection. Complementing these tools is the Automated Tabularization and Baseline Methods for MEDS (MEDS-Tab) (Oufattole et al., 2024), which focuses on converting complex medical event data into structured tabular formats suitable for analysis. MEDS-Tab provides baseline methodologies for processing MEDS-formatted data, facilitating easier integration with various machine learning pipelines.

Schema-based Standards In the realm of schema matching within the EHR space, efforts have been directed towards harmonizing disparate data representations to ensure semantic consistency across systems. By aligning different EHR schemas, researchers can integrate data from multiple sources more effectively, enhancing the comprehensiveness of clinical studies and the generalizability of machine learning models.

EHRmonize (Matos et al., 2024) is a framework that leverages large language models (LLMs) to extract and abstract medical concepts from electronic health records (EHRs). Using real-world medication data, it evaluates how well LLMs perform on free-text extraction and binary classification tasks across different prompting strategies. The study shows that this approach significantly improves efficiency, cutting annotation time by about 60%. However, it also emphasizes the need for clinician oversight to ensure accuracy and reliability in real-world clinical settings.

4.2 EVALUATION FRAMEWORKS

Evaluating the performance of large language models (LLMs) in clinical contexts necessitates multifaceted and granular benchmarks. CliBench (Ma et al., 2024) addresses this need by offering a comprehensive evaluation suite that assesses LLMs across various clinical decision-making tasks, including diagnoses, procedures, lab test orders, and prescriptions. By providing structured output ontologies, CliBench enables precise and detailed evaluations, shedding light on the capabilities and limitations of LLMs in healthcare applications. Similarly, ClinicalBench (Chen et al., 2024) provides a platform to compare the clinical prediction capacities of LLMs against traditional machine learning models. Encompassing a wide range of models and tasks, ClinicalBench offers insights into the strengths and weaknesses of different modeling approaches in clinical prediction scenarios.

The Medical Adaptation of Large Language and Vision-Language Models study (Jeong et al., 2024) critically examines the progress made in tailoring LLMs and vision-language models for medical applications. By evaluating the adaptations and performance of these models in medical contexts, the study provides valuable insights into their current capabilities and areas needing improvement. Evaluating the performance of predictive models, especially under class imbalance, is critical in healthcare applications. The paper "A Closer Look at AUROC and AUPRC Under Class Imbal-

Table 2: Summary of Benchmarks for Large Language Models in Healthcare

Benchmark	Key Focus	Evaluation Criteria and Use Cases
CliBench (Ma et al.,	Clinical decision-making	Assesses LLMs on diagnoses, procedures,
2024)	tasks	lab test orders, and prescriptions using
		structured output ontologies
ClinicalBench	Comparison of LLMs with	Evaluates predictive performance of differ-
(Chen et al., 2024)	traditional ML models	ent model architectures across clinical pre-
		diction scenarios
AgentClinic	AI agents in multimodal	Evaluates adaptability of AI agents using
(Schmidgall et al.,	clinical settings	multimodal data in simulated clinical envi-
2024)		ronments
EHRNoteQA	Patient-specific question an-	Assesses the ability of LLMs to pro-
(Kweon et al., 2024)	swering	vide accurate, context-aware answers us-
		ing patient-specific EHR data
LongHealth	Handling long clinical docu-	Tests LLMs on extracting and reasoning
(Adams et al., 2024)	ments	over detailed medical texts

ance" delved into evaluation metrics commonly used in predictive modeling. The authors analyzed the effectiveness of the Area Under the Receiver Operating Characteristic Curve (AUROC) and the Area Under the Precision-Recall Curve (AUPRC), providing insights into their applicability and limitations. The study emphasized the importance of selecting appropriate metrics to accurately assess model performance in the presence of class imbalance (McDermott et al., 2025). In the domain of foundation model representations, the FEET: A Framework for Evaluating Embedding Techniques (Lee et al., 2024c) offers a structured approach to assess various embedding methods used in medical machine learning. By providing standardized evaluation metrics, FEET aids researchers in selecting appropriate embedding techniques for their specific applications.

Recognizing the importance of multimodal data in clinical environments, AgentClinic (Schmidgall et al., 2024) introduces a benchmark to evaluate AI agents in simulated clinical settings. By incorporating various data modalities and clinical scenarios, AgentClinic provides a comprehensive platform to assess the performance and adaptability of AI agents in healthcare. To address the need for patient-specific question-answering capabilities, EHRNoteQA (Kweon et al., 2024) presents a benchmark designed to evaluate LLMs in clinical settings. By focusing on patient-specific questions, this benchmark assesses the ability of LLMs to provide accurate and relevant information based on individual patient records. Lastly, LongHealth (Adams et al., 2024) offers a question-answering benchmark that deals with long clinical documents. By challenging models to process and extract relevant information from extensive clinical texts, LongHealth evaluates the proficiency of LLMs in handling complex and detailed medical documents.

5 APPLICATION

In 2024, the landscape of predictive modeling in healthcare experienced significant advancements (Wang et al., 2024a), with researchers leveraging artificial intelligence (AI) to enhance diagnostic accuracy, personalize treatment plans, and improve patient outcomes. A comprehensive survey by Wang et al. systematically reviewed recent developments in deep learning-based predictive models utilizing electronic health records (EHRs). The study categorized various predictive models and highlighted the challenges and future directions in this domain.

In the realm of chronic disease management, Munirathnam & Kanchetti (2024) explored the application of AI-powered predictive models for conditions such as diabetes and cardiovascular diseases. Their findings demonstrated that machine learning models, including neural networks and random forests, effectively predict disease progression, enabling earlier interventions and improved risk stratification. Focusing on chronic kidney disease (CKD), Jawad et al. (2025) proposed an AI-driven predictive analytics approach that combines ensemble learning with explainable AI techniques. Their model not only predicts CKD progression but also provides insights into the contributing factors, thereby supporting clinicians in making informed decisions.

In the context of sepsis, a condition with high mortality rates, Chang et al. (2024) addressed the need for fairness and transparency in predictive modeling. They introduced a method that enhances model fairness and employs a novel feature importance algorithm to elucidate each feature's contribution to equitable predictions, promoting trust and reliability in clinical applications. In the realm of clinical decision support, research has explored the application of foundation models in prescribing appropriate treatments. The study by Lee et al. (2024a) examined how these models analyze patient data to recommend antibiotics in line with established clinical guidelines. While the results were promising, the study emphasized the necessity for rigorous validation to ensure safety and efficacy before such models can be reliably implemented in real-world clinical environments. In primary healthcare settings, the implementation of AI-based CDSS has shown promise. A study by Gomez-Cabello et al. (2024) reviewed outcomes of such systems, noting improvements in clinical management, patient satisfaction, and safety, along with reductions in physician workload. However, the study also highlighted challenges related to physician perceptions and cultural settings, suggesting that further research is needed to optimize AI-CDSS applications in diverse clinical environments.

The integration of AI into clinical trials has also been a focal point, with recent work (Anuyah et al., 2024; Wornow et al., 2025; Jin et al., 2024). exploring how deep learning and predictive modeling can optimize trial design, patient recruitment, and real-time monitoring. Their study highlighted the potential of AI to stratify patients, forecast adverse events, and personalize treatment plans, thereby bridging precision medicine and patient-centered care. Yu et al. (2025) introduced Health-LLM, a personalized retrieval-augmented disease prediction system that combines large-scale feature extraction with medical knowledge trade-off scoring. This framework integrates health reports and medical knowledge into a large language model, enhancing disease prediction accuracy and supporting personalized health management.

The role of LLMs in medical coding has also been critically evaluated. The paper Large Language Models are Poor Medical Coders—Benchmarking of Medical Code Querying by Soroush et al. (2024) assessed the performance of LLMs in generating correct medical codes from clinical descriptions. Despite their advanced language capabilities, the models demonstrated limited accuracy in this task. This finding points to inherent challenges LLMs face in understanding and applying the structured language of medical coding, suggesting that reliance on these models for automated coding may be premature without further refinement. One area of investigation centers on the proficiency of LLMs in interpreting medical codes. A study by Lindsey & Lee (2024) delved into this by assessing the ability of LLMs to accurately map alphanumeric codes, such as ICD-10, to their corresponding medical terminologies. The findings revealed that current LLMs face challenges in this domain, often struggling to establish precise mappings. This underscores a significant gap in their comprehension of structured medical coding systems, highlighting the need for enhanced representations within LLMs to improve their utility in clinical settings.

Beyond coding, LLMs have been applied to specific areas of healthcare, such as maternal health. The paper "NLP for Maternal Healthcare: Perspectives and Guiding Principles in the Age of LLMs" by Antoniak et al. (2024) discussed the application of Natural Language Processing techniques, powered by LLMs, in analyzing and interpreting data related to maternal health. The authors outlined potential applications and ethical considerations, advocating for the development of guidelines to ensure responsible and effective use of LLMs in this sensitive area of healthcare. Patient behavior analysis has also benefited from LLM applications. In the study Miao et al. (2024) researchers employed LLMs to analyze patient narratives, aiming to identify factors contributing to changes in contraceptive methods. The findings demonstrated the potential of LLMs to extract meaningful insights from unstructured data, thereby aiding in understanding patient behaviors and informing healthcare strategies.

6 Conclusion

The rapid advancements in Artificial Intelligence, particularly in machine learning and large language models, are profoundly reshaping the landscape of healthcare. This paper has highlighted the transformative potential of these technologies in enhancing clinical decision-making, diagnostics, and patient care. However, the pace of AI innovation poses significant challenges to the traditional

academic publishing model, which often lags behind, rendering scholarly contributions quickly obsolete.

To address this gap, we advocate for the adoption of an annualized citation framework that emphasizes the most recent AI-driven healthcare innovations. By systematically referencing the latest breakthroughs, this approach ensures that research remains current and relevant, fostering a more dynamic and informed academic discourse. Such a framework not only enhances the immediacy and applicability of AI research in healthcare but also aligns scholarly communication with the fast-evolving nature of the field.

Our exploration of recent developments in language models and Electronic Health Record (EHR) foundation models underscores the necessity for adaptable and scalable AI systems tailored to the complexities of medical data. Innovations like MediSwift, BMRetriever, and EHRMamba exemplify the strides being made towards more efficient and accurate healthcare AI applications. Additionally, the establishment of robust data standards and comprehensive evaluation frameworks, as discussed, is crucial for ensuring the reliability and reproducibility of AI models in clinical settings.

The applications of AI in predictive modeling further demonstrate its potential to revolutionize patient care through improved diagnostic accuracy, personalized treatment plans, and enhanced patient outcomes. Nonetheless, challenges such as model fairness, transparency, and the integration of AI systems into existing clinical workflows must be meticulously addressed to realize the full benefits of these technologies.

Looking forward, the proposed annualized citation framework represents a pivotal step towards synchronizing academic research with the swift advancements in AI. By embracing this innovative publication model, the healthcare AI community can ensure that research remains at the forefront of technological progress, ultimately driving more effective and timely solutions in patient care. Continued collaboration between researchers, clinicians, and policymakers will be essential in navigating the complexities of AI integration, fostering an environment where cutting-edge innovations can thrive and translate into meaningful clinical impact.

REFERENCES

- Josh Achiam, Steven Adler, Sandhini Agarwal, Lama Ahmad, Ilge Akkaya, Florencia Leoni Aleman, Diogo Almeida, Janko Altenschmidt, Sam Altman, Shyamal Anadkat, et al. Gpt-4 technical report. *arXiv preprint arXiv:2303.08774*, 2023.
- Lisa Adams, Felix Busch, Tianyu Han, Jean-Baptiste Excoffier, Matthieu Ortala, Alexander Löser, Hugo JWL. Aerts, Jakob Nikolas Kather, Daniel Truhn, and Keno Bressem. Longhealth: A question answering benchmark with long clinical documents, 2024. URL https://arxiv.org/abs/2401.14490.
- Maria Antoniak, Aakanksha Naik, Carla S Alvarado, Lucy Lu Wang, and Irene Y Chen. Nlp for maternal healthcare: Perspectives and guiding principles in the age of llms. In *The 2024 ACM Conference on Fairness, Accountability, and Transparency*, pp. 1446–1463, 2024.
- Sydney Anuyah, Mallika K Singh, and Hope Nyavor. Advancing clinical trial outcomes using deep learning and predictive modelling: bridging precision medicine and patient-centered care. World Journal of Advanced Research and Reviews, 24(3):001–025, December 2024. ISSN 2581-9615. doi: 10.30574/wjarr.2024.24.3.3671. URL http://dx.doi.org/10.30574/wjarr.2024.24.3.3671.
- Bert Arnrich, Edward Choi, Jason Alan Fries, Matthew B.A. McDermott, Jungwoo Oh, Tom Pollard, Nigam Shah, Ethan Steinberg, Michael Wornow, and Robin van de Water. Medical event data standard (MEDS): Facilitating machine learning for health. In *ICLR 2024 Workshop on Learning from Time Series For Health*, 2024. URL https://openreview.net/forum?id=IsHy2ebjIG.
- Elliot Bolton, Abhinav Venigalla, Michihiro Yasunaga, David Hall, Betty Xiong, Tony Lee, Roxana Daneshjou, Jonathan Frankle, Percy Liang, Michael Carbin, and Christopher D. Manning. Biomedlm: A 2.7b parameter language model trained on biomedical text, 2024. URL https://arxiv.org/abs/2403.18421.

- Gabriel A Brat, Joshua C Mandel, and Matthew BA McDermott. Do we need data standards in the era of large language models?, 2024.
- Chia-Hsuan Chang, Xiaoyang Wang, and Christopher C. Yang. *Explainable AI for Fair Sepsis Mortality Predictive Model*, pp. 267–276. Springer Nature Switzerland, 2024. ISBN 9783031665356. doi: 10.1007/978-3-031-66535-6_29. URL http://dx.doi.org/10.1007/978-3-031-66535-6_29.
- Canyu Chen, Jian Yu, Shan Chen, Che Liu, Zhongwei Wan, Danielle Bitterman, Fei Wang, and Kai Shu. Clinicalbench: Can Ilms beat traditional ml models in clinical prediction?, 2024. URL https://arxiv.org/abs/2411.06469.
- Emma Chen, Aman Kansal, Julie Chen, Boyang Tom Jin, Julia Reisler, David E Kim, and Pranav Rajpurkar. Multimodal clinical benchmark for emergency care (mc-bec): A comprehensive benchmark for evaluating foundation models in emergency medicine. *Advances in Neural Information Processing Systems*, 36:45794–45811, 2023.
- R Scott Evans. Electronic health records: then, now, and in the future. *Yearbook of medical informatics*, 25(S 01):S48–S61, 2016.
- Adibvafa Fallahpour, Mahshid Alinoori, Wenqian Ye, Xu Cao, Arash Afkanpour, and Amrit Krishnan. Ehrmamba: Towards generalizable and scalable foundation models for electronic health records, 2024. URL https://arxiv.org/abs/2405.14567.
- Cesar A Gomez-Cabello, Sahar Borna, Sophia Pressman, Syed Ali Haider, Clifton R Haider, and Antonio J Forte. Artificial-intelligence-based clinical decision support systems in primary care: A scoping review of current clinical implementations. *European Journal of Investigation in Health, Psychology and Education*, 14(3):685–698, 2024.
- K M Tawsik Jawad, Anusha Verma, Fathi Amsaad, and Lamia Ashraf. Ai-driven predictive analytics approach for early prognosis of chronic kidney disease using ensemble learning and explainable ai, 2025. URL https://arxiv.org/abs/2406.06728.
- Daniel P. Jeong, Saurabh Garg, Zachary C. Lipton, and Michael Oberst. Medical adaptation of large language and vision-language models: Are we making progress?, 2024. URL https://arxiv.org/abs/2411.04118.
- Junfeng Jiang, Fei Cheng, and Akiko Aizawa. Improving referring ability for biomedical language models. In Yaser Al-Onaizan, Mohit Bansal, and Yun-Nung Chen (eds.), *Findings of the Association for Computational Linguistics: EMNLP* 2024, pp. 6444–6457, Miami, Florida, USA, November 2024. Association for Computational Linguistics. doi: 10.18653/v1/2024.findings-emnlp.375. URL https://aclanthology.org/2024.findings-emnlp.375/.
- Qiao Jin, Zifeng Wang, Charalampos S Floudas, Fangyuan Chen, Changlin Gong, Dara Bracken-Clarke, Elisabetta Xue, Yifan Yang, Jimeng Sun, and Zhiyong Lu. Matching patients to clinical trials with large language models. *Nature communications*, 15(1):9074, 2024.
- Alistair Johnson, Lucas Bulgarelli, Tom Pollard, Steven Horng, Leo Anthony Celi, and Roger Mark. Mimic-iv. *PhysioNet. Available online at: https://physionet. org/content/mimiciv/1.0/(accessed August 23, 2021)*, pp. 49–55, 2020.
- Balaram Yadav Kasula. Ai-driven innovations in healthcare: Improving diagnostics and patient care. *International Journal of Machine Learning and Artificial Intelligence*, 2(2):1–8, 2021.
- Junu Kim, Chaeeun Shim, Bosco Seong Kyu Yang, Chami Im, Sung Yoon Lim, Han-Gil Jeong, and Edward Choi. General-purpose retrieval-enhanced medical prediction model using near-infinite history, 2024. URL https://arxiv.org/abs/2310.20204.
- Aleksia Kolo, Chao Pang, Edward Choi, Ethan Steinberg, Hyewon Jeong, Jack Gallifant, Jason A Fries, Jeffrey N Chiang, Jungwoo Oh, Justin Xu, et al. Meds decentralized, extensible validation (meds-dev) benchmark: Establishing reproducibility and comparability in ml for health. 2024.

- Sunjun Kweon, Jiyoun Kim, Heeyoung Kwak, Dongchul Cha, Hangyul Yoon, Kwanghyun Kim, Jeewon Yang, Seunghyun Won, and Edward Choi. Ehrnoteqa: An llm benchmark for real-world clinical practice using discharge summaries, 2024. URL https://arxiv.org/abs/2402.16040.
- Yanis Labrak, Adrien Bazoge, Emmanuel Morin, Pierre-Antoine Gourraud, Mickael Rouvier, and Richard Dufour. BioMistral: A collection of open-source pretrained large language models for medical domains. In Lun-Wei Ku, Andre Martins, and Vivek Srikumar (eds.), *Findings of the Association for Computational Linguistics: ACL 2024*, pp. 5848–5864, Bangkok, Thailand, August 2024. Association for Computational Linguistics. doi: 10.18653/v1/2024.findings-acl.348. URL https://aclanthology.org/2024.findings-acl.348/.
- Simon A. Lee, Trevor Brokowski, and Jeffrey N. Chiang. Enhancing antibiotic stewardship using a natural language approach for better feature representation, 2024a. URL https://arxiv.org/abs/2405.20419.
- Simon A Lee, Sujay Jain, Alex Chen, Arabdha Biswas, Jennifer Fang, Akos Rudas, and Jeffrey N Chiang. Multimodal clinical pseudo-notes for emergency department prediction tasks using multiple embedding model for ehr (meme). *arXiv preprint arXiv:2402.00160*, 2024b.
- Simon A Lee, John Lee, and Jeffrey N Chiang. Feet: A framework for evaluating embedding techniques. *arXiv preprint arXiv:2411.01322*, 2024c.
- Yikuan Li, Shishir Rao, José Roberto Ayala Solares, Abdelaali Hassaine, Rema Ramakrishnan, Dexter Canoy, Yajie Zhu, Kazem Rahimi, and Gholamreza Salimi-Khorshidi. Behrt: transformer for electronic health records. *Scientific reports*, 10(1):7155, 2020.
- Timothy Lindsey and Simon A. Lee. Can large language models abstract medical coded language?, 2024. URL https://arxiv.org/abs/2403.10822.
- Fei Liu, Hong-Yu Zhou, Kai Wang, Yunfang Yu, Yuanxu Gao, Hanpei Miao, Zixing Zou, Zhuomin Li, Bingzhou Li, Lan Wang, et al. Metagp: A generative foundation model integrating electronic health records and multimodal imaging for addressing unmet clinical needs.
- Mingyu Derek Ma, Chenchen Ye, Yu Yan, Xiaoxuan Wang, Peipei Ping, Timothy S Chang, and Wei Wang. Clibench: A multifaceted and multigranular evaluation of large language models for clinical decision making, 2024. URL https://arxiv.org/abs/2406.09923.
- João Matos, Jack Gallifant, Jian Pei, and A Ian Wong. Ehrmonize: A framework for medical concept abstraction from electronic health records using large language models. arXiv preprint arXiv:2407.00242, 2024.
- Matthew B. A. McDermott, Bret Nestor, Peniel Argaw, and Isaac Kohane. Event stream gpt: A data pre-processing and modeling library for generative, pre-trained transformers over continuous-time sequences of complex events, 2023. URL https://arxiv.org/abs/2306.11547.
- Matthew B. A. McDermott, Haoran Zhang, Lasse Hyldig Hansen, Giovanni Angelotti, and Jack Gallifant. A closer look at auroc and auprc under class imbalance, 2025. URL https://arxiv.org/abs/2401.06091.
- Brenda Y Miao, Christopher YK Williams, Ebenezer Chinedu-Eneh, Travis Zack, Emily Alsentzer, Atul J Butte, and Irene Y Chen. Identifying reasons for contraceptive switching from real-world data using large language models. *arXiv* preprint arXiv:2402.03597, 2024.
- R Munirathnam and D Kanchetti. Artificial intelligence (ai)-powered predic-tive models in chronic disease management: A data-driven approach. *International Journal of Computer Science and Information Technology Research (IJCSITR)*, 5(1):42–54, 2024.
- Mikkel Odgaard, Kiril Vadimovic Klein, Sanne Møller Thysen, Espen Jimenez-Solem, Martin Sillesen, and Mads Nielsen. Core-behrt: A carefully optimized and rigorously evaluated behrt, 2024. URL https://arxiv.org/abs/2404.15201.

- Nassim Oufattole, Teya Bergamaschi, Aleksia Kolo, Hyewon Jeong, Hanna Gaggin, Collin M. Stultz, and Matthew B. A. McDermott. Meds-tab: Automated tabularization and baseline methods for meds datasets, 2024. URL https://arxiv.org/abs/2411.00200.
- Ankit Pal, Logesh Kumar Umapathi, and Malaikannan Sankarasubbu. Medmcqa: A large-scale multi-subject multi-choice dataset for medical domain question answering. In *Conference on health, inference, and learning*, pp. 248–260. PMLR, 2022.
- Chao Pang, Xinzhuo Jiang, Nishanth Parameshwar Pavinkurve, Krishna S. Kalluri, Elise L. Minto, Jason Patterson, Linying Zhang, George Hripcsak, Gamze Gürsoy, Noémie Elhadad, and Karthik Natarajan. Cehr-gpt: Generating electronic health records with chronological patient timelines, 2024. URL https://arxiv.org/abs/2402.04400.
- Pranav Rajpurkar, Emma Chen, Oishi Banerjee, and Eric J Topol. Ai in health and medicine. *Nature medicine*, 28(1):31–38, 2022.
- Samuel Schmidgall, Rojin Ziaei, Carl Harris, Eduardo Reis, Jeffrey Jopling, and Michael Moor. Agentclinic: a multimodal agent benchmark to evaluate ai in simulated clinical environments, 2024. URL https://arxiv.org/abs/2405.07960.
- Wenqi Shi, Ran Xu, Yuchen Zhuang, Yue Yu, Jieyu Zhang, Hang Wu, Yuanda Zhu, Joyce Ho, Carl Yang, and May D Wang. Ehragent: Code empowers large language models for complex tabular reasoning on electronic health records. *arXiv* preprint arXiv:2401.07128, 2024.
- Karan Singhal, Tao Tu, Juraj Gottweis, Rory Sayres, Ellery Wulczyn, Mohamed Amin, Le Hou, Kevin Clark, Stephen R Pfohl, Heather Cole-Lewis, et al. Toward expert-level medical question answering with large language models. *Nature Medicine*, pp. 1–8, 2025.
- Ali Soroush, Benjamin S Glicksberg, Eyal Zimlichman, Yiftach Barash, Robert Freeman, Alexander W Charney, Girish N Nadkarni, and Eyal Klang. Large language models are poor medical coders—benchmarking of medical code querying. *NEJM AI*, 1(5):AIdbp2300040, 2024.
- Ethan Steinberg, Jason Fries, Yizhe Xu, and Nigam Shah. Motor: A time-to-event foundation model for structured medical records. *arXiv* preprint arXiv:2301.03150, 2023.
- Vithursan Thangarasa, Mahmoud Salem, Shreyas Saxena, Chen-Yu Leong, Joel Hestness, and Sean Lie. MediSwift: Efficient sparse pre-trained biomedical language models. In Lun-Wei Ku, Andre Martins, and Vivek Srikumar (eds.), *Findings of the Association for Computational Linguistics: ACL 2024*, pp. 214–230, Bangkok, Thailand, August 2024. Association for Computational Linguistics. doi: 10.18653/v1/2024.findings-acl.14. URL https://aclanthology.org/2024.findings-acl.14/.
- Jiaqi Wang, Junyu Luo, Muchao Ye, Xiaochen Wang, Yuan Zhong, Aofei Chang, Guanjie Huang, Ziyi Yin, Cao Xiao, Jimeng Sun, and Fenglong Ma. Recent advances in predictive modeling with electronic health records, 2024a. URL https://arxiv.org/abs/2402.01077.
- Yubo Wang, Xueguang Ma, Ge Zhang, Yuansheng Ni, Abhranil Chandra, Shiguang Guo, Weiming Ren, Aaran Arulraj, Xuan He, Ziyan Jiang, et al. Mmlu-pro: A more robust and challenging multi-task language understanding benchmark. *arXiv* preprint arXiv:2406.01574, 2024b.
- Michael Wornow, Suhana Bedi, Miguel Angel Fuentes Hernandez, Ethan Steinberg, Jason Alan Fries, Christopher Ré, Sanmi Koyejo, and Nigam H. Shah. Context clues: Evaluating long context models for clinical prediction tasks on ehrs, 2024. URL https://arxiv.org/abs/2412.16178.
- Michael Wornow, Alejandro Lozano, Dev Dash, Jenelle Jindal, Kenneth W Mahaffey, and Nigam H Shah. Zero-shot clinical trial patient matching with llms. *NEJM AI*, 2(1):AIcs2400360, 2025.
- Justin Xu, Jack Gallifant, Alistair EW Johnson, and Matthew McDermott. Aces: Automatic cohort extraction system for event-stream datasets. *arXiv preprint arXiv:2406.19653*, 2024a.

- Ran Xu, Wenqi Shi, Yue Yu, Yuchen Zhuang, Yanqiao Zhu, May Dongmei Wang, Joyce C. Ho, Chao Zhang, and Carl Yang. BMRetriever: Tuning large language models as better biomedical text retrievers. In Yaser Al-Onaizan, Mohit Bansal, and Yun-Nung Chen (eds.), *Proceedings of the 2024 Conference on Empirical Methods in Natural Language Processing*, pp. 22234–22254, Miami, Florida, USA, November 2024b. Association for Computational Linguistics. doi: 10.18653/v1/2024.emnlp-main.1241. URL https://aclanthology.org/2024.emnlp-main.1241/.
- Qinkai Yu, Mingyu Jin, Dong Shu, Chong Zhang, Lizhou Fan, Wenyue Hua, Suiyuan Zhu, Yanda Meng, Zhenting Wang, Mengnan Du, and Yongfeng Zhang. Health-llm: Personalized retrieval-augmented disease prediction system, 2025. URL https://arxiv.org/abs/2402.00746.
- Wayne Xin Zhao, Kun Zhou, Junyi Li, Tianyi Tang, Xiaolei Wang, Yupeng Hou, Yingqian Min, Beichen Zhang, Junjie Zhang, Zican Dong, et al. A survey of large language models. *arXiv* preprint arXiv:2303.18223, 2023.